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Life Cycle Regulation of Transportation Fuels: Uncertainty and its Policy Implications

by

Richard J. Plevin

A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy

in

Energy and Resources

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Michael O'Hare, Chair Adjunct Associate Professor Margaret Torn Professor Lee Friedman

Fall 2010

Life Cycle Regulation of Transportation Fuels: Uncertainty and its Policy Implications

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Abstract

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by

Richard J. Plevin

Doctor of Philosophy in Energy and Resources University of California, Berkeley Professor Michael O'Hare, Chair

Many national and regional governments have been promoted biofuels as a strategy to mitigate the climate change effects of the existing petroleum-based transportation system. New performance-based policies such as the California Low-Carbon Fuel Standard and the US Renewable Fuel Standard use Life Cycle Assessment (LCA) to estimate greenhouse gas (GHG) emissions to determine the life cycle global warming effects of each fuel production pathway. However, the current generation of policies have largely ignored the highly uncertain and often subjective nature of LCA assessments. Considering these uncertainties raises questions about the appropriateness of using an LCA-based estimate as a performance metric in public policy.

The objective of this dissertation is to characterize—qualitatively and quantitatively—the many data, parameter, model, and decision uncertainties inherent to estimates of the life cycle climate effects of transportation fuels, and to critically examine the robustness of these policies to these uncertainties. As demonstrated herein, LCA-based fuel regulations may accomplish much less than expected, and have the potential to cause more climate change than a business-as-usual scenario absent biofuels. Alternative policies that acknowledge uncertainty and respect the limitations of LCA—and thus of our understanding of the benefits of LCA-based policies—can be more robust in achieving GHG reductions.

For Olivia, whose buoyant spirit and humor keep me optimistic about the future.

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Part I Introduction

CHAPTER 1

INTRODUCTION

"Performance-based standards depend on the ability of government agencies to specify, measure, and monitor performance, but reliable and appropriate information about performance may sometimes be difficult if not impossible to obtain. When implemented in the wrong way, or under the wrong conditions, performance-based regulation will function poorly, as will any regulatory instrument that is ineffectually deployed."

Coglianese et al. (2003)

1.1 MOTIVATION

Carbon dioxide emissions from the transportation sector comprise about one third of total CO₂ emissions in the US, and 40% of the total in California (CARB, 2009a). Steep reductions in national and state greenhouse gas (GHG) emissions will therefore require reductions in the transportation sector. To help mitigate the climate change impact of this sector, new policies are being implemented to reduce the global warming intensity¹ (GWI) of transportation fuels, which are presently dominated by petroleum-based gasoline and diesel. These regulations attempt to account for the life cycle emissions of GHGs, i.e., the GHGs emitted during all phases of the fuel cycle, including production, distribution, and use of all transportation fuels. In California, the Low-Carbon Fuel Standard (LCFS) requires fuel blenders to reduce the GWI of the fuels they sell 10% or more by 2020 (CARB, 2009a). At the US federal level, the updated Renewable Fuel Standard (RFS2) combines volume mandates with life cycle GHG performance requirements (USEPA, 2010b). At least twelve US states are currently considering the implementation of fuel standards based on California's, though these may be superseded by a national standard (United States Congress, 2007b;

¹The more common terms "carbon intensity" and "low-carbon" are misnomers. Some climate-active emissions (e.g., N₂O) and biophysical effects (e.g., albedo, evapotranspiration) are not a function of carbon content, and some emissions of carbon (i.e., short-cycle biotic carbon) are *not* counted as part of "carbon" intensity. The form in which carbon is emitted (e.g., CO, CO₂, CH₄, black carbon, organic carbon) would not, in principle, affect a fuel's "carbon" intensity, but each molecular form imparts a distinct global warming effect. Finally, I note that the term "carbon intensity" was chosen for the LCFS not for scientific accuracy but because "low-global-warming-intensity fuel standard" was insufficiently mellifluous. As in my prior publications, I use the term *global warming intensity* herein.

Anon., 2009). Similar regulations have been proposed in British Columbia and the European Union (European Parliament, 2009).

Unfortunately, life cycle assessment (LCA) is as much art as science: it is common for different life cycle analysts to reach divergent conclusions when ostensibly examining the same product (Farrell et al., 2006b; Plevin, 2009; Hoefnagels et al., 2010). The divergence is generally attributable to different assumptions and methodological choices made by analysts (Farrell et al., 2006b; Cherubini et al., 2009; Hoefnagels et al., 2010). In addition to a lack of methodological consensus, process and emissions data are often variable or imprecisely known, especially for natural and agricultural systems. Finally, the regulations noted above require accounting for GHG emissions that occur elsewhere in the global economy, mediated by commodity markets, induced by biofuel production. Estimates of indirect effects are even more divergent and uncertain (Babcock, 2009; Liska and Perrin, 2009).

As I illustrate herein, life-cycle-based fuel GHG policies presuppose a level of accuracy that is beyond the reach of LCA. The many uncertainties inherent in standard LCA are well-characterized in the literature, and the subject of how uncertainty is handled in LCA has been addressed in several reviews (Lloyd and Ries, 2007; Heijungs and Huijbregts, 2004; Ross et al., 2002). The ISO standards for LCA state clearly that "LCA addresses potential environmental impacts; LCA does not predict absolute or precise environmental impacts due to", among other things, "the inherent uncertainty in modeling of environmental impacts" (ISO, 2006b). Standard LCA, which is based on supply chain analysis, does not attempt to address induced (market-mediated) effects beyond the supply chain. The techniques to estimate these effects are immature and subject to much debate, with efforts by regulatory agencies such as CARB and USEPA currently defining the frontier of the discipline.

Statistical uncertainties can be propagated through a life cycle model using various techniques, the most common being Monte Carlo simulation. This capability is supported in several commerciallyavailable LCA tools such as GaBi, SimaPro, and Umberto² and LCA databases such as EcoInvent (Frischknecht et al., 2007). However, the treatment of uncertainty in LCA remains inconsistent, incomplete, or more often, simply omitted (Lloyd and Ries, 2007). Studies that do quantify uncertainty tend to focus on parameter uncertainty and a few alternative scenarios (Lloyd and Ries, 2007). Model uncertainty (discussed further in Section 2.2) appears responsible for more of the overall uncertainty in biofuel GHG analysis than does variability and parameter uncertainty. Key areas of unresolved LCA methodology include disagreements over how to estimate marketmediated effects such as indirect land use change, how to handle co-products, questions about which climate forcings to include in our global warming intensity measure, and how exactly to aggregate these.

California's LCFS requires that the life cycle GHG emissions from fuels used in light-duty vehicles within California be 10% lower in 2020 than in 2010. To achieve this, each fuel is assigned a GWI rating, and fuel blenders are required to reduce their average fuel carbon intensity (AFCI) to

²For more information on these products see http://www.gabi-software.com, http://www.pre.nl (SimaPro), and http://www.umberto.de.

the targeted level through (i) efficiency improvements, (ii) blending with lower-rated fuels, (iii) using banked credits from earlier over-compliance, or (iv) trading with firms that have over-complied and thus generated reduction credits (CARB, 2009a). The LCFS fuel ratings are treated as accurate to within 0.01 g $CO_2e MJ^{-1}$, yet without any consideration of uncertainty. Therefore, an important question that has gone unanswered—and largely unasked—is this: *Given the uncertainty inherent in LCA, how confident are we that a nominally LCFS-compliant fuel scenario actually meets or exceeds the targeted 10% reduction in global warming intensity*? And if we aren't highly certain of meeting the reduction target, are we at least fairly certain that the policy will reduce, rather than increase, GHG emissions? Similar questions pertain to RFS2 and to LCA-based policies being considered or implemented elsewhere. To answer these questions requires an analysis of uncertainty. I believe that an examination of uncertainty will lead to policies that more robustly achieve their climate objectives. But first, we must overcome the habit of ignoring uncertainty.

1.2 GOALS

In the pages below, I analyze the efficacy of fuel policies that rely on life cycle assessment (LCA) to quantify the relative climate effects of transportation fuel alternatives, and to consider possible improvements to these policies. At the highest level, my question is simply this: *Are we reasonably sure that these policies mitigate, rather than exacerbate, climate change?* Given the high degree of uncertainty associated with the global warming intensity (GWI) of some fuel pathways—particularly for crop-based biofuels—and the lack of consideration to system responses such as market reshuffling and rebound effects, the answer is not obvious. The cumulative effect of these factors on the efficacy of fuel GHG policies is poorly understood.

The purpose of my research is to examine whether the uncertainty surrounding estimates of the relative climate effects of different transportation fuels is sufficiently broad that current policies may be producing little benefit, or worse, producing disbenefits. In particular, I examine these questions:

- 1. What is the character of the uncertainty in estimates of life cycle climate effects of transportation fuels? That is, what are the shapes of possible probability distributions under competing scenarios?
- 2. Under what conditions will existing LCA-based policies fail to achieve their intended goals, and under what conditions are they likely to succeed?
- 3. Given these uncertainties, what type of policies (or changes to existing policies) would be produce a more robust reduction in the climate change effects of transportation?

1.3 CONTRIBUTIONS

My research offers contributions in four areas:

- 1. I examine the uncertainties inherent in estimates of the life cycle greenhouse gas (GHG) emissions from transportation fuels. Although a few LCA studies consider and even quantify portions of the uncertainty, there have been few studies focused on the uncertainty itself.
- 2. I characterize the uncertainty associated with indirect land use change, countering the mistaken notion that ILUC emissions should be ignored because estimates are highly uncertain. Given the political environment surrounding ILUC (e.g., the Peterson (2009) amendment to the Waxman-Markey bill), I believe this is a particularly timely and important contribution. I believe my reduced-form model of ILUC can help shift the discussion of ILUC uncertainty to a more useful direction, from assertions of "too much uncertainty" toward better characterizations of that uncertainty and consideration of the implications of the uncertainty on policy design.
- 3. I examine the efficacy of two approaches to regulating the GWI of fuels, the California Low-Carbon Fuel Standard (LCFS) and the US Renewable Fuel Standard. Several other jurisdictions are planning to emulate the CA LCFS, so it is crucial that we understanding of the limits of this approach. I believe my work has the potential to inform and perhaps alter the trajectory of these efforts in the US and abroad.
- 4. Finally, I provide methodological guidance on the use of LCA in policies to mitigate climate change. The "ILUC debacle" has highlighted important shortcomings in the standard (attributional) approach to LCA. As I demonstrate, these shortcomings invalidate attributional LCA for use as a performance measure in public policy. However, the alternative (consequential) approach is inherently uncertain, raising important questions about policy robustness.

1.4 DISSERTATION STRUCTURE

This dissertation is organized in four parts, each consisting of multiple chapters.

Part I provides background information on the topics at the core of my research. Chapter 2 introduces the concepts of life cycle analysis, uncertainty, and uncertainty analysis. Chapter 3 introduces key uncertainties in the global warming intensity of biofuels.

Part II examines uncertainties in estimates of the GHGs directly emitted across the biofuel supply chain. Chapter 4 compares two life cycle models of GHG emissions from corn ethanol production—GREET and BESS—using a meta-model to examine differences in assumptions and identify errors and sources of disagreement. Chapter 5 uses Monte Carlo simulation in the GREET model to explore the uncertainty surrounding the GWI of corn and cellulosic ethanol, gasoline, and electricity.

Part III examines the uncertainty in estimates of emissions from land use changes induced by the expanded production of biofuels. Chapter 6 reviews the challenges of modeling ILUC emission. Chapter 7 explores the uncertainty in the ground-breaking Searchinger et al. (2008b) study of ILUC, using Monte Carlo analysis. Chapter 8 examines uncertainty in the ILUC emissions for corn ethanol, using Monte Carlo analysis and interval analysis based on a reduced-form model of ILUC.

Part IV concludes with an examination of the limitations of LCA-based fuel policy. Chapter 9 examines strategies for coping with uncertainty in the science-policy interface. Chapter 10 examines the efficacy of the LCFS at achieving emission reductions. Chapter 11 summarizes the main results of my research and suggests further research to improve the design of fuel and transportation GHG policies.

CHAPTER 2

BACKGROUND

"In the face of scientific uncertainty, regulatory outcomes depend critically upon what conclusions are drawn from the data, and upon what level of certainty is required as a prerequisite to regulatory action. The process of interpreting and applying incomplete data is full of judgments, some of the type familiar to research scientists, others of the type familiar to political actors. To the extent that these judgments are not objectively determined by the data, they are not scientific in the sense that dominates popular mythology. To the extent that factors other than scientific evidence inform them, they are not scientific even in an expansive sense."

Holly Doremus (2005)

2.1 PURPOSE AND SCOPE

This chapter introduces two core concepts underlying this dissertation: *uncertainty* (section 2.2) and *life cycle analysis* (section 2.3).¹ The intersection of these two topics, i.e., uncertainty in life cycle assessment, is discussed in section 2.4. This chapter provides background information of a more general nature. Chapter 3 focuses specifically on uncertainty in the LCA of biofuels.

The key points of this chapter (and of chapter 3) are that (i) owing to methodological challenges, LCA is incapable of producing definitive, objective results, and (ii) LCA results are, in many cases, highly uncertain. Although these limitations have been discussed frequently in the LCA literature, they appear to have been overlooked in the design of LCA-based regulations.

¹It is not my intention to provide complete reviews of these topics here, but rather to introduce concepts that are addressed in more depth in subsequent chapters. For a more complete introduction to LCA, I recommend the guidebook by Guinee et al. (2001), the report on *Market information in life cycle assessment* by Weidema (2003), and the many excellent documents found at www.calcasproject.net, the website of the *Co-ordination Action for innovation in Life-Cycle Analysis for Sustainability*. For more information on the representation and analysis of uncertainty, I recommend Morgan et al. (1990) and Krupnick et al. (2006).

2.2 UNCERTAINTY

Model building is a process of approximation, extrapolation, and simplification, resulting, inevitably, in divergence between modeled results and the processes modeled. That models are imperfect and their results uncertain is not controversial. However, when model results form the basis for a decision, it becomes essential to understand how and whether the uncertainty affects the decision (Morgan et al., 1990; Krupnick et al., 2006). This requires quantitative analysis of uncertainty. This section discusses the different types of uncertainty encountered in models, and technique for combining and propagating these uncertainties through to model results.

2.2.1 Types of uncertainty

Uncertainty can be viewed along several dimensions, and researchers have developed various typologies to categorize uncertainty (e.g., Morgan et al., 1990; Cullen and Frey, 1999; Krupnick et al., 2006; Refsgaard et al., 2007). It's generally agreed that the primary distinction among types of uncertainty is between (i) variability resulting from heterogeneity of individuals in a population, and across time or space, and (ii) lack of knowledge, which includes both parameter and model uncertainty. A third category, *decision uncertainty*, involves subjective choices that define the problem analyzed or how the model results are interpreted, e.g., the choice of analytic horizon to consider and whether to use discounting (Krupnick et al., 2006). This can be considered a type of epistemic uncertainty, since the decision-maker does not know which choice will best meet the goals motivating the analysis.

In practice, the specifics of the typology are not terribly important, as the main function of a typology of uncertainty is to guide analysts and decision-makers to consider all sources of uncertainty. Figure 2.1 illustrates the typology of Krupnick et al. (2006), itself a composite produced from several venerable sources such as Morgan et al. (1990) and Cullen and Frey (1999), among others.

2.2.1.1 VARIABILITY

Variability (also known as aleatory, stochastic, or objective uncertainty) occurs when some empirical quantity of interest actually exists within a population that varies across time, space, or individuals (Krupnick et al., 2006). The requirement in a model of choosing one value to represent this heterogeneity results in uncertainty. Variability is considered *irreducible* uncertainty in that additional knowledge or research cannot change the basic feature of heterogeneity. This type of uncertainty, however, is easier to represent objectively given the availability of empirical data from which statistics can be drawn.

2.2.1.2 LACK OF KNOWLEDGE

Lack of knowledge (also known as epistemic, or subjective uncertainty), by definition, is not supported by empirical data. In the typology presented here, lack of knowledge is divided into two



Figure 2.1: Typology of uncertainties, based on Krupnick et al. (2006)

categories: *parameter* and *model* uncertainty. Parameter uncertainty is similar to variability in that both refer to empirical quantities. However, where variability concerns the heterogenous nature of some quantity of interest, parameter uncertainty results from a lack of understanding of the quantity of interest, and thus this type of uncertainty can may be reduced through further research. The value of a single model parameter may have both stochastic and epistemic components. For example, in a life cycle assessment, we may lack data about a particular production process and use proxy data to represent that process. This component of the LCA will have stochastic uncertainty associated with the proxy data as well as epistemic uncertainty related to how well the proxy represents the process of interest. Since we lack data about the actual process in question, it is impossible to quantify objectively the error introduced through the use of proxy data.

Model uncertainty differs from parameter uncertainty in that the former is related not to empirical quantities, but to the relationships among model inputs and outputs. For example, we may not know if a certain relationship is linear or non-linear, owing to inconclusive data or disagreement among experts. However, as Morgan et al. (1990) note, the distinction is somewhat slippery since a model parameter can be defined to select among different functional forms, converting model uncertainty into parameter uncertainty. As noted above, the main purpose of the typology is to ensure that all uncertainties are considered; the specific category into which an uncertainty is grouped is of little concern.

2.2.2 UNCERTAINTY ANALYSIS

Decision-makers who rely on models should be apprised of the uncertainty surrounding model results (Morgan et al., 1990; Krupnick et al., 2006). Of particular importance is an understanding of when model results span outcomes that would result in different decisions. In the regulatory context, ignoring uncertainty can give a false impression of distinguishability among alternatives (Weidema, 2000b; Basson and Petrie, 2007), which can result in regulations that fail to achieve their goals, or worse, that promote outcomes contrary to those intended (Cherubini et al., 2009).

Here, I identify two important components of uncertainty analysis: *sensitivity analysis*, which examines the relationship between a single model parameter and a model result, and *uncertainty propagation*, which combines the uncertainties in model inputs to estimate the uncertainty in model outputs.

2.2.2.1 SENSITIVITY ANALYSIS

The most common approach to examining model uncertainty involves local sensitivity analysis: one model parameter at a time is perturbed while holding other parameters at their nominal value and the change in model results is reported (Saltelli et al., 2006). However, though widely used, this type of analysis generally understates the uncertainty in a model. Saltelli et al. (2006) consider local sensitivity analysis "illicit and unjustified" for all but strictly linear models, since in non-linear models, the sensitivity to any single factor generally depends on the state of other variables. As a result, the ranges in model output identified when perturbing single parameters will understate the range possible when model parameters are altered simultaneously.

In contrast, *global* sensitivity analysis examines the contribution of individual parameters to the overall uncertainty in the model output while allowing all parameters to vary. A common global sensitivity analysis technique (supported in the Crystal Ball and @Risk software packages for example) uses the results of a Monte Carlo simulation (discussed further below) to report the rank correlations between input parameters and output parameters across the full range of input values selected in the simulation. This type of decomposition, though inexact, identifies the (generally few) parameters that contribute most of the variance, and thus where research might most beneficially be focused to reduce uncertainty (Morgan et al., 1990).

The value of global sensitivity analysis is two-fold: (i) it identifies factors that might profitably be studied further to reduce the uncertainty, and (ii) it identifies factors that contribute negligibly to the total variance, thereby allowing for simplification of the model by treating those factors as certain (Cariboni et al., 2007). I employ global sensitivity analyses in chapter 5 in the examination of direct emissions, and in chapter 8, where I examine indirect land use change.

2.2.2.2 UNCERTAINTY PROPAGATION

Given representations of the uncertainty in model inputs, the uncertainty in model outputs can be estimated. This "propagation" can be performed using analytical methods or stochastic simulation.

ANALYTICAL METHODS. Uncertainties can be combined using error propagation equations such as those given below for addition and multiplication of uncertain quantities. However, these analytic methods are accurate only if (i) the uncertainties are uncorrelated, (ii) the uncertainties are normally distributed, and (iii) the standard deviations of the normal distributions are less than about 30% of the mean (IPCC, 2000). When these conditions are not met, numerical solutions such as Monte Carlo simulation can be used, as described in the next section. The following equations and explanations thereof are taken from IPCC (2000, p. 6.12).

When uncertain quantities are combined additively, their combined uncertainty (subject to the constraints above) can be computed as shown in equation 2.1.

$$U_{total} = \frac{\sqrt{(U_1 \times x_1)^2 + (U_2 \times x_2)^2 + \dots + (U_n \times x_n)^2}}{x_1 + x_2 + \dots + x_n}$$
(2.1)

where:

 U_{total} is the percentage uncertainty in the sum of the quantities (half the 95% confidence interval divided by the total (i.e., mean) and expressed as a percentage;

 x_i and U_i are the uncertain quantities and the percentage uncertainties associated with them, respectively.

When uncertain quantities are combined multiplicatively, their combined uncertainty (subject to the constraints above) can be computed as shown in equation 2.2.

$$U_{total} = \sqrt{U_1^2 + U_2^2 + \dots + U_n^2}$$
(2.2)

where:

 U_{total} is the percentage uncertainty in the product of the quantities (half the 95% confidence interval divided by the total and expressed as a percentage;

 U_i are the percentage uncertainties associated with each of the quantities.

STOCHASTIC SIMULATION. Also known as Monte Carlo simulation, this approach involves the assignment of a probability distribution to each uncertain model parameter and the repeated evaluation of the model using one value selected from each parameter distribution. The set of values for a single model output computed by these simulations defines a frequency distribution from which statistics can be calculated. Typical simulation use hundreds to thousands of model evaluations, depending on the precision required.

Unlike the analytical methods described above, stochastic simulation provides accurate results regardless of the shape of the probability distributions used to represent model parameters. How-

ever, for some models, running a full Monte Carlo analysis may be impractical owing to long solution times—because of system complexity or simply because the modeling system requires human intervention. In these cases, approximate results obtained using analytical methods may be preferable to having no analysis of uncertainty at all (See, for example, the use of the Gaussian Quadrature method to approximate uncertainty in the GTAP model in Hertel et al., 2010a).

Model uncertainty in particular and epistemic generally are challenging to represent probabilistically. These uncertainties are frequently excluded from Monte Carlo analyses and instead examined using discrete scenarios. However, when scenarios are used, it becomes difficult to produce a single persuasive frequency distribution for use in decision analysis or regulation. Importantly, in some models the differences between scenarios can overwhelm parameter uncertainty and variability (Morgan et al., 1990; Krupnick et al., 2006).

CORRELATED VARIABLES. Correlation among variables can increase or decrease the variance of functions of them. Generally, the variance of a sum or product of random variables is larger if they are positively correlated, smaller if negatively. These correlations can be represented in a Monte Carlo simulation to restrain the choice of values for correlated parameters to respect the stated correlation. In some cases, correlations are difficult to assess, but it is possible to structure the model so that the correlations are represented internally. For example, the difference in GWI between two fuels—which share dependencies on the production and upstream use of electricity, petroleum, natural gas, and so on—can be computed in each trial so that a distribution of the difference can be produced that respects the values of shared model structures.

REPRESENTING EPISTEMIC UNCERTAINTY. Ferson and Ginzburg (1996) demonstrate that calculations based on a uniform distribution are very different than those using an interval with the same bounds when nothing is known about the shape of the probability distribution between those bounds. Using a range asserts that the value of the parameter is located within the bound, but we make no statement about the likelihood of any particular location, while using a uniform distribution asserts that the value is *equally likely* to occur at any point between the stated minimum and maximum (Ferson and Ginzburg, 1996).

Aven (2010) comments on Ferson, downplaying the distinction between epistemic and stochastic uncertainty, and taking the personalist view of probability. Specifically, Aven says that there are two possible goals for an uncertainty analysis: (i) to obtain an objective description of the the unknown quantities, or (ii) to obtain a scientific judgment about the unknown quantities from a qualified group of people. The latter, of course doesn't claim to be objective. The latter approach recognizes that all uncertainty is relative to our present knowledge base and thus subjective (Morgan et al., 1990; Aven, 2010). From this perspective, it is perfectly legitimate to assign subjective probabilities that represent our *belief* that a parameter has a given probability. In this case, however, we must be careful to represent the resulting joint probability as similarly subjective. For a decision-maker, the estimation of a subjective probability based on expert judgment is generally better than no estimate of uncertainty at all, which is all too frequently the alternative (Morgan et al., 1990).

2.2.3 Avoiding uncertainty analysis

Uncertainty analysis is too frequently avoided completely or performed in a half-hearted manner and relegated to an appendix. There are clear disincentives for a modeler to perform uncertainty analysis: representing uncertainty can add significant complexity to a model, and Monte Carlo simulation can be very time-consuming. In many cases, an examination of uncertainty will demonstrate that the results of a modeling study are less clear than hoped. As Krupnick et al. (2006) write:

"Overall, there is a tendency to avoid formal uncertainty analyses unless the uncertainties can be included comprehensively and quantified precisely. An alternative arguably, preferred approach—would be to conduct uncertainty analysis as best as possible, even if abilities are limited; almost any uncertainty analysis is better than none at all."

I agree wholeheartedly with this assessment, assuming that the limitations of the analysis are properly characterized: if an analysis includes only a portion of the known uncertainties, it should not be represented as characterizing the full uncertainty. However, it may be more important that interested parties agree on the representation of uncertainty than that the representation is precisely quantified.

2.3 LIFE CYCLE ASSESSMENT

2.3.1 HISTORY AND PURPOSE

Life cycle assessment (LCA) is a tool to help assess the total resource use and environmental effects associated with products throughout their entire life cycle, from raw materials extraction, through production, transportation, use, and disposal (ISO, 2006a). The concept of LCA emerged in the late 1960s to early 1970s, with the first formal scheme in the US dating to 1969 to compare disposable versus reusable beverage containers (Hunt et al., 1996). An early focus of these studies, termed Resource and Environmental Profile Analyses (REPA) centered on the choice between reusable and disposable packaging or plastics versus paper products (Hunt et al., 1996). The OPEC boycott and energy crisis of 1973 sparked greater interest in the energy component of these analyses, but interest waned with the decline of petroleum prices, with public interest in LCA subsiding from 1975 to 1988 (Hunt et al., 1996).

According to ISO standard 14040 (ISO, 2006a), LCA can assist in

- "identifying opportunities to improve the environmental performance of products at various points in their life cycle,
- informing decision-makers in industry, government or non-government organizations (e.g. for the purpose of strategic planning, priority setting, product or process design or redesign),

- the selection of relevant indicators of environmental performance, including measurement techniques, and
- marketing (e.g. implementing an ecolabelling scheme, making an environmental claim, or producing an environmental product declaration)."

While a full LCA aims to describe all important environmental effects (e.g., global warming, eutrophication, acidification, human toxicity, resource consumption, biodiversity impacts), some studies and regulations concern only the life cycle inventory of GHG emissions associated with a product, typically expressed in terms of CO_2 equivalents (CO_2e), and generally including only emissions of CO_2 , CH_4 , and N_2O (Delucchi, 2010; Röös et al., 2010). These GHG-only analyses are sometimes called *carbon footprint* analyses.

2.3.2 METHODOLOGICAL ISSUES WITH LCA

Despite the existence of ISO standards 14040–14044 (ISO, 2006b,a), life cycle assessment is widely recognized in the literature as suffering from several methodological weaknesses (e.g., Weidema, 1993; Finnveden, 1999; Weidema, 2000b; Ekvall and Finnveden, 2001; Björklund, 2002; Delucchi, 2004; Reap et al., 2008b,a; Zamagni et al., 2008; Guinée et al., 2009; Finnveden et al., 2009; Kendall et al., 2009; Delucchi, 2010). As a result, LCA is not capable of producing a single, definitive description of the environmental footprint of a product. Rather, each LCA is a subjective analysis based on a wide array of analyst choices, approximations, and simplifications—and many uncertainties. An LCA result is best understood as a single plausible scenario among potentially many plausible scenarios. These key methodological issues are discussed in the sections below.

2.3.2.1 DATA GAPS

Life cycle assessments require an enormous amount of data. Reconstructing the supply chain contributing to any non-trivial product is a challenging task. If the specific origin of an input is known, the producer may prefer not to reveal the details of the production practices. In many cases, the specific origin is unknown, so the specific inputs and technologies employed are estimated, or a process for which data *is* available is used as a proxy. In practice, many—if not most—of the data for upstream processes in a life cycle inventory will be approximations or proxies.

2.3.2.2 System boundaries and truncation

To be practicable, LCA requires that system boundaries be set; processes beyond this boundary are ignored on the principle that n^{th} -order effects make ever-smaller contributions to the life cycle as n increases. However, according to Suh et al. (2004), "there is no theoretical or empirical basis that guarantees that a small mass or energy contribution will always result in negligible environmental impacts". Reap et al. (2008a) note that "while the individual inputs and outputs cutoff may be insignificant, their total sum might change the results considerably." In a consequential analysis,

market-mediated effects such as indirect land use change can strongly determine the outcome of an LCA even though these effects are completely outside the supply chain.

2.3.2.3 Aggregation over time and space

Most LCAs aggregate environmental effects spatially (Reap et al., 2008b). For well-mixed greenhouse gases (CO₂, CH₄, and N₂O), the location of emission is unimportant, so spatial aggregation is appropriate. However, for most other environmental effects, (e.g. water consumption, discharge of local and regional pollutants, and effects that are receptor-controlled) spatial aggregation produces results that may be of little value to decision-makers. As an example, summing water consumption across wet and dry regions, or local air pollution over densely- and sparsely-populated regions, produces values that bear little useful information for decision-making.

LCA also aggregates effects over time (Reap et al., 2008b). When emissions decay slowly (e.g., CO_2 , N_2O , persistent organic pollutants) the timing of discharges matters: when effects are measured relative to a fixed point in time, early discharges cause more damage than later discharges (O'Hare et al., 2009; Levasseur et al., 2010).

2.3.2.4 TREATMENT OF ELECTRICITY

The GHG emissions from electricity production systems vary greatly with fuel source and production technology (Kim and Dale, 2005; Jaramillo et al., 2007). However, unlike material flows, electricity does not flow from a specific power plant to a specific consumer; the electricity available at any point in time is a function of the total, instantaneous production in an electrically-contiguous grid.

In the US, average emissions in coal-dominated regions such as the portions of the midwest and Rocky Mountains exceed 1000 g $CO_2e MJ^{-1}$, whereas in regions dominated by hydroelectric or natural gas production systems, average emissions can be as low as 300–400 g $CO_2e MJ^{-1}$ (Plevin and Mueller, 2008). However, given regional interconnections and transmission limitations, the boundaries of the most relevant grid are not obvious. For US-based studies, some analysts use political (e.g., state) boundaries (e.g., CARB, 2009a), others use one of the aggregation levels defined by the National Electricity Reliability Council (NERC) (e.g., Sheehan et al., 2003; Plevin, 2009), and yet others use the US national average (e.g., Wang, 1999; Liska et al., 2009).

Electricity production varies not only spatially, but temporally, to meet demand that varies over the day and year. Systems meeting the base load generally have higher capital costs but lower marginal costs (e.g., nuclear, hydro, coal), whereas load-following systems that are used only a portion of the day or year have lower capital costs and higher marginal costs (e.g., natural gas). Thus the mix of production systems in use, and thus the GHG emissions, depends on which systems are dispatched at any moment. In the short run, a different mix of plants is running during peak production periods than is running during low production periods. In the long run, some production systems are retired and new ones introduced, changing emission profiles over longer timeframes as well. Therefore, if an analysis calls for using marginal emissions, it's important to

identify whether the short term "run margin" or the long term "build margin" is more appropriate.

Despite—or perhaps because of—the complexity resulting from this regional and temporal variance, LCA studies generally assume average US grid emissions when electricity is consumed (Weber et al., 2010)—or displaced, as in the case of cellulosic ethanol systems (Aden et al., 2002; Sheehan et al., 2003; Wu et al., 2006). This is even the case in some nominally consequential LCA studies such as the USEPA's modeling for RFS2 (USEPA, 2010a).

To estimate the short-run change in emissions resulting from a new load, or the electricity displaced by a new power source like a cellulosic ethanol biorefinery, an electricity dispatch model can be used. For example, McCarthy and Yang (2010) use an hourly dispatch model to simulate the mix of plants that will run to meet new demand for plug-in and fuel cell vehicles in California, concluding that the marginal emission rate will exceed 600 g CO_2e kWh⁻¹, which is higher than the CA grid average. Estimating long-run marginal emissions would require an electricity system planning and investment model that considers the effects of policies such as renewable portfolio standards and GHG emission caps.

2.3.2.5 TREATMENT OF CO-PRODUCTS

Many product systems—and virtually all bioenergy systems—yield multiple products. To isolate the environmental effects of one of the co-products, the environmental effects of the other co-products are subtracted from the total effects of the combined system. There are two main approaches to accounting for co-products in LCA. *Allocation* methods uses simple accounting principles (e.g., relative mass, energy content, or market price) to apportion gross emissions among co-products. In contrast, the *system expansion* method (also known as *displacement* or *substitution*) estimates the emissions avoided by the substitution by co-products for other products in the market. ISO 14040 recommends the use of system expansion where feasible, but considers allocation methods to be valid alternatives (ISO, 2006b). LCA results are highly sensitive to the choice of allocation method (Kim and Dale, 2002; Wang et al., 2004; Thomassen et al., 2008; Luo et al., 2009; Jaramillo et al., 2009; Guinée et al., 2009; van der Voet et al., 2010).

Many researchers have recognized that allocation methods fail to capture actual environmental impacts (Weidema, 1993; Ekvall and Finnveden, 2001; Reap et al., 2008a; Hoefnagels et al., 2010; Wang et al., 2010). Consider two identical biodiesel facilities that co-produce glycerin. One facility sells the glycerin to a cosmetics producer who uses it to produce soap, displacing some other (presumably more expensive) source of glycerin. The other facility sells the glycerin to a home heating fuel service where the glycerin is used instead of residual fuel oil. No matter which allocation method is used, allocation incorrectly estimates the environmental effects of at least one of these options. (And if it gets one right, it is only by sheer coincidence.) Other examples show the difficulties of applying these methods as a general rule: electricity cannot be meaningfully allocated on a mass basis, and ash, a combustion by-product which may contain useful minerals cannot be meaningfully allocated on an energy basis.

Market price is sometimes justified as a means of allocating environmental burdens by claiming that the price of a good reflects the motivation for creating each of the co-products. However, using

this approach, the environmental burden assigned to each co-product fluctuates with changing market conditions, even if the environmental outcomes are unchanged. The main failing of this approach is that it conflates cause and effect: LCA should be concerned with estimating outcomes, irrespective of underlying motivations.

A more realistic estimate of the environmental effects of a co-product requires a market analysis that reflects the changes in the market (and related environmental effects) induced by the introduction of the co-product into the market (Delucchi, 2004). Unfortunately, a market analysis requires a great deal of data, and models do not exist for all markets. Thus, LCA practitioners are faced with a choice between (i) difficult and uncertain market analyses that reflect reality, and (ii) simple accounting rules that don't reflect reality. Edwards et al. (2007b, p. 17), in their highly-cited study of transport fuels in Europe wrote:

Many other studies have used "allocation" methods whereby energy and emissions from a process are arbitrarily allocated to the various products according to e.g. mass, energy content, "exergy" content or monetary value. Although such allocation methods have the attraction of being simpler to implement they have no logical or physical basis. It is clear that any benefit from a by-product must *depend on what the by-product substitutes:* all allocation methods take no account of this, and so are likely to give flawed results.

The situation is more pithily summarized by Weidema (1993): "The advantage of allocation by physical properties—its ability to give consistent results—may thus be offset by these results being consistently wrong."

STUDIES OF CO-PRODUCT TREATMENT. Wang et al. (2004) examined the effect of different allocation methods on life cycle results for petroleum refinery products (figure 2.2.) Huo et al. (2008) examined the effect on the soybean biodiesel life cycle of differences in allocation (figure 2.3.) Both studies show that the relative GHG emissions per unit energy changes as a result of allocation method.

Other studies have suggested that the choice of co-product treatment isn't terribly important. For example, Curran (2007) examines five allocation methods (mass, volume, energy, market value, demand) in comparing corn ethanol to gasoline, concluding that the choice of allocation method doesn't substantially change the result of the comparison. While this may be true for the specific case examined, there is no theoretical basis for expecting this to be a generalizable result. More importantly, Curran fails to recognize that these methods are "consistently wrong", in the words of Weidema (1993).

In study of a similar flavor, Wang et al. (2010) examine the effect of the choice of co-product allocation method on GHG emissions for four biofuel pathways—corn ethanol, switchgrass ethanol, soybean biodiesel, and renewable diesel. The study considers allocation by mass, energy content, market value, and process purpose, as well as displacement. The results are shown in figure 2.4. Even while recognizing that the allocation methods fail to reflect environmental outcomes, Wang et al. (2010) conclude that "[c]onsistency in choice of co-product method may not serve the



Figure 2.2: Well-to-pump GHG emissions for petroleum refinery products (g $CO_2 e MJ^{-1}$) (Source: Wang et al., 2004).

purpose of providing reliable LCA results." (Though, importantly, the term "reliable" is left undefined.) Arguments presented by Wang et al. (2010) against the displacement method include that (i) it is "time intensive and resource consuming" compared to the convenient-but-unrepresentative allocation methods, and (ii) that for co-products that are really the main product (e.g., 82% of crushed soybean mass is soybean meal, not oil for biodiesel), the displacement method gives the "unreliable" result that the meal displaces 130% of the emissions from the joint process. This latter complaint, however, isn't an indictment of the displacement method, merely of its implementation. The question that should be asked is not "*What is displaced by the soybean meal when I use soybean oil to produce biodiesel?*" but rather, "*What is the net effect on GHG emissions when I produce biodiesel (including its co-products) compared to the case in which I don't produce the biodiesel?*" The GHG consequences estimated in the latter case will depend on the net change in GHG emissions in all related markets—protein meal, vegetable oils, animal feed, petroleum diesel.

The bottom line is that co-product credits are generally a large percentage of overall biofuel GHG emissions; if we cannot reliably estimate co-product credits, we cannot reliably estimate biofuel GHG emissions.

2.3.2.6 TREATMENT OF BIOGENIC CARBON

Biomass growth fixes atmospheric CO_2 , which is released back to the atmosphere when the biomass decays or is combusted. Rather than counting the offsetting photosynthetic sequestration of carbon



Figure 2.3: Life cycle GHG emissions and emission changes of soybean biodiesel relative to conventional fuels. 1, displacement; 2, energy-value-based allocation; 3, market-value-based allocation; 4, hybrid I; 5, hybrid II. (Source: Huo et al., 2008).

and emissions, LCA studies frequently use an accounting short-cut in which both the photosynthetic sequestration and subsequent emissions from combusting biogenic carbon are ignored in GHG emission calculations (Rabl et al., 2007; van der Voet et al., 2010).

Several problems with this approach have been identified. First, while plant growth always absorbs carbon in the form of CO_2 , the subsequent decay or combustion can release carbon as CO_2 , CH_4 , non-methane volatile organic compounds, black carbon, or organic carbon, each with a distinct warming (or cooling) effect. Second, sequestration and oxidation are balanced only for short-cycle growth and harvesting: deforestation releases long-standing stores of carbon into the atmosphere that are not necessarily replaced (Searchinger et al., 2009). Several studies have demonstrated that GHG policies that treat all biogenic carbon as climate-neutral can lead to large-scale deforestation since biofuels are credited with displacing fossil fuels, yet the loss of long-sequestered biomass is ignored (Wise et al., 2009; Melillo et al., 2009).

A third, closely related problem is evident under a consequential framing: unless the CO_2 sequestration is additional to what would have occurred without, say, a biofuel program, the assumed benefits of sequestration are necessarily indirect (Searchinger, 2010). Consider placing a new corn ethanol plant in Iowa and using local corn to produce ethanol. Assume the corn was already being produced for the feed or food markets. The carbon in the kernels would have been respired as



Figure 2.4: WTW greenhouse gas emissions of petroleum fuels and biofuels (g CO_2e MMBtu⁻¹) (Source: Wang et al., 2010).

 CO_2 by cattle or humans, but instead is emitted from fermentation and combustion. This ethanol produced from these corn kernels is climate-neutral only if the feed and food are not replaced. If replacement food is required, the production of that food must be counted. Searchinger (2010) make the case that the supposed climate-neutrality of biofuels are subject to precisely the same uncertainty as are ILUC emissions, as the two phenomena result from the same process.

A fourth problem with assuming carbon neutrality relates to co-product handling. For systems that don't generate co-products, assuming balanced biogenic carbon produces the same results as counting the sequestration and combustion. However, in systems with co-products, where and when the carbon is assumed to be sequestered and emitted can affect the life cycle results; under the climate neutrality shortcut, the CO_2 is not allocated with other flows (Luo et al., 2009). Several analysts have recommended that biogenic carbon be handled explicitly in LCA, which would be consistent with the treatment of all other environmental flows (Rabl et al., 2007; van der Voet et al., 2010)

2.3.3 ATTRIBUTIONAL VERSUS CONSEQUENTIAL LCA

The LCA typology includes two distinct approaches: *attributional* and *consequential* LCA (Ekvall and Weidema, 2004).² An attributional LCA (ALCA) inventories and analyzes the direct environ-

²Some earlier papers referred to the attributional and consequential framings as "retrospective" and "prospective", respectively (e.g., Tillman, 2000).

mental effects of some quantity of a particular product or service, recursively including the direct effects of all required inputs across the supply chain, as well as the direct effects of using and disposing of the product (ISO, 2006b). In simple terms, an attributional LCA of producing and using a pencil catalogues the environmental effects of making and processing bits of wood, brass, paint, rubber, and graphite, reaching back to include (for example) burning gasoline in a chain saw and, in principle, making the electricity used to sharpen the chain saw blade.³ The chain of inputs to inputs adds smaller and smaller quantities to the result, so cut-off critera are typically employed to reduce the collection requirements, although it is recognized that this introduces a truncation error of unknown magnitude (Suh et al., 2004).

ALCA relies on average activity levels and emission factors, and tends to focus on a small functional unit, e.g., 1 MJ of biofuel. In its pure form, attributional LCA handles co-products through allocation, as system expansion implies an analysis of change (Weidema and Ekvall, 2009). An important simplification employed in ALCA is that analysis is performed on a static system increasing production of a product is treated as having no effect on prices or on other production processes. Besides effects on other processes, a static analysis also treats environmental effects *within* the supply chain as if they scale linearly with increases in the functional unit: the results of an analysis for 1 liter of biofuel are assumed to scale linearly to tens of billions of liters. As the case of indirect land use change (addressed in Part III) demonstrates, this *ceteris paribus* treatment can result in significant errors in estimating environmental outcomes.

A consequential LCA (CLCA), in contrast, aims to describe the environmental effects of an action or policy (Ekvall and Weidema, 2004). This approach estimates the net changes in environmental effects given changes in a production system, recognizing that production is embedded within an economic system that adjusts in response to these changes—and these adjustments produce additional environmental effects (Ekvall and Weidema, 2004; Delucchi, 2006; Kløverpris et al., 2008). Simply put, while an attributional life cycle inventory (LCI) traces material and energy flows, a consequential LCI follows causal chains (Ekvall and Weidema, 2004). Thus, a consequential analysis of a policy to promote pencils would incorporate the effects of using—and thus producing—fewer ballpoint pens and crayons.

The life cycle inventory compiled in support of an attributional LCA differs from that compiled for a consequential LCA. Ekvall and Weidema (2004) write,

"When the aim is to describe the consequences of changes, it is usually not sufficient, and perhaps not even relevant, to trace the materials in the product investigated back to the cradle—that is, to the extraction or generation of the natural resources. The decision to buy the product does not necessarily imply an increase in the amount of natural resources extracted. In general terms, the consequences of an action do not necessarily propagate through the life cycle, but through the overall economic and technological systems in chains of cause-and-effect relationships, somewhat resembling the ripples caused by a stone thrown in a lake.

³Thanks to Mike O'Hare for the pencil and pens example.
The natural starting point of a consequential LCI of a specific decision is the decision itself—that is, the point where the stone hits the water. The consequential LCI describes how the decision affects the technological activity, both directly where the decision is implemented and its secondary effects on the use of intermediate products. It goes on to describe how this decision is expected to affect, for example, the production of these intermediate products as well as the use of the intermediate products in other processes. If it is possible to go further, the consequential LCI describes how these changes, in turn, are expected to affect other production processes, the use of energy, material and products in other parts of the technological system, and the environmentally relevant physical flows to and from the affected activities. Hence, the consequential LCI model does not resemble the traditional LCI model, where the main material flows are described from raw material extraction to waste management. Instead, it is a model of chains of causal relationships."

CLCA relies on marginal rather than average activity levels and emission factors, and considers the actual scale of change envisioned, e.g. billions of gallons of biofuel rather than 1 MJ of biofuel. Importantly, the life cycle inventory in a CLCA is not limited to the supply chain, but includes processes affected indirectly by the system under consideration as mediated through economic markets.

The number of published LCAs using a consequential framework has increased sharply since 2008, with studies appearing on biofuels-induced land use change (Kløverpris et al., 2008; Reinhard and Zah, 2009), vegetable oils (Schmidt and Weidema, 2008; Schmidt, 2008, 2010), soybean meal (Dalgaard et al., 2008), milk production (Thomassen et al., 2008), wind power Pehnt et al. (2008), and product price differences (Thiesen et al., 2008). However, other than the works of Kløverpris and Pehnt, none of these CLCAs utilize economic models. Rather, the authors simplistically assume that a single marginal supplier and marginal product can be identified (Kløverpris et al., 2008). This assumption may be valid for very small changes in the world's market basket of goods, but policy-scale changes such as those resulting from a national biofuel policy are probably large enough to affect multiple suppliers and products (Ekvall et al., 2005; Mathiesen et al., 2009). Indeed, the need to identify the affected commodities (i.e., technology and location) is one of the reasons to deploy an economic model.

But while it's easy to criticize the failings of more simplistic CLCAs, implemention of a more methodologically satisfying analysis (i.e., employing global economic models) presents its own challenges. Ekvall and Weidema (2004) note the benefits of integrating partial equilibrium analysis into LCI to perform causal chain analysis, while recognizing the greater uncertainties that result from this approach:

"It is reasonable to expect that the uncertainties in the economic analysis will be significant. Describing the consequences of decisions also means facing the general challenge of futures studies. The future is inherently uncertain, and the actual future consequences of decisions are highly uncertain. Dealing with this uncertainty requires that methods of futures studies are applied in the consequential LCI. The large uncertainties also make it impossible or pointless to estimate the consequences far down the cause-and-effect chains. This implies that the boundaries of the system investigated should ideally be defined at the point where the consequences are so small, or the uncertainties so large, that further expansion of the boundaries will yield no information that is significant for any realistic decision."

I believe Ekvall and Weidema are incorrect to suggest categorically that large uncertainties "yield no information". As shown in chapter 8, if the uncertainty range excludes some critical value (e.g. zero), we have very important information despite broad uncertainty.

2.3.3.1 ALCA GENERALLY ANSWERS THE WRONG QUESTION

The attributional and consequential frameworks describe different systems and answer fundamentally different questions (Weidema, 2003; Ekvall et al., 2005; Thomassen et al., 2008; Finnveden et al., 2009). An ALCA is a static decomposition of natural and industrial emissions organized by supply chain (Curran et al., 2005). This is a legitimate exercise that can provide useful information to manufacturers about production alternatives (Finnveden, 2000). ALCA is incapable, by design, of predicting the environmental effects of changes in production processes of a scale that affects other markets.

For example (as discussed in $\S2.3.2.4$), when the environmental burden of electricity use is estimated in ALCA, the average grid mix is usually considered. In CLCA, the result depends on the environmental burden of the next unit of electricity, which in turn depends on the timeframe considered. In the short-run, this is a question of dispatch order, so the answer varies over time. In the long-run, it's a question of electricity industry expansion, i.e. the next power plant that would be built. The consequential result also depends on policies such as renewable electricity quotas, CO_2 pricing, and emission caps on SO₂, NO_X, and so on (Pehnt et al., 2008).

Weidema and Ekvall (2009) argue that the results of an LCA are virtually always applied to effect a *change*, thus CLCA is relevant in most application areas of LCA. They write:

"It can be argued that all LCAs ultimately aim at supporting decisions on the substitution between two product systems (Weidema 2003). In one way or the other, studies of a single product are always later used in a comparative context. Even for hot-spotidentification and product declarations, what appears to be stand-alone assessments of single products have the ultimate goal to improve the studied systems, thus supporting decisions that involve comparisons."

Weidema and Ekvall (2009) identify a small number of cases in which ALCA could be considered: (i) "Studies at a societal level, where the entire environmental impact of all human activities is studied", though improvements or changes would need to be analyzed using CLCA; (ii) "Studies on environmental taxation, where the focus is less on the consequences of the tax, but rather on who is to carry the burden", although, again, the effect of the tax would need to be modeled using CLCA; and (iii) "Studies that seek to avoid blame or to praise or reward for past good behaviour", as such an analysis is inherently not about change, but about attribution, which can follow any desired rules. For essentially all other uses of LCA, a consequential approach is preferred.

2.3.3.2 Scale effects and non-linearity

In general, the environmental effects of a production system depend on the magnitude examined. Effects are not linear with scale because resource constraints can increase marginal (monetary and environmental) cost at increasing scales, and because economic feedbacks in the form of price changes can amplify or dampen effects (Bento and Landry, 2009; Porder et al., 2009).

Guinee et al. (2001) recognize that attributional LCA offers a crude representation of reality that might not be appropriate for decision-making:

"LCA deals with complex, interwoven networks of industrial, agricultural, household and waste management activities dispersed over many locations and potentially spanning many decades. The mechanisms governing the dynamics of these activities are of a technical, economic, social, cultural and political nature. The mathematical relationships that describe these real mechanisms are, by principle, non-linear and dynamic and will often exhibit hysteresis and irreversibility. No such a model of 'true reality' exists, and an LCA model must inevitably introduce a multiplicity of crude simplifications."

The authors concede that when considering "strategic decisions having large-scale implications" such as the use of LCA-based performance measures in public policy, "dynamic, non-linear, complex modeling may be imperative" (Guinee et al., 2001, Part 3, p. 18).

A policy-relevant LCA should consider market affects: in general, an environmental policy would accomplish little if its effect on markets were negligible. Since CLCA alone attempts to capture market effects, policy-relevant LCA requires the consequential approach (Ekvall et al., 2005). Although this approach is difficult and the results uncertain, we are better off asking the right question and dealing explicitly with uncertainty than asking the wrong question because we prefer specious precision. The latter approach recalls the drunk who, though he lost his keys in a dark corner of the parking lot, looks for them under the lamppost because the light is better (Weidema, 2009).

2.3.3.3 BLENDED ATTRIBUTIONAL AND CONSEQUENTIAL LCA IS INCOHERENT

Elements of CLCA and ALCA are often blended in practice (Weidema, 2003). Consequential analysis frequently enters into ALCA in the handling of co-products. When analyzing a system that produces multiple products, the ISO standard for LCA recommends the use of systems expansion (discussed in section 2.3.2.5) to account for these (ISO, 2006b). However, the system expansion approach is consequential in nature since any analysis of displacement effects must include a comparison to a baseline (Weidema, 2000a). Importantly, this is a fundamentally different framing than used in an attributional analysis, which relies on static decomposition.

Under system expansion, if a system produces two products, P_1 and P_2 , an analysis focused on P_1 would subtract from the total effects those estimated to be avoided through the production of P_2 , on the assumption that some substitute for P_2 is displaced in the market. If one focuses instead on P_2 , treating P_1 as the co-product, credit would be given to P_1 for displacing some other product. However, the sum of the credits for P_1 and P_2 do not, in general, equal the result of the ALCA for the combined product system. Take the example of corn ethanol and its coproduct, distillers grains (DGs). Corn ethanol displaces gasoline, while DGs displace animal feeds such as whole corn and soybean meal. There's no reason to expect an ALCA of the ethanol-DG system to equal the sum of the ALCAs for displaced gasoline and animal feed. The sum of coproduct credits, however, does—by definition—equal the first-order *consequential* effects of the combined production system: the net change in emissions resulting from co-producing P_1 and P_2 is the emissions from production minus the emissions avoided when these products enter the marketplace, net of price and income effects (Delucchi, 2005).

Combining static ALCA of the main product with consequential analysis of co-products produces a result that is methodologically incoherent, representing neither a static system nor the effects of a change in production. If the purpose of the analysis is a static decomposition to allocate emissions among different end products, then ALCA can be used, and any arbitrary allocation method is equally acceptable. However, if the purpose of the analysis is to estimate the net environmental effects of a change in the quantity of some product produced, then a marginal analysis is appropriate for all aspects of the system—unless we believe average values approximate marginal values. This, however, will differ across products and inputs and should be demonstrated rather than simply assumed.

2.3.3.4 DEFINING "NEW" LCA

A project is underway in Europe to address the many limitations of what they call "ISO-LCA", to produce a "new LCA" that is more informative. The *Co-ordination Action for innovation in Life-Cycle Analysis for Sustainability* (CALCAS) project⁴ has published many useful reports on the limitations of ISO-LCA as well as proposed improvements. Documents produced for the CALCAS projects provide a thorough examination of the shortcomings of traditional (attributional) LCA and guidance for how to broaden LCA to overcome these limitations (e.g., Zamagni et al., 2009; Weidema and Ekvall, 2009; Schepelmann et al., 2009).

2.3.4 ECONOMIC INPUT-OUTPUT LCA

An alternative (or, increasingly, a complement) to process-based LCA is Economic Input-Output LCA (Suh et al., 2004). EIO-LCA is based on national input-output tables such as those produced

⁴See http://www.calcasproject.net for more information.

in the US by the Department of Commerce, with data added to reflect resource extraction and environmental discharges (Hendrickson et al., 2006). EIO-LCA represents average emissions per dollar expended in each sector, within the bounds of the IO table. To model global economic linkages would require a global IO data for both expenditures and emissions.

Within the bounds of the IO data used, EIO-LCA solves the truncation problem associated with process-based LCA (Suh et al., 2004). Lenzen (2000) argues that the truncation error inherent in process-based LCA can underestimate environmental impacts by as much as 50% in some cases, whereas the uncertainties of IO-based LCAs are often lower. However, while EIO-LCA is more complete in assessing (some) upstream impacts, EIO-LCA lacks the detail needed to distinguish individual products such as specific fuel pathways (Heijungs et al., 2006; Hendrickson et al., 2006). EIO-LCA also assumes that environmental effects are linearly related to expenditures, which is likely a poor assumption in a rapidly expanding and evolving sector such as the biofuels sector (Reap et al., 2008a). (Attributional process LCA also assumes linearity of effects; consequential LCA does not.) Other important limitations of the EIO-LCA approach are discussed in Reap et al. (2008a).

A hybrid approach combining process-based and EIO-based has been used in numerous studies to combine the strengths and avoid the pitfalls of the two separate approaches (Facanha and Horvath, 2006; Suh and Huppes, 2005). A hybrid fuel cycle analysis could be implemented in which the primary fuel pathway would be analyzed using process-based methods, with some upstream emissions factors based on EIO-LCA.⁵ The hybrid approach has been employed in several manufacturing applications (Hendrickson et al., 2006).

In a hybrid fuel cycle model, EIO-LCA would be most useful for estimating the effects of elements such as building materials, capital equipment, and the upstream emissions for fuels such as coal and uranium for which prices are relatively stable. Many of the emissions from the fuel cycle are due to use of other fuels (or other fractions of the crude slate, in the case of refining), such as petroleum and natural gas, which suffer high price volatility, decreasing the accuracy of an expenditure-based approach such as EIO-LCA.⁶

2.4 UNCERTAINTY IN LCA

Most LCA studies do not attempt to quantify uncertainty. Indeed, several surveys of the handling uncertainty in LCA have concluded that uncertainty is generally handled badly or not at all (Björklund, 2002; Ross et al., 2002; Heijungs and Huijbregts, 2004; Lloyd and Ries, 2007). Although this situation is improving, most analyses of uncertainty in LCA consider only param-

⁵Heijungs et al. (2006) argue that such a hybrid tool is a virtual *requirement* for implementing the LCA-based portions of the EU's integrated product policy, since EIO-LCA lacks data on the product use and disposal phases, whereas performing detailed process-based LCAs on a wide range of consumer products is highly impractical.

⁶Even if average prices are used to smooth volatility for a single fuel, large inter-annual variations could create instabilities in the relative expenditures among fuel-dependent sectors, due to potential differences in short- and long-run price elasticities between sectors. This would result in an unpredictable divergence between the historical data and current impacts.

eter uncertainty (Lloyd and Ries, 2007; Finnveden et al., 2009; de Koning et al., 2010). Besides data gaps and variability, there is *model* uncertainty surrounding GHG estimates, including which GHGs to account for (Brakkee et al., 2008); whether to use the *de facto* standard 100-year global warming potentials or some other aggregation period (ISO, 2006b), or perhaps longer integration periods with discounting (Delucchi, 2003). As discussed in §2.3.2.5, there is also considerable debate surrounding the proper treatment of co-products in LCA, resulting in unresolved model uncertainty.

The life cycle assessment (LCA) literature is replete with discussions of the challenges posed by uncertainty (see, for example: Huijbregts, 1998; Finnveden et al., 2000; Lenzen, 2000; Björklund, 2002; Ross et al., 2002; Ciroth et al., 2004; Heijungs and Huijbregts, 2004; ISO, 2006b; Lloyd and Ries, 2007; Reap et al., 2008b; Liska and Perrin, 2009; Weidema, 2009; Finnveden et al., 2009). Björklund (2002) writes,

"The credibility of LCA can be questioned if the results cannot be accompanied by adequate uncertainty analyses. Presenting results merely as point estimates without uncertainty distributions is an unreasonable overestimation of their exactness. However, there is also a risk that incomplete methods for uncertainty analysis give a false sense of credibility.

It is likely that quantitative uncertainty analyses of many comparative LCAs would not be able to show any significant differences between the alternatives, either because estimates of uncertainty are too conservative, or because LCA practitioners actually have too much trust in the reliability of the results."

Similar conclusions are reached by other analysts (e.g., Finnveden, 2000; Reap et al., 2008b). Even the ISO LCA standard states that "LCA does not predict absolute or precise environmental impacts" (ISO, 2006a). Yet, despite broad recognition of the importance of uncertainty in LCA, many life cycle studies continue to ignore uncertainty, creating an illusion of precision (Weidema, 2009). This illusion has resulted in LCA-based regulations which, as this dissertation demonstrates, expect more than LCA can deliver.

CHAPTER 3

UNCERTAINTY IN LIFE CYCLE GHG EMISSION ESTIMATES FOR BIOFUELS

"It is likely that quantitative uncertainty analyses of many comparative LCAs would not be able to show any significant differences between the alternatives, either because estimates of uncertainty are too conservative, or because LCA practitioners actually have too much trust in the reliability of the results."

Anna Björklund (2002)

3.1 PURPOSE AND SCOPE

Chapter 2 presented general information about uncertainty and life cycle assessment, including the treatment of uncertainty in LCA. This chapter continues with this theme, focusing on important uncertainties in life cycle GHG analyses of transportation fuels, with a focus on biofuels. Subsequent chapters will quantify many of the uncertainties, but first we examine them qualitatively. Note that uncertainty in estimates of indirect emissions is addressed at length in part III and thus not discussed in this chapter.

3.2 UNCERTAINTY IN FUEL CYCLE ANALYSIS

Uncertainty has played a large role in the public discourse surrounding fuel greenhouse gas (GHG) regulations, stakeholders have focused primarily on the uncertainty surrounding estimates of the emissions from land conversion induced by the expansion of biofuel feedstock production (Gallagher, 2008; Babcock, 2009; Kim et al., 2009; Liska and Perrin, 2009).¹ Meanwhile, important uncertainties in the rest of the life cycle analysis have gone largely unexamined.

Most fuel cycle GHG studies produce only point estimates (e.g., Chambers et al., 1979; Pimentel, 1991; DeLuchi, 1993; Shapouri et al., 1995; Wang, 1999; Wang et al., 2004; Pimentel and Patzek, 2005; Farrell et al., 2006c; Wang, 2007; Pont, 2007). Where uncertainty *is* treated quantitatively, the analysis is often incomplete: not all important uncertain parameters are analyzed, and

¹This conversion can occur directly by planting feedstocks on former grassland or forest, or indirectly through market linkages. The latter case is generally referred to as indirect land use change, or ILUC.

the criteria for deciding which parameters to include in the uncertainty analysis are frequently not stated (e.g., Contadini, 2002; Bernesson et al., 2006; Brinkman et al., 2005; Edwards et al., 2007b).

The two most comprehensive studies to date are those by Brinkman et al. (2005) in the US, and Edwards et al. (2008) in Europe. Brinkman et al. (2005) estimated uncertainty in the emissions of GHGs and criteria pollutants from a wide range of transportation fuels and vehicles used in the US, based on the GREET model. This analysis did not examine uncertainty importance, so while some 700 GREET model parameters are assigned probability distributions, there is no indication of the relative importance of these uncertainties. (I address this shortcoming in my own analysis of uncertainty using GREET in chapter 5). It is interesting to note that despite having added a stochastic capability to the GREET model for the Brinkman et al. study in 2005, none of the subsequent GREET-based reports released by Argonne National Lab have used this capability.

Edwards et al. (2008) examined the effect on biofuel GHG emissions of the uncertainty in direct (most notably emissions of N_2O from agricultural soils) and indirect effects, concluding that "[t]he uncertainties of the emissions due to indirect effects, much of which would occur outside the EU, mean that it is impossible to say with certainty that the net GHG effects of the biofuels programme would be positive."

Malca and Freire (2010) studied uncertainty in the life cycle energy use and GHG emissions of rapeseed oil, including both parameter uncertainty and model uncertainty associated with the choice of co-product allocation method. This study also examined the contribution to variance of each uncertain model parameter. For no allocation or allocation by mass, energy, or economic value, soil N₂O emissions contributed about 40% of the variance, and carbon emissions from soil (at the feedstock production site) contributed about 37% of the variance. Under these allocation assumptions, the total variance related to nitrogen fertilization was about 57%, including N₂O (40%), N₂O GWP (9%), N fertilizer application rate (4%) and N fertilizer production (4%). System expansion resulted in much greater uncertainty, with different contributions to variance: soy meal substitution credit contributed 35% of the variance, and soil N2O emissions and soil carbon emissions contributed 26% and 23%, respectively. The total variance associated with N fertilization of about 37%. Figure 3.1 shows the results of this study, highlighting the much greater uncertainty associated with system expansion. The authors conclude that "the high uncertainty observed in GHG emissions limits the conclusions and does not confirm the significant GHG emission savings reported" in studies that didn't consider uncertainty. Notably, this study assumed that rapeseed oil was produced on set-aside land and thus doesn't include any emissions from indirect land use change. Nor did the study consider the other model and decision choices an analyst must make, such as those discussed in $\S3.3$.

3.3 DEFINING LIFE CYCLE CLIMATE EFFECTS

One reason that different fuel GHG analyses yield different results is that the phrase "life cycle climate effects" doesn't describe a unique analysis, but a class of possible analyses which approximate this idea with potentially very different operational definitions (as demonstrated by Farrell



Figure 3.1: Greenhouse gas (GHG) emissions results: scenario and parameter uncertainty. Whiskers represent the range from 5^{th} to 95^{th} percentile and the box represents the interquartile range. The diamond shows the median. Dashed lines identify the 5^{th} and 95^{th} percentile values for GHG emissions from fossil diesel (FD). Econ = economic; S Exp = system expansion; CV = coefficient of variation. (Source: Malça and Freire, 2010)

et al., 2006b; Hammerschlag, 2006; Plevin, 2009). For example, a modeler must decide, *inter alia*, the following:

- 1. Use regional or national averages for feedstock production and conversion processes, or focus on a specific production system?
- 2. Which regional and temporal approach should be used to estimate the GHG emissions related to electricity use or displacement? (Weber et al., 2010)
- 3. Estimate marginal or average effects?
- 4. How will co-products be handled?
- 5. Which climate effects should be included—just three primary GHGs, or other gases and particulates, as well as biophysical effects such as albedo, and evapotranspiration?
- 6. How are GHG effects aggregated into a single indicator?

- 7. Examine a system retrospectively or anticipate technological changes?
- 8. Examine only the supply chain, or include indirect effects?
- 9. If indirect effects are included, which ones, and how exactly will these be modeled?
- 10. Should several scenarios be examined, and if so, which?

Different choices by modelers will result in analyses that answer slightly different questions. LCA results are highly dependent on these and other subjective choices made by the modeler and as a result, neither absolute nor relative GHG ratings are stable across analyses. Since LCA results are not observable, we cannot compare a set of results to empirical data to determine which set of choices most accurately represents the relative climate effects of different fuels.

3.3.1 WHICH EMISSIONS TO CONSIDER

LCA typically considers only one category of climate effects—direct greenhouse gases. Within this category, studies generally consider at most six gases (or groups of gases) defined in the Kyoto Protocol as contributing to global warming effects: CO_2 , methane (CH₄), nitrous oxide (N₂O), hydroflourocarbons (HFC), perflourocarbons (PFC), and sulfur hexafluoride (SF₆). Fuel cycle models typically consider only the first three gases, on the presumption that little or no HFC, PFC, or SF₆ is emitted in the life cycle of transportation fuels (USEPA, 2009b, p. 302). The standard approach for estimating climate effects is to count the emissions of the "big three" gases— CO_2 , CH₄, and N₂O—and to weight these by the latest IPCC global warming potential values (e.g., Forster et al., 2007) using a 100-year time horizon (Wang, 1999, 2008b; CARB, 2009a; USEPA, 2010b).

However, several other compounds emitted over fuel life cycles are climate-active: carbon monoxide (CO), non-methane volatile organic compounds (NMVOC), sulfur dioxide (SO₂) oxides of nitrogen (NO_X), black carbon (BC), and organic carbon (OC) all affect climate, though their global warming potentials are generally more uncertain (Delucchi, 2003; Larson, 2006; Sanhueza, 2009).

3.3.2 BIOGEOPHYSICAL CLIMATE EFFECTS

In addition to the emissions of direct and indirect GHGs and aerosols, biogeophysical changes caused directly or induced by biofuels can result in changes in radiative forcing and precipitation (Feddema et al., 2005; Thompson et al., 2009; Georgescu et al., 2009).

Albedo measures the fraction of incident solar radiation reflected by an object or surface (Forster et al., 2007; Thompson et al., 2009). Land cover with lower albedo absorbs more solar energy than land cover with higher albedo. For example, forests are generally darker than agricultural land, and therefore absorb more solar radiation, reducing, and in some cases, reversing the climate benefits of afforestation (Thompson et al., 2009). Similarly, deforestation to grow crops

in some cases will increase albedo, counteracting some of the negative climate effects induced by biofuel expansion. Indeed, desertification is considered to have contributed substantial negative radiative forcing—equivalent to the warming of 20% of the anthropogenic CO_2 emitted—in the past several decades (Rotenberg and Yakir, 2010). The cooling effect of reduced tillage, owing to the higher albedo of crop residues, can be as large as the carbon sequestration benefits associated with this practice (Lobell et al., 2006).

An estimation of the albedo and other biogeophysical changes on radiative forcing induced by biofuels, and combining these effects, which are largely regional (Feddema et al., 2005), with those of global GHGs is beyond the scope of this dissertation.

3.3.3 Aggregation of climate effects

The Global Warming Potential (GWP) system used by the IPCC provides "CO₂ equivalence" factors for non-CO₂ GHGs, thereby allowing bundles of GHG emissions to be aggregated into a single metric (Forster et al., 2007). However, as different gases have different atmospheric lifetimes, the "equivalence" is not absolute, but relative to a very specific definition: *the radiative forcing (RF) caused by a 1 kg pulse of a non-CO*₂ *gas, divided by the RF caused by a 1 kg pulse of CO*₂, *integrated over a fixed time horizon* (Forster et al., 2007).

There are two important implications of this definition: (i) GWPs truncate climate effects at the end of the integration period, so that while CO_2 continues to affect climate long beyond 100 years, only the first 100 years of radiative forcing is considered; and (ii) gases such as CH₄, with shorter residence times than that of CO_2 , have very different GWP values under different choices of time horizon, as illustrated in table 3.1.

Table 3.1: Global warming potentials for the	"big three"	greenhouse gases from the IPCC's Four	th
Assessment Report (Forster et al., 2007).			

Chemical	Lifetime (years)	20-year GWP	100-year GWP	500-year GWP
CO ₂	$\sim 100^a$	1	1	1
CH ₄	12	25	72	7.6
N_2O	114	289	298	153

^{*a*}CO₂ equilibrates between atmosphere, ocean, and terrestrial biosphere. The ~ 100 lifetime reflects the time particular CO₂ molecules remain in the atmosphere, but neglects this equilibration process. Thus, although the ~ 100 year lifetime is generally accepted, 20–30% of fossil fuel CO₂ remains in the atmosphere for centuries. As a result, the mean lifetime of elevated CO₂ concentration is on the order of tens of thousands of years (Archer et al., 2009).

Although the Kyoto Protocol has settled on 100-year GWPs for national GHG inventories, it is worth considering whether climate policies should reflexively use this timeframe for comparison,

as this choice implicitly prioritizes reductions in long-term warming over reductions in near-term warming. This tradeoff is especially pronounced for black carbon, a short-lived aerosol with a high near-term GWP. The choice of time horizon is ultimately arbitrary in an LCA, yet this choice affects which set of emissions, and ultimately, which set of activities may be targeted for reduction (Jackson, 2009).

Finally, we note that the IPCC assigns a 35% uncertainty (describing a span of two standard deviations) to its global warming potential estimates (Forster et al., 2007). This uncertainty is frequently omitted even in fuel cycle models that do model uncertainty (e.g., GREET).

3.4 CO-PRODUCTS OF BIOFUELS

Most biofuel production systems yield co-products in addition to the biofuel. Grain ethanol systems co-produce distillers grains with soluble (DGS), which is widely used as animal feed. Many oilseeds produce both oil and high-protein meal, also used as animal feed. Fatty-acid methyl ester (FAME) biodiesel systems co-produce glycerin, which can be used for energy or as a chemical feedstock. Cellulosic and sugarcane ethanol systems can generate surplus electricity that is exported to the grid. The choice of allocation method strongly determines the results of many biofuel GHG assessments (Farrell et al., 2006b; Cherubini et al., 2009; Huo et al., 2009; Kim et al., 2009; Luo et al., 2009; Hoefnagels et al., 2010).

In the case of corn ethanol, the state of the art for assigning credit for co-produced distillers' grains (DGs) is to estimate the quantity of other feed products displaced by the DGs and to subtract from the ethanol life cycle the GHG emissions associated with these displaced products. The question asked, therefore, is "What is the marginal effect on GHG emissions for utilizing DGs in place of other feed?" This raises several methodological problems. First, the actual quantity of DGs used is based on a cost and nutritional optimization that differs by type of livestock, and is thus subject to disagreement over the most appropriate static values to assume for uses that respond dynamically to commodity prices. Second, as discussed in §2.3.3.3, blending a change-based analysis of co-products with a static analysis of the main product, though common practice, is incoherent. A fully consequential analysis answers a coherent question, i.e., the net GHG emissions resulting from a change in production of a given magnitude. The blended model answers no coherent question.

Cellulosic ethanol production provides another interesting case for estimating co-product credits. As modeled in GREET and most other analyses, cellulosic ethanol is awarded a credit for the fossil carbon emissions avoided by the export of co-produced electricity to the grid. In most analyses, this additional biomass-fired electricity is assumed to replace the average grid electricity in the local region. However, determining the net change in electricity production requires consideration of short- and long-run system dynamics, which are affected by policies such as CO_2 caps and renewable portfolio standards (RPS). For example, the Energy Information Agency projects that the greatest contribution of distributed biomass power generation in states with an RPS will be cellulosic ethanol facilities (EIA, 2010, p. 70). Under a binding RPS, co-produced electricity from ethanol facilities will displace more expensive renewable electricity that would otherwise be required by the standard. Without a detailed electricity dispatch and investment model, it is difficult to project which sources are actually displaced (Jaramillo et al., 2009), and therefore to project the GHG credits to assign to the ethanol. (Note: figure 5.1 shows the effect of different assumptions about the electricity displaced by cellulosic ethanol facilities.)

Modeling system expansion requires detailed knowledge of the (often, global) markets affected by co-products. Modeling global markets is indeed uncertain, but this uncertainty reflects the state of our knowledge of the net climate effects of expanding biofuels production. A method that is wrong but less uncertain does not reduce uncertainty, it merely hides it. When these results are used in public policy, we risk promoting higher-GHG fuels over lower-GHG fuels, in direct conflict with policy goals (Cherubini et al., 2009).

Despite this risk, some regulatory efforts have chosen allocation over system expansion. For example, recent German biofuel legislation settled on allocation by lower heating value since this is the most predictable (Fehrenbach et al., 2007), apparently preferring "precise but inaccurate" over "accurate but imprecise". This approach gives the same credit to two co-products of equal heating value when one is combusted to displace a high-GHG alternative and the other converted to methane on disposal in a landfill.

Analysts often justify allocation methods by appealing to expediency. For example, Huo et al. (2009) write:

When the choice is between the displacement method and the allocation method, the displacement method tends to be chosen if the uncertainties and difficulties associated with it are solved, because it can reflect the energy use and emissions actually saved as a result of the coproducts replacing other equivalent products. Nevertheless, the allocation approaches have been more widely used, because they are less data-intensive and less challenging than the displacement approach.

Mark Delucchi has suggested that if we're willing to accept methods that don't reflect actual environmental outcomes, an even less data-intensive approach would be to allocate burdens based on the relative number of letters in the names of each co-product (pers. comm. 2009).

3.5 FEEDSTOCK PRODUCTION

The LCA of natural systems such as biofuel feedstocks is more challenging than that of industrial systems. Spatial and temporal variability in natural systems, not only among producers but for individual producers, is generally much greater than variability in engineered systems. As a result environmental effects such as GHG fluxes from cropland are more challenging to measure or model than those of industrial systems.

The supply-chain focus in ALCA misrepresents the effects of changes in production from natural systems, as this implicitly compares the production process to a fictitious "null" option that suggests that if the product were not created, the impacts associated with its production would be avoided (Kaltschmitt et al., 1997). This assumption is surely incorrect for crop-based biofuels. Take the example of a new corn ethanol facility. Corn biorefineries are generally built where corn is already grown, which means that the corn use by the new facility was previously used in some other manner. While we can use sophisticated methods to measure or model the GHG fluxes in the specific corn fields producing the feedstock consumed by the biorefinery, this corn was produced before the biorefinery arrived, so its emissions are part of the baseline. Thus, the GHG effect of a new biorefinery is a function of the *replacement* of the displaced corn. Note that the prior use of corn (e.g., as animal feed) may not be replaced with corn at all, but perhaps by some combination of distillers grains, protein meal, urea, and other feedstuffs—or not replaced at all as a result of price-induced demand reduction.

In general, there is no reason to expect that the processes used to replace the corn that was diverted to ethanol production have GHG emissions that are approximated by those of the corn consumed at the biorefinery. Therefore, improved modeling or measurement at the corn field that is actually in the supply chain may improve precision, but not accuracy. If the production is displaced abroad, the change in emissions can be quite large, owing to differences in yield, and to different practices in the production of agrochemicals. For example, Chinese ammonia (from which nitrogen fertilizer is produced) is derived from coal, often in inefficient facilities, resulting much higher GHG emissions than for the same fertilizer used in the US, which is generally derived from natural gas (Zhou et al., 2010). Thus the GHG emissions for any corn production displaced to China would not be approximated by those of average Midwest corn.

3.5.1 SOIL GHG FLUXES

3.5.1.1 N₂O Emissions from soil

Nitrous oxide (N₂O) is released from soils by nitrification and denitrification processes. N₂O is a potent greenhouse gas: emission of 1 kg N₂O produces about 300 times the global warming of 1 kg CO₂ over 100 years (Forster et al., 2007). The release of N₂O from agricultural soils is the single largest contributor to the life cycle greenhouse gas (GHG) for crop-based biofuels, and one of the largest contributors across many biofuel production cycles (Smeets et al., 2009; Hsu et al., 2010). The rate of emissions of N₂O (per unit N applied) is perhaps the most uncertain direct effect in the GHG profile of crop-based biofuel feedstocks (Crutzen et al., 2007; Edwards et al., 2008; Erisman et al., 2009; Smeets et al., 2009; Soimakallio et al., 2009; Del Grosso et al., 2010; Hsu et al., 2010).

Soil emissions of N_2O depend on several site-specific characteristics such as soil moisture, temperature, pH, and availability of nitrogen and organic carbon (Mosier et al., 1998; Erisman et al., 2009). N_2O emissions generally vary with fertilizer application rate, but also result from nitrogen fixation by legumes and from atmospheric deposition of NO_X and NH_3 from combustion sources (Mosier et al., 1998). The emissions are highly variable over very small distances (i.e. 10 inches or less), and they vary in time (e.g. large pulses can occur after rain soaks the soil) (Mosier

et al., 1998; Dalal et al., 2003; Gibbons et al., 2006). Nitrogen that runs off into waterways can be emitted as N_2O far from the field in question (Mosier et al., 1998). Recent research indicates that N_2O emissions from anoxic zones caused by fertilizer runoff may be much higher than previously understood (Codispoti, 2010).

The Tier I method described in the IPCC's guidelines for GHG inventories includes several N₂O emission pathways, as show in table 3.2. The first is the direct of N₂O from the fertilized field, resulting from nitrification and denitrification. This emission rate is expressed as a percentage of elemental N that is directly released to the atmosphere as N₂O. In addition to these direct emissions, a fraction of the applied N is volatilized as NH₃, and oxides of nitrogen (NO_X). When these gases and their products (NH₄⁺ and NO₃⁻) are deposited onto soils and waterways they result in additional N₂O emissions. The default values for these factors, and their associated uncertainty ranges (expressed as ± 2 standard deviations, or approximately a 95% confidence interval) are shown in 3.2 (De Klein et al., 2006, table 11.1).

The rate of emission of N₂O per unit of nitrogen (N) fertilizer applied is highly uncertain, with a distinct right tail. Figure 3.2 shows the joint distribution for N₂O emission rate, with the parameters represented by lognormal distributions with 5^{th} and 95^{th} percentile values set according to the ranges given by the IPCC, as shown in table 3.2.² Owing to this skew, the mean of the joint distribution (1.65%) is greater than the point estimate based on the default values (1.325%).

Parameter	Default value	Uncertainty range
For N additions from mineral fertilizers, etc. (kg N_2O -N [kg N] ⁻¹)	0.01	0.003 - 0.03
Fraction of N volatilization	0.10	0.03-0.3
Conversion of volatilized N to N ₂ O (kg N ₂ O-N [kg N] ⁻¹)	0.01	0.002-0.05
Fraction leached	0.30	0.1-0.8
Conversion of leached N to N ₂ O (kg N ₂ O-N [kg N] ⁻¹)	0.0075	0.0005-0.025

Table 3.2: Uncertainty ranges for factors used in Tier 1 N_2O emission calculations. (Source: De Klein et al., 2006, Tables 11.1 and 11.3)

3.5.2 SOIL CARBON

Agricultural soil can sequester carbon, thereby offsetting other GHG emissions, or they can release carbon as CO_2 (Anderson-Teixeira et al., 2009). Soils can also be a net source or sink of methane

²The IPCC guidelines do not specify the probability distribution associated with these parameters, only the ranges.



Figure 3.2: N_2O emissions rate for applied N fertilizer, assuming lognormal distributions for input parameters with the 5th and 95th percentile values set to the ranges given by the IPCC guidelines and presented in table 3.2.

(CH₄) (Torn and Harte, 1996; Lashof et al., 1997). Some biofuel GHG models (e.g., GREET, discussed below) include an assumed change in soil carbon resulting from bioenergy production (Wang, 1999). Estimates of soil carbon changes are very uncertain: the sign and magnitude of the change vary with feedstock, climate, soil type, land use history, and management practices, and the effect varies over time and space. Any estimate of SOC change is therefore dependent on the specific scenario modeled (e.g., switchgrass replacing corn versus switchgrass on former grassland) and given any scenario, there will be spatial and temporal variability.

For example, the GREET model assumes large soil carbon sequestration benefits for cellulosic ethanol produced from switchgrass and farmed trees: 48,500 g CO₂ per dry ton of switchgrass, and 112,500 g CO₂ per dry ton of farmed trees. These values produce in credits of 6.3 and 14.7 g CO₂e MJ⁻¹ in the respective ethanol pathways.³ However, this level of sequestration depends on

³These carbon sequestration estimates are exactly half the value cited in GREET documentation (Wang, 1999, p. 80) as coming from personal communication with Mark Delucchi in 1998. Neither Delucchi nor GREET developers at Argonne National Lab could explain why the values were halved, nor could they explain the assumptions underlying

assumptions about the nature of the land on which the crops are growing. The specific switchgrass scenario modeled in GREET (Wu et al., 2006) is based on a 2002 analysis using the POLYSYS model and an assumed switchgrass price of \$27.50 per dry ton, projecting that 39% of the switchgrass would be grown on conventionally-tilled cropland, and assuming none would be grown on CRP land (Andress, 2002). If this were the case, then the switchgrass would presumably induce ILUC emissions, which were not considered in GREET. If, instead, switchgrass were produced on CRP land, the potential gain in soil carbon would depend on the length of time since the land went out of cropping; if the land were in grasses long enough, there would be no additional carbon storage associated with producing switchgrass (Andress, 2002, p. 4). Indeed, tilling the grass to plant switchgrass would result in net emissions of CO₂.

In its analysis for RFS2, USEPA assumes switchgrass sequesters a large amount of SOC, although the report it cites on this subject notes that the "SOC response to a conversion to switchgrass will depend on initial SOC levels and management, projecting SOC accumulation under soils with low initial C content in the top 30-cm of soil (< 40 Mg C ha⁻¹) with "higher rates of accumulation under lowland ecotypes. (Thomson et al., 2009, p. 7). However, Figure 3.3 (Thomson et al., 2009, p. 8) shows that the range of SOC accumulation levels was quite wide for initial SOC < 40 Mg ha⁻¹, while for higher initial SOC levels, a loss of SOC occurred in several locations.

3.5.2.1 TILLAGE AND SOIL CARBON SEQUESTRATION

Many studies have found that conservation tillage increases soil C sequestration compared to conventional tillage—however this finding is now in dispute. Baker, Ochsner et al. (2007) show that the conventional wisdom is a result of insufficiently deep soil sampling. Samples are generally taken from less than 30 cm of depth, which appears to be above the level at which conventional tillage deposits carbon, whereas most of the soil C increase under no-till occurs at these shallower depths. Thus the studies upon which conventional wisdom is based may have significantly underestimated the soil C sequestration from conventional tillage. Baker et al. (2007) conclude that "it is premature to predict the C sequestration potential of agricultural systems on the basis of projected changes in tillage practices, or to stimulate such changes with policies or market instruments designed to sequester C". Additional studies have confirmed these findings (Gál et al., 2007; Blanco-Canqui and Lal, 2008; Yang et al., 2008). For example, Blanco-Canqui and Lal (2008) report that no-till increases soil organic C (SOC) concentrations in the upper layers of some soils, but it doesn't store SOC more than plow tillage for the whole soil profile, confirming Baker's conclusion. Gál et al. (2007) write:

"[w]hile no-till clearly resulted in more OC [organic carbon] and N accumulation in the surface 15 cm than moldboard plow, the relative no-till advantage declined sharply with depth. Indeed, moldboard plowing resulted in substantially more OC and N, relative to no-till, in the 30–50 cm depth interval despite moldboard plowing consistently to less than a 25 cm depth. Our results suggest that conclusions about OC or N gains

the values. Delucchi disclaims these 12-year-old estimates (pers. comm.)



Figure 3.3: Simulated annual change in soil organic C (SOC) to 30-cm depth as related to initial soil C levels at the seven calibration dataset locations in the upper southesastern United States. (Thomson et al., 2009, p. 8).

under long-term no-till are highly dependent on sampling depth and, therefore, tillage comparisons should be based on samples taken well beyond the deepest tillage depth."

They conclude that "the most important contribution of our study was to confirm the necessity of deep sampling for improved accuracy in the assessment of C or N sequestration with no-till versus conventional tillage." Yang et al. (2008) conclude that the differences in soil C sequestration between no-till and conventional till disappear when the entire plow layer is considered, and importantly (relative to Gal et al.) write that sampling beyond the plow layer would be prohibitively expensive given the number of samples required to detect statistically significant differences that are small compared to the large amount of carbon in deeper samples.

In addition, shifting from conventional-till (CT) to no-till (NT) can increase N_2O emissions for a decade or more, eliminating any climate benefits from the carbon storage of no-till in some regions (Six et al., 2004). Six et al. write: "NT systems increase GWP relative to CT practices, in both humid and dry climate regimes, and longer-term adoption (410 years) only significantly reduces GWP in humid climates. Mean cumulative GWP over a 20-year period is also reduced under continuous NT in dry areas, but with a high degree of uncertainty." (Note that this paper relies on shallow samples to estimate carbon storage of NT, and so it may overestimate the increase carbon storage of NT, which only strengthens their result.)

3.5.2.2 REVERSIBILITY

Most biofuel LCAs treat the sequestration of one unit of carbon in soil or biomass as equivalent to the avoided emission of one unit of fossil carbon. However, as sequestration is reversible, whether these are equivalent depends on the storage duration. When viewed over a 100-year interval, sequestering a unit of carbon for 55 years is equivalent to avoiding emission of the same unit of carbon as CO_2 (Moura Costa and Wilson, 2000). In terms of biofuel GHG analysis, the climate benefit of a given quantity of carbon sequestration is uncertain because the date of future release of the CO_2 is unknowable. To address this uncertainty, Moura Costa and Wilson suggest crediting each unit of sequestered carbon with $1/55^{th}$ (0.0182) of a unit of carbon per year, thereby providing incentives to the credit recipient to ensure the continued storage of the carbon.

Alternatively, an LCA could account for this uncertainty by discounting the carbon storage benefit based on the probability of reversal before 55 years, though there may little empirical basis for estimating such probabilities. For example, conservation tillage can be reversed to combat pests, the arrival of which are unpredictable: despite a rise in no-till agriculture in the US, some farmers are finding that they have to return to tillage to combat "super-weeds" that are resistant to the herbicide Roundup, which has been used extensively for years on GMO corn and soybean crops engineered to resist the herbicide (Neuman and Pollack, Neuman and Pollack).

3.5.3 UNCERTAINTIES IN AGRICULTURAL PRODUCTION DATA

In the US, agricultural data collected by the US Department of Agriculture's National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) underlie all major life cycle analyses of biofuels currently produced in the US. USDA reports these data as averages for each parameter (e.g. agrichemical application rates, yield, on-farm energy use, incidence of no-tillage), per state, as if the values were independent. In general, a different result would obtain if the global warming intensity of feedstock production were computed for each farm, with these "whole system" results averaged across some region of interest (Farrell et al., 2006c; Plevin, 2009) rather than computing the LCA based on independently averaged factors. This is because, in general, for a non-linear function f(x,y), $f(avg(x), avg(y)) \neq avg(f(x,y))$. The computation of GWI is non-linear as it involves the product of factors such as fertilizer application rates and the fraction of acres receiving fertilizer application, as well as division by yield to produce the desired functional unit. Thus, LCAs have unwittingly used f(avg(x), avg(y)) as a proxy for avg(f(x,y)).

Other issues with agricultural data are discussed in chapter 4.

3.6 **BIOFUEL PRODUCTION**

The emissions from the conversion of feedstocks to biofuel are less uncertain than those of feedstock production, as virtually all the emissions result from the combustion of easily-measured quantities of fossil fuels. The main uncertainty in biofuel production phase is whether the chosen method for accounting for co-products accurately represents environmental effects, discussed in §2.3.2.5.

Estimates of production emissions also depend on the timeframe considered and whether we seek a value for the average production of a fuel (say, across the US) or for a specific facility. For use in the LCFS, average values are of little interest, as the regulation targets individual producers. For RFS2, EPA has made determinations regarding classes of biofuels, so it should consider the uncertainty inherent in averaging across facilities. There is additional epistemic uncertainty associated with projections of future technologies, as USEPA has done for RFS2.

Part II

UNCERTAINTY ANALYSIS OF DIRECT LIFE CYCLE EMISSIONS

CHAPTER 4 GREET-BESS ANALYSIS META-MODEL (GBAMM)

"All models are wrong, but some are useful." George Box

4.1 **PURPOSE AND SCOPE**

The BESS model has been promoted by its creators as an "improved" model of the life cycle GHG emissions from corn ethanol, suitable for use in regulations such as the California LCFS. BESS's estimate is 25% lower than that of the GREET model, on which the LCFS is based. This large difference raised questions about which model was more accurate. I developed a life cycle meta-model to compare the GREET and BESS models in detail and to explain why the results from these models diverge. I found two main reasons for the divergence: (i) BESS models a more efficient biorefinery than is modeled in the cases to which its results have been compared, and (ii) in several instances BESS fails to properly count upstream emissions. The detailed examination of these two models highlights the data gaps and subjective choices that are inherent to LCA.

Although this analysis explains the gap between the two models, I found that both models would be improved with better data on corn production practices and by better treatment of agricultural inputs. However, as explained in Part III, the differences between GREET and BESS are overwhelmed by uncertainty in the emissions from indirect land use change.

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4.2 INTRODUCTION

4.2.1 BACKGROUND

With the development of fuel regulations based on life cycle greenhouse gas (GHG) emissions (e.g., CARB, 2009a; USEPA, 2009a) the accurate assessment of the global warming intensity

(GWI) of transportation fuels has acquired new and important financial implications. Regulators in California have decided to rely on the GREET model (Wang, 2008b, 1999), but other models exist and warrant examination. One such model is BESS, which produces much lower estimates of the life cycle greenhouse gas (GHG) emissions from the production of corn ethanol than do prior models (Liska et al., 2009).

The goal of this analysis is to document why the results from BESS and GREET diverge so widely. This analysis is based on GREET 1.8b, released in September of 2008, and focuses on the "Midwest natural gas" (MW-NG) scenario in Liska et al., for which details are provided in spreadsheet form in their article's supporting materials (Liska et al., 2009). The MW-NG scenario describes a dry-grind facility in the Midwest using average Midwest corn as feedstock and natural gas for thermal energy, assuming that 35% of the DGS co-product is dried, another 30% partially dried, with the final 35% delivered wet to local markets.

We note that this analysis does not include estimates of the GHG fluxes attributable to indirect land use change (iLUC). Including iLUC emissions has a potentially large effect on the corn ethanol life cycle (CARB, 2009a; Searchinger et al., 2008b; USEPA, 2009a), however, as neither GREET nor BESS includes iLUC emissions, this issue is not addressed further in this comparison.

4.2.2 COMPARING LIFE CYCLE MODELS

Liska et al. (2009) compared results from their BESS model to results from three other models: GREET (Wang, 1999), EBAMM (Farrell et al., 2006b), and BEACCON (Plevin and Mueller, 2008). BESS incorporates updated crop production, co-product credit and biorefinery performance data to produce fuel global warming intensity (GWI) ratings (g $CO_2e MJ^{-1}$) for corn ethanol. The BESS estimates are much lower than those from other models. The authors indicate that their lower GWI estimates result from the use of newer data, however our analysis shows that (i) the technical characteristics of the corn ethanol production systems modeled in BESS differ in important ways from the systems represented in the other models, and (ii) the BESS model does not include several upstream elements of the corn ethanol life cycle that are accounted for in the other models.

There are three primary areas of interest in comparing life cycle models:

- 1. Life cycle inventory (LCI) data: the quantities and emission factors for all inputs and processing steps, and the quality of the data.
- 2. System boundaries: which life cycle elements are included in the analysis and which production systems are modeled?
- 3. Implementation: the behavior of the analytic system, as implemented. Does the model behave as advertised?

To understand differences between models in any of the above areas requires holding the other factors constant across the comparisons. For example, to compare the effect of updating agricultural and process efficiency data requires holding system boundaries and implementation constant while using different LCI data. A single life cycle model can also be used to compare estimates for different system configurations, such as systems with and without cogeneration units, or systems with and without an anaerobic digester. However, simultaneously changing all of these factors confounds the analysis. As shown in Table 4.1, Liska et al. compare model results for fundamentally incommensurate scenarios which use different system boundaries and functional units. Liska et al. compare their result in BESS for a natural-gas fired dry-grind biorefinery located in the U.S. Midwest in which only 35% of the co-produced distiller's grains with solubles (DGS) are fully dried, to scenarios examined in the three other models in which 100% DGS drying is assumed. Reduction in co-product drying represent an important industry trend, however, a more illuminating model comparison would examine the same the scenario in each model.

	BESS MW-NG	GREET ^a	BEACCON ^b	EBAMM
Functional unit	1 MJ anhydrous ethanol, delivered	1 MJ anhydrous ethanol	1 MJ denatured ethanol, delivered and combusted	1 MJ anhydrous ethanol
Plant type(s)	Dry-grind	Dry-grind	Dry-grind	Weighted US average of dry-grind and wet- mill facilities
Plant fuel(s)	${ m NG}^p$	NG^c	NG	NG and coal
Distiller's grains produced	35% dry, 30% modi- fied, 35% wet	100% dry	100% dry	100% dry
Includes non-CO ₂ emissions from combustion of ethanol	No	Unclear ^a	Yes	No
Agricultural data region and vintage	2001 inputs and en- ergy use for 12-state Midwest average, 2003-2005 average yield	1996 ^d inputs and energy use for 9-state Midwest average, 2001-2003 average yield	Same as GREET	Same as GREET
Electricity mix	NS	SU	MRO region	NS
GWI (g CO_2e MJ^{-1})	45	70	65 ^b	76
^a GREET is a flexible model that proc of ethanol plant types and fuels. Lisk Wo have seemed here that that they use	duces values with and wi ta et al. don't describe w	thout denaturant or comb hat they modeled in GR1	ustion emissions, for a p EET to produce the value thout counting non-CO-	rogrammable mixture e of 70 g CO ₂ e MJ ⁻¹ .

Table 4.1: Scenarios compared in Liska et al. The results of these scenarios are compared despite their inherent incommensurability due to differing system boundaries and functional units.

combustion or fuel distribution. We also note that they used an older version of GREET (1.8a) whereas the present analysis was performed with version 1.8b.

 \overline{b} Liska et al. don't indicate how they parameterized BEACCON to produce a rating of 71 g CO₂e MJ⁻¹. BEACCON model authors Plevin and Mueller (2008) report 65 g CO_2e MJ⁻¹ for a 2006 natural gas dry-mill.

^c NG = natural gas.
^d GREET 1.8a, used in Liska et al., used 1996 agricultural data. GREET 1.8b (Sep 2008) uses 2001 agricultural data.

My analysis focuses on GREET for three reasons: (i) EBAMM and BEACCON were designed for specific studies and are derivative of older versions of GREET¹, (ii) Argonne National Laboratory continually updates and fixes errors the GREET model, and (iii) GREET (with regional modifications) serves as the basis for the fuel ratings under California's Low-Carbon Fuel Standard, among other regional and state efforts (CARB, 2009a).

4.3 Methods

To understand the divergence between BESS and GREET we developed the GREET-BESS Analysis Meta-Model (GBAMM) to directly compare all key elements in the LCA of corn ethanol as performed by the two models. The model is similar in many respects to the ERG Biofuel Analysis Meta-Model (EBAMM) developed by the Energy and Resources Group at the University of California, Berkeley (Farrell et al., 2006a), however in the present case we also compare the emission factors used in the two models.

I first define consistent terms of analysis:

- 1. **Functional unit:** 1 MJ of denatured ethanol, containing 4.7% (vol) conventional gasoline denaturant. We assume the denaturant has a global warming intensity (GWI) of 92 grams of carbon dioxide equivalent per megajoule (g CO₂e MJ⁻¹).²
- 2. Figure of merit: Grams per MJ of denatured ethanol of life cycle emissions of CO₂, CH₄, and N₂O, weighted by their 100-year CO₂-equivalent global warming potential values (GWPs), as per the Intergovernmental Panel on Climate Change's (IPCC) fourth assessment report (Forster et al., 2007). GREET also accounts for conversion of carbon in volatile organic compounds (VOC) and carbon monoxide (CO) to CO₂ in the atmosphere, but this amounts to less than 0.3 g CO₂e MJ⁻¹ for the pathway analyzed, so we disregard it in this analysis.
- 3. **System boundary:** The analysis includes agricultural input production and transport, farm equipment production³, feedstock production, feedstock transport, biorefinery equipment production, feedstock conversion, co-product processing and distribution, denaturant production and transport, and ethanol distribution. Credit is assigned for avoided life cycle

¹ EBAMM was developed in 2005 to enable a meta-analysis of prior studies of the energy balance of corn ethanol production, and its greenhouse gas (GHG) accounting is based on GREET 1.6. BEACCON was designed to explore the differential effects on ethanol production cost of a price on CO_2 , across a range of dry-grind system configurations and policy options. BEACCON is derivative of GREET 1.7.

² Greenhouse gases (GHGs) are often measured in the mass of CO_2e , or the amount of CO_2 that would cause the same level of radiative forcing as the emissions of the greenhouse gas in question. One megajoule (MJ) = 106 joules (J, SI) 239 kilocalories (kcal) 948 British Thermal Units (BTU).

³ GREET 1.8b models farm equipment only, whereas BESS includes a line item for "depreciable capital" both on the farm and at the biorefinery. The total emissions estimate for capital in both models, however, is very similar (0.7 g $CO_2e MJ^{-1}$ in GREET versus 0.726 g $CO_2e MJ^{-1}$ in BESS for their IA-NG case.)

GHG emissions for products displaced by co-produced distiller's grains. Non-CO₂ emissions from fuel combustion are *not* included.

Spatial boundary: corn and ethanol production are assumed to take place in the U.S. Midwest, using average production and electricity production data for the top 12 ethanol producing states. (The two base cases use each models' estimate of US average electricity emissions; the adjusted cases use the same Midwest average emission factor.) GHG fluxes associated with direct and indirect land use change are not considered in this analysis.

4. **Temporal boundary:** We attempt to model current practices, although data limitations prevent accurately modeling corn production. Both models rely on on-farm energy use data from 2001. For fertilization rates, GREET and BESS use 2001 and 2005 data, respectively, however GREET extrapolates from these values to estimate practices in 2010, and BESS uses average corn yield from 2003-2005 to approximate current practices.

Using these definitions, we estimate two values for each model: (i) a baseline value using the data provided with the model attempting to match the values reported in BESS and GREET, and (ii) a value based on adjusting system boundaries and model data as required to meet the definition stated above or to correct errors. The adjusted results are indicated with an asterisk after the name, i.e. BESS* and GREET*. Modified values are clearly indicated in the spreadsheet model.

4.3.1 BASELINE ESTIMATES

The well-to-tank GWI for 4.7% denatured ethanol estimated in GREET for a natural gas dry-grind facility, using average US grid emissions, excluding GREET's estimated CO₂ emissions from land use change (about 1 g CO₂ MJ⁻¹) and including emissions for farm equipment is 64.4 g CO₂e MJ⁻¹. We use this as the baseline GREET value.

The baseline value for the BESS MW-NG scenario is given as $45.1 \text{ g } \text{CO}_2 \text{e } \text{MJ}^{-1}$ in the BESS supporting materials. Thus we have a gap of $(64.4 - 45.1) = 19.3 \text{ g } \text{CO}_2 \text{e } \text{MJ}^{-1}$ to explain. The following sections explain the specific differences found between the models.

GBAMM matches the baseline results to within 0.5% of the values estimated in the original models.

4.3.2 Adjustments to the models

This section briefly summarizes the adjustments made to the two models. The rationale for and implications of these adjustments are discussed in the subsequent sections.

4.3.2.1 Adjustments to BESS

BESS* adopts emission factors from GREET with one exception: the original BESS emission factors for seed production and field emissions of N_2O are maintained. All BESS corn production data are maintained in BESS* except for lime application rate, which is taken from GREET. BESS*

adopts from GREET fuel lower heating values, as per table S2.6 (available in Supplement S2 on the Journal's Web site), as well as the emissions for production of corn farming equipment. Biorefinery data in BESS* were adjusted to an anhydrous basis.

4.3.2.2 Adjustments to GREET

GREET* adopts biorefinery performance assumptions from BESS since these define the target of analysis. BESS and GREET estimate slightly different co-product GHG credits: 16.9 and 17.4 g CO_2e MJ⁻¹, respectively. Since biorefinery performance assumptions include natural gas consumption for drying distiller's grains, GREET* also adopts BESS's co-product credit assumption. GREET* adopts the 12-state Midwest average electricity emission factor (weighted by 2009 ethanol production). GREET* adopts the emissions for biorefinery equipment from BESS.

4.4 **RESULTS**

4.4.1 LIFE CYCLE EMISSION FACTORS

An important difference between GREET and BESS is the models' treatment of upstream emissions. GREET tracks energy flows through the full fuel life cycle, for a wide range of transportation fuels, estimating emissions from production, transport, and storage of fuels and feedstocks, combustion of fuels. It augments these combustion emissions by tracking important non-combustion GHG sources such as field emissions of N_2O . At its base, GREET relies on values from other studies or exogenous calculations, for example, to estimate the energy and emissions for the production of fertilizers, and for the energy required to produce a bushel (bu) of corn.

To estimate the GWI of corn ethanol, GREET uses its own calculations of the life cycle GHG emissions for the production and combustion of fossil fuels, and for the production of electricity. However, since GREET does not separately model foreground and background processes, changes made to model a specific production process (e.g., for corn ethanol) can have unintended side-effects. For example, changes to the electricity grid affect all uses of electricity throughout the model, effectively placing the entire life cycle of all modeled processes within the defined grid. Similarly, modeling a specific ethanol refinery affects the use of ethanol pervasively in the model, such as for goods transport. Derivative models such as EBAMM (Farrell et al., 2006a), Biofuels Emissions and Cost Connection (BEACCON) (Plevin and Mueller, 2008), and GBAMM that import life cycle emission factors from GREET separate the foreground analyses from background, avoid this "bleed-through" effect.

BESS is a more narrowly-focused model, addressing only corn ethanol produced in dry-grind facilities. It does not model the life cycle of fossil fuel or electricity production, but instead adopts emission factors from other sources. In several cases, BESS relies on emission factors from the IPCC's guidelines for national greenhouse gas inventories, but these are not life cycle emission factors, so reliance on these factors undercounts emissions. For fossil fuel and electricity use on

the farm and by the biorefinery, BESS estimates life cycle emissions based on the fuels' production efficiencies, but as shown below, this also generally undercounts emissions.

4.4.1.1 UPSTREAM EMISSIONS FOR FOSSIL FUELS

To estimate the life cycle emissions for fossil fuels, BESS first divides the quantity of each fuel used by the corresponding "energy efficiency" for that fuel, following Shapouri et al. (2004), to estimate total energy use. To compute GHG emissions, this larger quantity of fuel is multiplied by the fuel's direct combustion emission factor, sourced from IPCC inventory guidelines.

The "efficiency" approach is reasonable for calculating an *energy* balance, as Shapouri et al. do, since in an energy balance, only the total energy matters—other fuel characteristics are irrelevant. However, this approach does not produce a correct life cycle GHG result, since it treats all upstream energy use for each fuel as simply combustion of more of the same fuel, and therefore doesn't account for the variable GHG intensity of upstream processes.

For example, BESS uses a conversion efficiency of 94% for natural gas, meaning that of the total natural gas consumed to meet a given end use, 6% is lost *en route*. However, the upstream emissions calculated in GREET account for about 15% of the total life cycle emissions per unit of natural gas combusted in industrial boilers, more than double the upstream emissions estimated using the "efficiency" method. This difference is because the combustion of natural gas (Forster et al., 2007).⁴ This distinction is irrelevant in energy accounting, but essential in GHG accounting.

In addition, upstream processes for each fuel don't simply use more of the same fuel: coal production involves mining and transport, using a variety of energy sources, as well as leakage of coal-bed methane, so applying the energy efficiency of coal production understates the life cycle GHG emissions from coal use.

We note that while the implied emission factors in BESS are generally lower than those derived in GREET, the diesel factor is higher in BESS. Since the ethanol pathway modeled uses much more natural gas than diesel, the net effect of the BESS approach is to underestimate emissions. Table 4.2 shows the GHG intensities for fossil fuels in GREET and BESS. In GREET, these are life cycle GHG intensities, but in BESS they represent the emissions from burning a greater amount of each fuel based on the energy efficiency of production. For example, if the energy efficiency of producing natural gas is 94%, and the emission factor for combusting natural gas is 56 g CO₂e MJ^{-1} , then the "life cycle" emission factor in BESS is (56 g CO₂e MJ^{-1}) / 0.94 = 60 g CO₂e MJ^{-1} . BESS* adopts life cycle emission factors for fossil fuel from GREET, increasing the GWI estimated in BESS by 2.3 g CO₂e MJ^{-1} .

We note that the LPG production efficiency used in BESS, as reported by Shapouri et al. (2004, Table 2) appears too high at 98.9%. GREET 1.8 shows a well-to-pump energy efficiency of 89.3% for LPG. Curiously, in an earlier paper, Shapouri et al. (2002) show an efficiency of 89.8% for

⁴The factor of 25 is for a 100-year integration period; CH_4 is 72 times more potent than CO_2 over a 20-year integration period. Thus, for a model using 20-year GWPs, the approach used in BESS diverges yet further.

Table 4.2: Comparison of fuel GHG intensities in BESS and GREET, (g $CO_2e MJ^{-1}$). BESS uses energy efficiency as a proxy for upstream GHG emissions. GREET calculates life cycle GHG emissions, including fuel combustion.

Fuel	BESS	GREET
Gasoline	88	93
Diesel	98	91
LPG	64	77
Natural Gas	60	66

LPG. It appears that the digits were transposed in the 2004 report showing 98.9%. LPG is a small contributor to total GWI: applying the GREET factor increases GWI by only 0.2 g CO_2e MJ⁻¹.

4.4.1.2 ELECTRICITY

BESS's handling of electricity is deficient in three ways: (i) inappropriate aggregation levels are used to determine the relevant mix of power plants, (ii) upstream emissions for fuel production and transport are based on energy efficiency rather than actual emissions, and (iii) transmission and distribution (T&D) losses are handled incorrectly.

In the US, electricity is produced in tightly-connected grid regions with interconnects between regions through which a relatively small amount of electricity is imported and exported Kim and Dale (2005). The most appropriate aggregation level for determining per-kWh emissions are these North American Electricity Reliability Council (NERC) regions. Although this approach misses the smaller regional imports and exports, the NERC region provides a more accurate representation of local electricity grid mix than either the state or national level, neither of which effectively captures the electrical reality of the grid.

Following the "Midwest average" approach of the MW-NG scenario, we compute the average emission factor for the 12 states for which corn farming data are averaged.⁵ Coal-fired electricity is more prevalent in this region than in the US as a whole, resulting in a higher regional emission factor. The life cycle emission factor for electricity "at the plug" (including 8% transmission and distribution [T&D] losses) in GREET for the US is 780 kg CO₂e MWh-1, whereas the 12-state Midwest average emission factor is 910 g CO₂e kWh-1. The value assumed in BESS is 745 kg CO₂e MWh-1.

Liska et al. cite Shapouri et al. (2004) as the source for electricity production efficiency of 38.5%. In fact, Shapouri et al. use the figure 39.6% efficiency for electricity production, with a

⁵ This average is based on regional emission factors computed in GREET 1.8b using 2004 electricity data from US EPA's eGRID 2006 v1.2, weighted by each states' fraction of US annual ethanol production as of January, 2009. See the spreadsheet model for details.

misnamed T&D "efficiency" of 1.087%. Estimates of energy losses during electricity transmission and distribution are typically in the range of 8% (as in GREET 1.8b) to 9.5% (Kim and Dale, 2005). An 8% T&D loss represents 92% efficiency, or a "loss factor" of (1/0.92) = 1.087. It appears that Liksa et al. may have subtracted the mislabeled 1.087 "percent" from 39.6% to yield their efficiency factor of 38.5%.

The combined efficiency of 39.6% conversion efficiency and 92% T&D efficiency is the product of these values, or 36.4%. However, although the 38.5% value is mentioned in the BESS documentation, it's not clear whether this value is used in the model itself. BESS* adopts the life cycle emission factors for electricity estimated for GREET*, increasing the GWI estimated in BESS by 1.5 g CO_2e MJ⁻¹.

4.4.1.3 FUEL HEATING VALUES

BESS and GREET assume slightly different lower heating values for fossil fuels and ethanol, as shown in Table 4.3. Fossil hydrocarbons contain a variable mixture of molecules; estimates of heating values depend on assumptions about the composition of these blends. Anhydrous ethanol, in contrast, consists of a single molecule (C_2H_5OH) so estimates of heating value are more consistent. BESS* adopts the energy values from GREET, although this has a negligible effect on the estimated GWI.

Heating (LHV)	values	Units	GREET	BESS
Gasoline		MJ/L	32.6	31.8
Non-road die	esel	MJ/L	38.5	36.2
LPG		MJ/L	23.7	25.6
Natural gas		MJ/m ³	36.6	34.0
Anhydrous e	ethanol	MJ/L	21.3	21.1

Table 4.3: Lower heating values for fuels in GREET and BESS.

4.4.2 GENERAL ISSUES WITH AGRICULTURAL PRODUCTION DATA

Agricultural survey data collected by the USDA's National Agricultural Statistics Service (NASS) and Economic Research Service (ERS) underlie all major life cycle analyses of US corn ethanol and soybean biodiesel. USDA reports these data as averages for each parameter (e.g. agrichemical application rates, yield, on-farm energy use, incidence of no-tillage). Individual agrichemical rates are also reported using separate averages for application rate and percent of acres treated—and in

the case of lime, the number of years between treatments. Although this reporting approach treats these parameters as independent, some of these values are clearly correlated (Farrell et al., 2006c).

In general, estimates of the GWI of corn will differ if estimated (a) using independentlyaveraged parameters or (b), averaging individual per-farm estimates. The latter approach inherently accounts for correlations; the prior approach does not. The size of the bias introduced by the pervasive use of separately averaged parameters in life cycle assessment can only be estimated by comparison with a bottom-up analysis. However, since a bottom-up analysis is not available, this study uses the USDA data as reported.⁶

4.4.3 PLANTED VERSUS HARVESTED ACRES

An issue that was overlooked in several earlier corn ethanol energy analysis is that agricultural data on energy use and inputs are reported *per planted acre*, whereas yields are typically reported *per harvested acre* (Wu et al., 2006, section 3.3). Calculations can be performed on a per-planted or per-harvested acre basis; either approach requires adjusting some of the data.

GREET adjusts agricultural inputs to a harvested acre basis, applying a 90% harvested-toplanted acre ratio, as documented in Wu et al. (2006). This is based on USDA data from 1988 to 2005, and although not stated, appears to be for all corn planted in the US. However, the cornbelt has a higher than average ratio of harvested to planted acres, as shown in Table 4.4.

4.4.4 WATER AND SEED ENERGY

Energy for irrigation and seed production, which are included as separate line items in BESS, are accounted for in GREET's estimate of total farm energy use. This factor is left unchanged in BESS*.

We note that Liska et al. assume that 100% of the energy for seed production is in the form of agricultural diesel fuel. This seems incorrect, given that seed production is basically corn production, and diesel contributes only 10% of total emissions in corn production. The 9.7 MJ kg⁻¹ for seed corn used in BESS originates with Graboski (2002, p. 27-28), estimated as 467% of the total per unit energy for corn production. This higher energy demand is a result of the much lower yields for hybrid seed corn (owing to less dense planning), and to higher drying demands.

4.4.5 CUSTOM WORK AND INPUT HAULING

When computing on-farm energy usage, BESS appears to exclude two categories of energy use included in prior USDA studies and in GREET: custom work and input hauling. Custom work refers to energy used by third parties hired to perform a range of field operations. Input hauling refers to energy required to move inputs to the farm. In Shapouri et al. (2004), these two categories amount to 9% of the total on-farm energy use for the average of nine major corn-growing states based on 2001 USDA survey data. It's worth noting that the energy used for custom work is

⁶ The author is currently developing a bottom-up analysis of corn GWI based on USDA survey data.

State	Planted (10^6 acres)	Harvested (10^6 acres)	Harvested:Planted ratio
Illinois	11.00	10.85	99%
Indiana	5.80	5.67	98%
Iowa	11.70	11.40	97%
Kansas	3.45	3.05	88%
Michigan	2.20	1.90	86%
Minnesota	6.80	6.20	91%
Missouri	2.700	2.60	96%
Nebraska	8.100	7.75	96%
North Dakota	0.88	0.71	80%
Ohio	3.40	3.17	93%
South Dakota	3.80	3.40	89%
Wisconsin	3.40	2.60	76%
United States	75.70	68.76	91%
12-state avg	63.23	59.29	94%

Table 4.4: Corn acres planted and harvested in 2001. (Source: USDA Quick Stats, http://www.nass.usda.gov/QuickStats).

quite uncertain: the USDA survey data include only the expenditure for custom work, from which fuel use must be estimated (Graboski, 2002), and Shapouri et al. (2004) do not document the assumptions underlying their calculation. This energy use is included in GREET, but since it's unclear whether it's included in BESS, BESS* does not add this factor.

4.4.6 AGRICULTURAL DATA VINTAGE AND YIELD

Life cycle studies of biofuels typically average crop yields over a few years to avoid giving too much weight to a single anomalous year. Shapouri et al. (2004) use this approach in their energy balance for 2001 corn ethanol, combining the average yield from 2000-2002 with data on corn production practices for 2001. Assuming a long-term trend in yield, bracketing the year in question helps smooth out annual variations owing to temperature and precipitation differences.

Liska et al. use average yield data from 2003-2005 with on-farm energy use data from 2001, fertilizer data from 2005⁷, and manure application data from 1997, with all values based on weighted averages by harvested area in 12 states: South Dakota, Minnesota, Iowa, Wisconsin, North Dakota, Illinois, Indiana, Michigan, Nebraska, Ohio, Kansas and Missouri.

The use of yields, energy use, and production practices from different periods introduces a bias, though owing to a lack of complete data, the magnitude and direction of the bias are unclear. Dividing per-acre energy use for 2001 by the higher average yield achieved in later years—9.6 Mg ha⁻¹ for 2003-2005 versus 8.7 Mg ha⁻¹ for 2000-2002—reduces the estimate of GHG emissions versus the approach used by Shapouri et al. All else equal, higher yields require greater per-hectare fuel use for certain operations (e.g., harvesting and drying corn), although this effect may be mitigated by increases in energy efficiency. The approach used by Liska et al. implicitly assumes that despite a 9% increase in yield, per-hectare energy use remained constant.

GREET is based on 2001 USDA corn production data, using average values from 9-states rather than 12-states as in BESS. GREET, however, extrapolates from the 2001 data to predict chemical application rates, biorefinery energy use, and many other parameters.⁸ By default, GREET uses values extrapolated to 2010, providing a "forward-looking" analysis. Table 4.5 shows the values of several important corn ethanol parameters in GREET for years 2001 and 2010. The GREET scenarios in this analysis use the 2010 projections since this best matches the intention in BESS to reflect current practices.

Excluding lime, which is discussed below, the difference between the BESS and GREET approaches is negligible in practice: applying the GREET agricultural input assumptions (other than lime) to BESS increases the GWI estimate by only 0.3 g CO_2e MJ⁻¹. However, while the two approaches yield similar results, it is difficult to say whether either one accurately represents cur-

⁷ According to table 4 in the BESS User's Guide (version 2008.3.1) and table 1 of the spreadsheet version of BESS examined here, the MW-NG scenario relies on year 2001 data for on-farm energy use and agricultural inputs. However, according to Liska (responding to an earlier draft of this analysis), the fertilizer inputs for the MW-NG scenario are mislabeled and all BESS scenarios use 2005 fertilizer data.

⁸ GREET also extrapolates yield, but this is used only for corn stover yield and machinery energy use. GREET represents all agricultural inputs and energy use on a per-bushel basis.

Parameter	Units	2001	2010
Energy	Btu gal-1	15,363	12,635
Nitrogen	g N bu $^{-1}$	480	420
Phosphorus	$g \ P_2 O_5 \ bu^{-1}$	167	149
Potassium	$g \ K_2 O \ bu^{-1}$	196	174
Lime	g CaCO ₃ bu ⁻¹	1,370	1,202
Anhydrous ethanol yield	gal bu $^{-1}$	2.65	2.72
Biorefinery energy demand	Btu gal-1	36,900	36,000

Table 4.5: Key Agricultural and biorefinery parameters in GREET 1.8b for 2001 and 2010. Assumes 100% drying of distillers grains.

rent corn production practices. Clearly, what is required for an accurate assessment is an updated set of corn production data. Hopefully the U.S. Department of Agriculture (USDA) will resume collection of these data.

4.4.7 AGRICULTURAL LIME

4.4.7.1 TYPES OF LIME

Lime is added to agricultural soils to neutralize acidity. Agricultural lime (aglime) is generally calcitic or dolomitic limestone that is crushed and ground (De Klein et al. 2006, 11.27). Calcitic limestone consists mostly of calcium carbonate, or CaCO₃, whereas dolomitic limestone contains 10-50% dolomite (CaMg(CO₃)₂), and 50-90% calcium carbonate (Spectrum Analytic, Inc., 2009a). Another form is calcium oxide (CaO), also known "burnt lime" since it results from heating CaCO₃ to liberating the CO₂ molecule, leaving CaO.

The emission factors for lime production and use depend on which type of lime is assumed. The production of CaO releases the CO_2 from calcium carbonate in the production phase, whereas the application of aglime results in a loss of CO_2 from the field. The IPCC's Tier 1 method for estimating the field emissions from liming assumes that 100% of the carbon in aglime is emitted as CO_2 , though with a one-sided uncertainty range of -50%, meaning the value might be less that 100% (De Klein et al., 2006, 11.27-11.30). Recent empirical data also support a lower emission rate (Biasi et al., 2008).

Unfortunately, the USDA's corn production surveys that provide the liming rates used by GREET and BESS did not ask the farmer what type of lime was used. In the GREET model, lime is assumed to be $CaCO_3$, and 100% of the CO_2 from lime is assumed to be emitted in the field.

For lime production emissions, GREET adopts the production emissions assumed for potash (KCl), while using distinct transportation distances for lime (Wu et al., 2006). The basis for this equivalence isn't clear. In an earlier study, Graboski estimated much lower energy use for limestone mining (54 Btu/lb) than for potash mining (2,059 Btu/lb), since most limestone is produced in surface quarries, whereas most of the potash used in the Midwest is produced in Saskatchewan using more energy-intensive shaft mining operations (Graboski, 2002, 86-88).

Although the BESS User's Guide is silent on the type of lime assumed, the BESS spreadsheet indicates the use of "high Ca" lime, and adopts the IPCC's emission factor for production of CaO, which accounts for the CO_2 emission in production rather than in the field (Hanle et al., 2006, 2.23). However, this factor excludes emissions from the mining and transportation of lime.

The GREET emission factors for lime production and field emissions appear to be too high. The BESS factor is clearly too low, since it omits mining and transport. BESS* currently uses the lime emission factors from GREET, although neither model's treatment of lime is completely satisfactory.

4.4.7.2 LIME APPLICATION RATE

Lime application rate has been a source of considerable confusion in analyses of corn ethanol. Prior life cycle studies cite various USDA reports showing application rates that ranged across three orders of magnitude, with the high and low values ultimately attributed to errors in reporting (Graboski, 2002; Farrell et al., 2006c; Wu et al., 2006). USDA reports lime rate using three terms (i) the percentage of acres receiving lime, (ii) the tons of lime per treated acre, and (iii) the number of years between applications. The average lime rate is thus product of the first two terms divided by the third. The average rate for corn in 2001 was about 400 lb ac^{-1} (Wang et al., 2007).

A footnote in the spreadsheet prepared by Liska and colleagues states: "Average lime application rates for all states were determined by multiplying the percent of area with lime applications by the national average lime application rate of 400 lb ac^{-1} (448 kg ha^{-1})". The lime application rate derived this way and used in BESS is 212 kg per ha. However, since the average already accounts for the percentage of acres treated, applying this fraction again incorrectly reduces the application rate.

The 2010 lime application rate in GREET (1,202 g $CaCO_3 bu^{-1}$) is extrapolated from an average per planted acre rate in 2001 of 1,264 g $CaCO_3 bu^{-1}$ (Wu et al., 2006). At the 2010 yield of 158 bu ac^{-1} assumed in GREET, this is equivalent to 469 kg $CaCO_3 ha^{-1}$, more than double the rate used in BESS, but close the value noted in the BESS documentation, prior to the adjustment.

BESS* adopts the lime application rate from GREET. Adjusting BESS* to use GREET's lime application rate and emission factors increases the GWI estimate in BESS by 3.8 g CO_2e MJ⁻¹.
4.4.8 FERTILIZERS

BESS takes data from several sources for its estimates of the energy requirements to produce fertilizers (N, P, and K), and lime. Nitrogen fertilizer energy is taken from Snyder et al. (2007), phosphate and potassium from Kongshaug (1998), and lime from Graboski (2002) via Farrell et al. (2006b). Several issues with these data are discussed below.

4.4.8.1 NITROGEN FERTILIZER

Snyder et al. report energy values from GREET 1.8a (Snyder et al., 2007, Table 4) for three types of nitrogen fertilizer: (i) ammonia (actually including anhydrous ammonia, aqua ammonia, nitrogen solution and "other"), (ii) urea, and (iii) ammonium nitrate (actually including ammonium nitrate, ammonium sulfate, and ammonium thiosulfate) (Wang 2008). The energy value in BESS (45 MJ kg⁻¹ N) is the value for category (i) only, and it is the lowest value of the three. The values for the categories (ii) and (iii) are 53 and 65 MJ kg⁻¹ N, respectively. The weighted average of these in GREET (assuming that 71% of the N is applied in the form of anhydrous ammonia, 21% as urea, and 8% as ammonium nitrate) is 49 MJ kg⁻¹ N, 10% greater than the value adopted in BESS.

Although Snyder et al. also report life cycle CO_2e emission factors for fertilizers and lime, Liska et al. adopt the emission factor for ammonia production given in the IPCC's greenhouse gas inventory guidelines as their emission factor for N fertilizer. This factor excludes emissions from the production and transport of natural gas (the primary input to the ammonia process), the conversion of ammonia to the various forms of fertilizer actually used, and for the transport of the resulting fertilizer.

Production phase GHG emission factors vary widely across N fertilizer types (Kongshaug 1998; Nemecek and Erzinger 2005). Nitric-acid-based fertilizers in particular have high global warming potentials owing to N_2O losses in the synthesis of nitric acid (Snyder et al. 2007). To represent average production practices in an LCA, the weighted average of the emissions from the various type of fertilizers used should be used (Nemecek and Erzinger, 2005).

According to the USDA, anhydrous ammonia accounted for only 15% of nitrogen fertilizer applied in 2005, as shown in Table 4.6. Indeed, most of the ammonia produced in the US is converted to other forms of nitrogen fertilizer (Worrell et al., 2000). However, it is difficult to find data on which types of fertilizers are applied to a specific crop; statistics reported by USDA generally show only total nitrogen applied without distinguishing the form used.

Snyder et al (2007), report that the current mix of N sources used in North America have an average life cycle GHG emission factor of about 4 kg $CO_2e kg^{-1}$ N, though this is diminishing over time as the use of ammonium nitrate declines and the use of anhydrous ammonia and urea increases. The emission factors in GREET and BESS are 3.06 and 2.63 kg $CO_2e kg^{-1}$ N, respectively. BESS* adopts GREET's nitrogen fertilizer emission factor, adding 0.72 g $CO_2e MJ^{-1}$ to the GWI in BESS*.

Form applied	Material tons	Percentage
Anhydrous ammonia	3,857,891	15%
Aqua ammonia	420,879	2%
Ammonium Nitrate	1,420,653	6%
Ammonium Sulfate	1,181,609	5%
Nitrogen solutions	10,499,854	42%
Sodium nitrate	21,353	0%
Urea	5,211,665	21%
Other	2,629,043	10%
Total	25,242,947	100%

Table 4.6: Forms of nitrogen fertilizer applied in 2005, and percentage by mass. Source: http://www.ers.usda.gov/Data/FertilizerUse/Tables/FertilizerUse.xls.

4.4.8.2 SOIL EMISSIONS OF NITROUS OXIDE AND CO2

Both BESS and GREET rely on the IPCC Tier I method for calculating N_2O released from agricultural soils. BESS estimates that 1.8% of applied N is released as N_2O . This rate includes emissions resulting from manure application and from nitrogen in above- and below ground biomass, but is expressed in terms of applied chemical N.

Although GREET's stated emission rate for N_2O emissions from applied N fertilizer is 1.325%, GREET accounts separately for the N in above- and below-ground biomass. Combining all soil N_2O sources in GREET and expressing these emissions in terms of N fertilizer application results in an effective emission rate of 1.74%. As these rates are very close, we didn't adjust the N_2O emissions in either model.

BESS includes emissions from manure, however this estimate is based on manure data from 1997. It's unclear whether these data are representative of current practices. It's also unclear whether the USDA corn production data for nitrogen applications already include manure. In this regard, both models would be greatly improved by access to current and more complete data.

GREET also accounts for field emissions of CO_2 from the portion of nitrogen fertilizer assumed to be in the form of urea. (It accounts for the capture of atmospheric CO_2 in the production of urea as well.) Adding these emissions to BESS* add 0.5 g CO_2 MJ⁻¹ to the fuel's GWI.

4.4.8.3 PHOSPHORUS AND POTASSIUM FERTILIZER

As with nitrogen and lime, several forms of phosphorus and potassium fertilizers are used in agriculture. To simplify matters for farmers, phosphorus and potassium fertilizers are rated by their K_2O and P_2O_5 equivalence, respectively, although these two chemical forms are never present in the actual fertilizer (Spectrum Analytic, Inc., 2009c,b). Thus the masses of P_2O_5 and K_2O reported by USDA do not reflect the actual mass of fertilizer produced, transported, or applied, and the LCI must be adjusted accordingly (Graboski 2002, 86-87).

Approximately 90% (by mass) of the potassium fertilizer applied to US crops is in the form of potassium chloride (KCl) (USDA 2009, Table 5; Graboski 2002). KCl is rated as 60-62% K₂O equivalent, so applying, say, 100 lbs of K₂O-equivalent requires about 100/0.61 or 163 lbs of KCl, 63% more mass than suggested by the "K₂O" application rate reported by USDA, affecting production and transport emissions (Spectrum Analytic, Inc., 2009c; Graboski, 2002). Other forms of potassium fertilizer (e.g., potassium sulfate, potassium-magnesium sulfate, potassium nitrate) have lower K₂O-equivalence ratings, so the remaining 10% of potassium fertilizer would require yet larger mass adjustments (Spectrum Analytic, Inc., 2009c).

BESS takes life cycle GHG emission factors for P_2O_5 and K_2O from EBAMM (Farrell et al., 2006b), which are derived from GREET 1.6. GREET adjusts production energy and emissions of phosphorus fertilizer to a P_2O_5 basis, but the assumptions underlying this (particularly the P_2O_5 equivalence ratio) are not clear. GREET treats the mass of K_2O reported by USDA as equal to the mass of fertilizer applied, which understates the mass produced and transported, and thus undercounts emissions, as indicated above. However, as GREET is the ultimate source for the emission factors for K_2O in both models, we ignore this mass adjustment for the present analysis.

4.4.9 FUEL ETHANOL PRODUCTION

Fuel ethanol plants produce *denatured* ethanol: pure anhydrous ethanol is blended with some form of gasoline to render the alcohol non-potable, thereby avoiding beverage alcohol taxes. ASTM D 4806, the standard for fuel ethanol, permits only natural gasoline, gasoline components, or unleaded gasoline to be used as a denaturant. Denaturant volume can range from 1.96 to 5%; producers adjust the fraction between these limits to minimize cost (Kotrba, 2008).

The most common denaturant is natural gasoline, also known as natural gas condensate, a low-density, liquid hydrocarbon by-product of natural gas production (NaturalGas.org, 2009). To our knowledge, the life cycle of natural gasoline production remains unexamined. In practice, fuel cycle LCAs that include denaturant generally use conventional unleaded gasoline as a proxy, even though the production processes for natural gasoline and these refined petroleum products are quite distinct. However, as most of the life cycle GHG emissions from natural or conventional gasoline result from the fossil carbon in the fuel, we don't expect the GWI of natural gasoline to be substantially lower than that of gasoline. Lowering the GWI of denaturant in GBAMM from 92 to 85 g CO_2e MJ⁻¹ reduces the fuel ethanol GWI by only 0.5 g CO_2e MJ⁻¹. The present analysis nominally uses conventional gasoline as denaturant.

Denaturant is often omitted in ethanol LCAs. Even in studies that are careful to distinguish between denatured and pure anhydrous ethanol, the denaturant fraction may not be reported (e.g., Wu, 2008). BESS models anhydrous (non-denatured) ethanol since it takes no account of denaturant blending. Biorefinery data underlying the MW-NG scenario are based on survey data from the Renewable Fuels Association (RFA), documented by Argonne National Laboratory (Wu, 2008; Liska et al., 2009). These survey data (e.g. biorefinery yield and energy use) are provided on a *denatured* basis, assuming 4.7% denaturant.⁹ We adjusted the biorefinery performance data in BESS* to an anhydrous basis by assuming 4.7% denaturant, reducing yields and increasing energy usage given that each denatured liter contains only 0.953 L anhydrous ethanol. That is, we multiplied yields by 95.3% and divided energy inputs by 95.3%. As with GREET, we then add denaturant to anhydrous ethanol to estimate the GWI of the final product. Table 4.7 shows an example calculation using the reported GWI (43.7 g CO₂e MJ⁻¹) of ethanol from the MW-NG plant modeled in BESS (after subtracting 1.4 g CO₂e MJ⁻¹ for distribution), assuming a 4.7% denaturant level using conventional unleaded gasoline (92 g CO_2e MJ⁻¹). Note that GWI calculations require weighting the blendstocks by their percentage contribution to energy, not to volume. Accounting for denaturant adds 3.5 g CO_2e MJ⁻¹ to the calculated GWI in BESS*.

Fuel	By volume	By energy	$\begin{array}{c} GWI \\ (g \ CO_2 e \ MJ^{-1}) \end{array}$	Energy content (Btu/gal, LHV)
Denaturant (conv. gaso- line)	4.7% ^a	7.15%	92.0 ^b	116,920
Anhydrous ethanol	95.3%	92.85%	43.7 ^c	76,330
Denatured ethanol	100%	100%	47.2	77,722

Table 4.7: Characteristics of anhydrous ethanol (as per BESS), denatured ethanol, and denaturant.

^{*a*} According to May Wu of Argonne National Lab, the denaturant level averaged 4.7% for plants in the RFA survey (pers. comm.).

^b Assuming conventional gasoline as denaturant.

^{*c*} Example value calculated in BESS, minus 1.4 g CO_2e MJ⁻¹ for distribution.

4.5 DISCUSSION

The baseline values for the GWI of corn ethanol, as estimated by BESS and GREET, are 45.1 and 64.4 g CO_2e MJ⁻¹, respectively, indicating an initial difference of 19.3 g CO_2e MJ⁻¹. Adjusting

⁹ According to email correspondence with May Wu of Argonne National Lab, author of the memo cited by Liska, et al. "RFA suggested 4.7% denaturant for the analysis."

GREET to use biorefinery performance and co-product credit assumptions from BESS's MW-NG scenario reduces GREET's estimate of GWI by 3.9 g CO_2e MJ⁻¹ to 61.3 g CO_2e MJ⁻¹.

Adjusting BESS* to account for missing upstream emissions and denaturant, adjusting biorefinery data to a denatured basis, and adopting GREET's lime rate and agricultural input emission factors, raises the estimated GWI from that model to 60.7 g CO_2e MJ⁻¹, effectively closing the gap between the models.

Table 4.8 shows the major differences between the two models, by category, with differences expressed in the change in g CO_2e MJ⁻¹ attributable to changing a single value from the baseline case in the indicated model to the value used in the adjusted case. Owing to interactions among parameters, the values associated with adjusting each factor separately depends on the order in which the changes are applied. However, the values shown do reflect the relative magnitudes of the individual differences.

Table 4.8: The changes to baseline GWI estimates from BESS and GREET, expressed in grams of $CO_2e MJ^{-1}$, adjusting each factor separately. With all factors considered simultaneously, the adjustment to BESS totals 15.6 g $CO_2e MJ^{-1}$.

Parameter or category	Results of adjustments to BESS (g $CO_2e MJ^{-1}$)	Results of adjustments to GREET (g $CO_2e MJ^{-1}$)
Biorefinery performance		-4.3
Lime rate and emission fac- tors	+3.8	
Denaturant blending	+3.4	
Adjust data to denatured basis	+3.1	
Fossil fuel emission factors	+2.3	
Electricity emission factor	+1.5	
Corn farming equipment	+0.8	
CO ₂ field emissions from urea	+0.5	
Co-product credit		+0.4
Ag. input emission factors	+0.3	
Heating values	+0.03	
Total adjustment	+15.7	-3.9

Both models rely primarily on 2001 corn production data—the last year for which comprehensive data are available from USDA, and both attempt to adjust these data to approximate current performance. Lacking current data, it is difficult to know whether GREET's approach of extrapolation, or BESS's approach of updating a portion of the agricultural data results in a more accurate assessment of current corn production practices. Better data is clearly required.

Figure 4.1 shows the contribution of each emission category to the gross emissions per MJ of anhydrous ethanol, before applying co-product credit. Although this graph is based on GREET*, the graph for BESS* is quite similar, as the purpose of this exercise was to close the gap between the adjusted versions of these models. This figure illustrates that properly accounting for lime and nitrogen fertilizer emissions is quite important to the life cycle of corn ethanol, and that reducing the natural gas use at the biorefinery is essential to lowering the GWI of corn ethanol.



Figure 4.1: Contribution to gross emissions per MJ anhydrous corn ethanol, before considering co-product credit, as estimated in GREET*. (N.B. This figure does not include land use change.)

The modeling of corn ethanol could be improved in both models. BESS would be improved if the authors (i) adopt the life cycle GHG emission factors from a reputable life cycle inventory database or spreadsheet model such as GREET or GHGenius for fossil fuels and electricity, (ii) improve treatment of lime use, and (iii) model denatured rather than anhydrous ethanol. GREET's modeling of corn ethanol would be improved with (i) endogenous calculation of on-farm energy use, (ii) explicit modeling of denaturant, especially natural gasoline, and (iii) better treatment of K_2O and P_2O_5 fertilizer usage and lime production energy. Both models—indeed all life cycle models of biofuels—would benefit from more complete and current agronomic data on feedstock production and bottom-up estimates of feedstock GWI.

CHAPTER 5 GREET UNCERTAINTY ANALYSIS

"Calculating the climate impact of biofuels is so complex, and our understanding is so incomplete, that we can make only general qualitative statements about the overall impact of biofuels on climate."

Mark Delucchi (2010)

5.1 PURPOSE AND SCOPE

This chapter presents uncertainty analyses of life cycle GHGs of several fuel pathways based on the Greenhouse Gas, Regulated Emissions and Energy use in Transportation (GREET) model, developed by Argonne National Laboratory (ANL) (Wang, 1999). The purposes of this chapters are (i) to identify which parameters are the most important contributors to the variance in ethanol and gasoline GWI, and (ii) to produce a rough characterization of the relative magnitude of the uncertainty in GWI for bio- and petro-fuels. This analysis allows me to compare the direct emission uncertainties (estimated herein) with those of indirect land use change for corn ethanol, described in the chapter 8. For these purposes, it is sufficient to restrict my analysis to ethanol (from corn, switchgrass, and farmed trees) and gasoline. I consider the two cellulosic ethanol pathways (switchgrass and farmed trees) to examine the importance to GWI uncertainty of assumptions regarding soil carbon sequestration and electricity co-product credits.

In this analysis, I did not attempt to review and refine the default GREET probability distributions for most of the model parameters. To do so would be require a large effort that, in my view, would add little additional value. GREET is primarily an attributional life cycle model, though it uses system expansion in many cases for co-product handling. As noted in chapter 2, the life cycle inventory in attributional models such as GREET rely on supply chain analysis and do not include indirect effects such as ILUC. As discussed in chapter 2.3.3.3, combining an attributional analysis in GREET with a consequential analysis of ILUC (and other indirect effects) is incoherent. Understanding the consequences of expanded biofuel production requires consequential modeling, which requires a different life cycle inventory than the one modeled in GREET. If our objective is to anticipate or guide policy consequences, attributional modeling can be misleading.

That said, the uncertainty analysis presented in this chapter is still valuable since regionalized versions of GREET provide the basis for GWI ratings in the California LCFS, and for similar

regulations being considered in the Northeastern US. It is therefore useful to (roughly) characterize the uncertainty in this type of attributional modeling and understand its magnitude relative to that of ILUC emissions.

5.2 INTRODUCTION

During the development of the California Low-Carbon Fuel Standard and the federal Renewable Fuel Standard, stakeholders and regulators engaged in a vigorous debate over the uncertainty in estimates of indirect land use change.¹ In this debate, the GWI estimates for the remainder of the fuel cycle—calculated using the GREET model in the case of the LCFS—were treated as though known precisely. Indeed, in the California LCFS, values for each fuel pathway are treated as though known to the hundredeth of a gram of CO₂e per megajoule (CARB, 2009a).

As demonstrated herein, the global warming intensity (GWI) of petroleum fuels is much narrower than that of biofuels. About 80% of the life cycle global warming effect of petroleum fuels results from the combustion of the fossil carbon in the fuel (NETL, 2008). The upstream portion of the petroleum fuel life cycle is variable owing to heterogeneity in the chemical composition of different crude oil feedstocks in refinery configuration, however this variance has only a small effect on total GWI, so even allowing for these uncertainties results in a relatively narrow distribution. The global warming effects of biofuels, in contrast, are *entirely* upstream or indirect², and result from several highly variable natural processes such as soil N₂O emissions and soil carbon sequestration. We therefore expect the global warming effects of crop-based biofuels to be far less certain, even excluding indirect land use change.

In this chapter, I examine the uncertainty in GWI for the fuels most immediately relevant to the California LCFS: California reformulated gasoline (CARFG), California electricity, Midwest corn ethanol, switchgrass ethanol, and farmed tree ethanol. More specifically, I determine which parameters are key contributors to uncertainty in GWI for these fuel pathways, and quantify and compare the uncertainty in GWI for these pathways.

5.2.1 PRIOR STUDIES

Several studies have examined the uncertainty in the life cycle GHG emissions from transportation fuels (e.g., Brinkman et al., 2005; Edwards et al., 2008; Malça and Freire, 2010). These studies are summarized below.

Argonne National Laboratory (ANL) collaborated with General Motors (GM) in 2005 to apply GREET to a range of fuels as produced and consumed in the US (Brinkman et al., 2005). During this project, ANL added the ability to run GREET under Crystal Ball³ to perform Monte

¹I examine uncertainty related to emissions from indirect land use change in chapter 8.

²This assumes that the emission of biogenic carbon is treated as climate-neutral, which is approximately correct for short growth cycles, but untrue for unsustainably harvested biomass.

³ANL later abandoned Crystal Ball, distributing instead a much simpler (but free) Excel add-in to perform Monte Carlo simulation.

Carlo analysis, and distributions were defined for some 700 model parameters. For criteria pollutants, ANL established probability distributions by reading 1999 emissions data from the National Emissions Inventory into Crystal Ball and having the software perform curve-fitting, then projecting these values to 2016, accounting for anticipated emission controls (Brinkman et al., 2005, p. 34). ANL assembled a group of experts to develop projections of future technology and subjective probability distributions informed by the 1999 data and expert judgment.

The Brinkman et al. study reported results for E85 rather than for pure denatured ethanol. The uncertainty ranges for biofuels in that study were narrower and more symmetrical than the results presented herein. For E85 from cellulose and corn they estimated 154 ± 27 and 451 ± 35 g CO₂e mile⁻¹, respectively, where the range identifies the 80% confidence interval (from the 10% to the 90% value of the output frequency distribution); for reformulated gasoline, they estimated GHG emissions of 552 ±21 g CO₂e per mile driven (Brinkman et al., 2005, Table D-1).

The definitive study of GHG emissions from fuel and vehicle systems in Europe has been conducted (with regular updates) by a consortium of EUCAR (the European Council for Automotive R&D), CONCAWE (the oil companies' European association for environment, health and safety in refining and distribution) and JRC/IES (the Institute for Environment and Sustainability of the EU Commission's Joint Research Centre) (Edwards et al., 2007a, 2008). This series of reports is sometimes referred to as the JEC (JRC-EUCAR-CONCAWE) study. In concordance with this chapter and other studies, the authors concluded that biofuel GWI is dominated by the "huge uncertainty" in estimates of GHG emissions from soils. The JEC study rejected the commonly used IPCC Tier I method for calculating N_2O emissions, which uses generic (not crop or region specific) emission factors for direct and indirect (leached) N_2O emission as a function of N applied. Rather, the JEC study used the DNDC soil chemistry model to calculate daily N_2O emissions based on specific crop and soil characteristics across Europe.

Unlike the Brinkman et al. (2005) report, the JEC study used an incremental approach to estimate the difference in GHG emissions between two "realistic" future scenarios, one with a given alternative fuel and one without.⁴ GHG emissions from refining operations were based on altering the product slate of European refineries to produces less of the refined product (gasoline or diesel) assumed to be displace by the alternative fuel under examination. Co-product credits were assigned for avoided production, assumed displaced by co-products.

The JEC study was implemented using the E3database⁵ LCA tool. Unfortunately, neither the JEC studies nor the E3database documentation present the probability distributions assumed by the model. However, a review of the E3database documentation indicates that the uncertainty analysis in this tool is more limited than in GREET or in the present chapter (Schurig et al., 2009). The only parameters that can be treated stochastically are restricted to energy and material inputs and emissions of CH₄ and N₂O. Global warming potentials, emissions or sequestration of CO₂ from agricultural soils, variance in the physical and chemical characteristics of petroleum and refined products, and model choices such as co-product allocation methods are therefore *not* included in

⁴A similar approach was followed by the USEPA in its RFS2 analysis.

⁵See http://www.e3database.com/.

the uncertainty analysis. Only four types of input distributions are supported: normal, uniform, triangular, and double triangle. Uncertainty results in the JEC study are limited to graphical presentation of error bars for which the meaning of the bars is not stated. It is therefore difficult to compare these results to those of GREET or of this study. JEC estimates of GWI for both petroleum and biofuels are generally lower than those of GREET.

Malça and Freire (2010) examined uncertainty in the GWI and energy efficiency of rapeseed oil (RO) as a substitute for fossil diesel fuel in an attributional LCA. Their analysis considered parameter uncertainty and model uncertainty related to the choice of co-product handling. They assumed rapeseed was grown on set-aside land and thus incurred no indirect land-use change emissions. Unlike most other studies, Malça and Freire (2010) include the $\pm 35\%$ uncertainty for the 90% confidence interval around GWP values, as per the IPCC (Forster et al., 2007), though they considered only the 100-year time horizon. The study also considered a range of possible soil organic carbon (SOC) changes, from carbon uptake to carbon emissions. They conclude that uncertainties in the rate of N₂O emission and in soil carbon changes are the main contributors to uncertainty in the GWI of most biofuels. (The Malça and Freire study is discussed further in §3.2, and GHG results from that study are presented in figure 3.1.)

MacLean and Spatari (2009) examined the contribution of enzymes and process chemicals to the conversion of corn and cellulosic feedstocks to ethanol. They found that while the contribution of these inputs in the corn case is minor (approximately 3% of life cycle GHGs), enzymes and chemical production contributes 30-35% of life cycle GHGs in the cellulosic ethanol pathways examined, or approximately 9 g CO₂ MJ⁻¹ out of 27–29 g CO₂ MJ⁻¹ for two near-term simultaneous saccharification and co-fermentation (SSCF) processes. Other estimates are even higher: MacLean and Spatari note that the GHGenius model developed by Natural Resources Canada (based on earlier work by Mark Delucchi) estimates that enzymes contribute approximately 50 g CO₂ MJ⁻¹ to the cellulosic ethanol life cycle, though this is for currently available technology. Despite the magnitude of the emissions from these inputs, most LCA studies of cellulosic ethanol neglect to include them. Notably, GREET does not include enzymes and chemicals in its life cycle inventory for cellulosic ethanol (Wu et al., 2006). This oversight, as well as the longstanding exclusion of ILUC emissions in biofuel LCA, demonstrates that unlike observable quantities, LCA-based metrics are only as good as our modeling.

These studies evaluate average fuels, thereby propagating variance across production facilities through estimates of GWI. I follow the same approach here. An alternative would be to analyze the GWI uncertainty for a specific facility, holding performance parameters such as energy use, fuel yield, co-product yield constant, while allowing feedstock production parameters to vary. However, it is not clear whether facilities opting for specific ratings under the LCFS will be able to include the rating of specific feedstock production systems. This would further narrow the uncertainty by pinching agrochemical application rates and on-farm energy use, with the remaining uncertainty reflecting mostly N_2O emission rate and, for cellulosic feedstocks, soil carbon sequestration rate. Of course, these final parameters could be measured (within limits) rather than using national or regional averages. There is thus a trade-off between modeling very specific systems with relatively low uncertainty, and modeling more generic systems that include not only parameter uncertainty such as the N_2O emission rate, and model uncertainty such as co-product credits, but also variability across production systems. Which of these is most appropriate depends on the purpose served by the analysis. In a regulatory setting, the appropriate choice of uncertainty and variability to include should reflect the specificity of the regulatory accounting protocol.

Under the California LCFS, fuel produced from known types of facilities are assigned a GWI rating appropriate to that the combination of feedstock and conversion technology used. This combination is referred to as a *pathway*. The regulation allows facilities to apply for a facility-specific rating if the result is at least 5 g CO₂e MJ^{-1} lower than the default rating for that pathway. In these cases, the variability among production facilities is eliminated, but the result applies only to a specific facility. In the context of the LCFS, the present analysis can be thought of as characterizing the uncertainty in the default values for each modeled pathway.

5.3 Methods

5.3.1 THE GREET MODEL

This analysis is performed in the Greenhouse Gas, Regulated Emissions and Energy use in Transportation (GREET) model, developed by Argonne National Laboratory (ANL) (Wang, 1999). GREET tracks life cycle energy use and emissions of CO₂, N₂O, CH₄, CO, NO_X, SO₂, nonmethane volatile organic compounds (NMVOCs), and particulate matter as PM2.5 and PM10 for a wide range of fuel production systems and vehicles. GREET estimates total greenhouse gases (GHGs) as CO₂ equivalent emissions by applying the 100-year GWPs from the IPCC's Fourth Assessment Report (Forster et al., 2007) to total life cycle emissions of CO₂, N₂O, and CH₄, as well as counting the oxidation of the carbon fraction of CO and NMVOCs to CO₂. GREET does not account for direct or indirect GWPs for the other emissions it tracks. It includes (direct) soil carbon changes associated with the production of bioenergy feedstocks, but does not include emissions from indirect land-use change (ILUC).

5.3.2 UNCERTAINTY ANALYSIS

I used Monte Carlo simulation to perform both uncertainty importance analysis and uncertainty propagation. The stochastic analysis module provided with GREET does not include an uncertainty importance analysis capability, nor does it provide access to the simulation data, which would allow uncertainty importance to be estimated using other tools.⁶ GREET does, however, include probability distributions for over 700 model parameters. These distributions are declared on the "Distributions" worksheet by identifying the worksheet and cell address of each variable, naming the distribution (e.g., NORMAL, LOGNORMAL, UNIFORM), and providing parameters that define the named distribution. Rather than manually entering into Crystal Ball the hundreds

⁶I verified this in conversations with GREET developers at ANL and the programmers who developed GREET's stochastic module. Although ANL declined to fund the programmers to add an uncertainty importance analysis capability to the module, ANL was very helpful during my development effort.

of distributions in GREET, I developed a Visual Basic module⁷ to read the distribution definitions and apply them programmatically in Crystal Ball using the Visual Basic application programming interface available with Crystal Ball. My VBA module is listed in Appendix A; my modifications to the distributions provided in GREET are discussed in §5.3.4.

For both uncertainty importance and uncertainty propagation, I ran a 2,500-trial Monte Carlo simulation. GREET uses circular calculations that, by default, are evaluated using 100 iterations. To make the Monte Carlo simulation tractable, I reduced the number of iterations per trial to 10.

5.3.2.1 UNCERTAINTY IMPORTANCE

In many cases, a small number of parameters account for the majority of uncertainty in model results (Morgan et al., 1990). Identifying these parameters helps guide further research to reduce uncertainty, and helps streamline uncertainty propagation since the typically much larger set of parameters that contribute very little to overall uncertainty need not be represented as uncertain.

To estimate uncertainty importance, Crystal Ball saves all inputs to and outputs from a Monte Carlo simulation and computes the rank correlation between the inputs and each output parameter, then normalizes these to sum to 100%. This provides a global measure of sensitivity, i.e., the contribution of each parameter to the overall variance, across the full range of values for all uncertain model inputs.

5.3.2.2 Scenarios

As shown in figure 5.1, the GWI of cellulosic biofuels depends on the type of electricity assumed to be displaced. To analyze uncertainty importance, I used a discrete uniform distribution to select between four electricity displacement options in GREET: (i) US grid average, (ii) natural gas combined-cycle (NGCC), (iii) coal integrated gasification combined cycle (IGCC) and (iv) biomass IGCC.

To separate this scenario uncertainty from variability in the pathways defining the cellulosic ethanol pathway, I also performed a two-dimensional Monte Carlo analysis that used a 2500-trial simulation for each electricity displacement possibility. The results are shown in figure 5.10.

5.3.3 FUEL PATHWAYS CONSIDERED

I examine uncertainty in five fuel pathways: California reformulated gasoline (CARFG), California electricity, and ethanol from corn, switchgrass, and farmed trees. All scenarios are run for the year 2010.

This analysis uses the baseline cellulosic ethanol facilities defined in GREET. For corn ethanol, I updated GREET to use dry mill performance characteristics taken from Mueller (2010). The

⁷The Visual Basic Module is available at http://plevin.berkeley.edu/tools/CBG.xlm.

biorefinery performance characteristics, as modeled, are shown in table 5.1. For cellulosic feedstocks, a GREET parameter declares the fraction of the feedstock that is converted to ethanol; the remainder is used for process energy.

Table 5.1: Default ethanol biorefineries modeled in GREET. Energy use = total imported energy consumed in ethanol production (natural gas plus electricity); EtOH fraction = fraction of biomass used to produce ethanol – the remainder is used for process energy.

Feedstock	Yield	Energy use	EtOH fraction
Corn	$2.8 \text{ gal } \mathrm{bu}^{-1}$	31,480 Btu gal ⁻¹	n/a
Farmed trees	90 gal (dry ton) ⁻¹	n/a	55%
Switchgrass	95 gal (dry ton) ^{-1}	n/a	60%

5.3.3.1 CORN ETHANOL

To model corn ethanol in natural-gas-fired dry mills, I applied data presented in a recent dry mill survey (Mueller, 2010), which indicates that natural gas dry mills use 8.1 MJ (HHV) of natural gas and 0.192 kWh of electricity and per liter ethanol. Converting these to English units yields values nearly identical to those assumed by the BESS model (Liska et al., 2009; Plevin, 2009). For GREET purposes, these translate to a total of 31,480 Btu gal⁻¹ ethanol, with 92% of the energy used in the form of natural gas, and 8% in the form of purchased electricity. The survey results presented in Mueller (2010) show a 12% coefficient of variation (CV) for natural gas use, a 31% CV for electricity use, and a 4% CV for ethanol yield. Yield averaged 2.81 gal (anhydrous) bu⁻¹.

These performance parameters are adopted for the present analysis, with normal distributions defined with the given standard deviations. Given that natural gas provides over 90% of the total energy, I ignored the larger CV of electricity and assigned a 12% CV to the total energy value in GREET. Although these performance parameters are clearly not independent, I treat them as independent in the analysis owing to lack of data on correlations. The best way to handle these data would be to compute the GWI of each facility separately, treating the production system as an integral whole, thus bypassing the need to represent correlations among the averaged parameters. Unfortunately, the data are proprietary and unavailable.

In this analysis, I adopt GREET's assumptions regarding corn production. In my comparison of the BESS and GREET models, I concluded that the differing assumptions in these models resulted in insignificant differences in terms of GHG emissions from corn production (Plevin, 2009).

5.3.3.2 Cellulosic ethanol

Two bio-chemical cellulosic ethanol pathways were considered, based on switchgrass and farmed trees. Both pathways are represented by the stock GREET parameters and distributions. Farmed trees and switchgrass production are assumed to result in a net gain in soil CO_2 . The sequestration parameters for these feedstock were represented in GREET by the distributions shown in table 5.2. Table 5.3 lists the distributions for ethanol yield for the two cellulosic ethanol pathways.

Table 5.2: Parameters defining triangular distributions for CO ₂ emissions for land use change for
ethanol feedstocks. Negative values indicate sequestration.

Feedstock	Units	Minimum	Likeliest	Maximum
Corn	$g \operatorname{CO}_2 bu^{-1}$	0	195	390
Switchgrass	$g \operatorname{CO}_2 [dry ton]^{-1}$	-97,000	-48,500	0
Farmed trees	$g \operatorname{CO}_2 [\operatorname{dry} \operatorname{ton}]^{-1}$	-225,000	-112,500	0

Table 5.3: Parameters defining normal distributions for ethanol yield emissions for cellulosic ethanol feedstocks.

Feedstock	Units	20 th percentile	80 th percentile
Switchgrass	gal [dry ton] ⁻¹	80	103
Farmed trees	gal [dry ton] ⁻¹	76	98

5.3.3.3 CALIFORNIA REFORMULATED GASOLINE

Given the predominance of the carbon in the fuel in the GWI of gasoline and diesel, there isn't a great deal of value in precisely identifying the uncertainties in upstream emissions. Even a 50% variance would only alter the total GWI by $\pm 7\%$ or so. Therefore, I simply adopt the parameter values and distributions provided in GREET related to California reformulated gasoline (CARFG).

5.3.3.4 ELECTRICITY

To estimate the GWI of electricity used in electric vehicles, I used GREET's representation of average CA grid electricity, with generation from the following sources 0.0% oil, 36.6% natural

gas, 13.3% coal, 20.5% nuclear, 1.3% biomass, and 28.3% "other" sources, which are assumed in GREET to produce no GHG emissions. The GWI of electricity (at the plug) includes GREET's estimate of 8% losses from transmission and distribution.

For comparison on a MJ-to-MJ basis with liquid fuels, I adopted the approach defined in the CA LCFS of applying an energy efficiency ratio (EER) to represent the inherently greater efficiency with which a MJ of "fuel electricity" is used in an electric or plug-in hybrid vehicle, compared to the efficiency of an internal combustion gasoline engine. CARB defines the EER as the ratio of the miles driven per energy unit of an alternative fuel to the miles driven per energy unit consumed for a comparable vehicle using gasoline (CARB, 2009a, p. ES-18). CARB calculated EER values by dividing the fuel economy for a given fuel-vehicle combination by the fuel economy for a reference gasoline vehicle, where the reference vehicle chosen was the one that is "most similar in size and style", however when data was lacking, the agency used engineering analyses to determine EER (CARB, 2009a, p. IV-16). CARB notes that the actual ratio varies with battery size, vehicle size, and drive cycle, and for many vehicle types, the data required to make these estimates was quite limited (CARB, 2009a, p. ES-18). Moreover, the EERs initially calculated (e.g., for electric vehicles: 4.0 for 2000 Nissan Altra; 2.3 for 2003 Toyota RAV4; 3.5 for 2006 AC Propulsion eBox) were then divided by 1.3 to account for an projected 30% increase in reference gasoline efficiency between 2009 and 2016 owing to AB1493 (CARB, 2009b, p. C-9). The required choice of scenarios and vehicles to consider lends a certain arbitrariness to the estimate of EER (Andress et al., 2010).

CARB has set the EER for electric vehicles to 3.0, but recognizes that the value is only approximate, writing that "the staff has provided EER values that are to be used until such time that there is more robust data available to better establish the EER" (CARB, 2009a, p. ES-18). To represent these many uncertainties, I conservatively characterized the EER using a triangular distribution with minimum and maximum values of 2.7 and 3.3, respectively, using a best estimate of 3.0. As discussed in §5.4.1.1, even with this narrow uncertainty range, EER was by far the largest contributor to variance for "fuel electricity."

This analysis assumes that vehicles charge using the current average CA grid mix. In fact, the actual emissions associated with EV use depends on the mix of power plants generating when the vehicle plugs in, and so varies according to when users charge their vehicles. It also depends on whether one considers vehicle charging to be marginal, in which emissions calculations would be based on the dispatch margin (last plant dispatched), or if vehicles are assigned the average emissions of all generation online at the time of charging. (These challenges related to treatment of electricity in LCA, including assumptions of average and marginal electricity, are discussed in $\S 2.3.2.4$.)

5.3.4 MODIFICATION TO GREET PARAMETERS AND DISTRIBUTIONS

GREET includes probability distributions for over 700 parameters, about half of which relate to vehicles and are outside the scope of this study. The other half of the parameters relate to the many fuel production pathways represented in GREET. Most of these parameters were used as

defined in the model. In addition, several parameters that are treated as constants in GREET were assigned the probability distributions described in §5.3.4. Lacking empirical data for these, I generally assigned triangular distributions with maximum and minimum values 10% or 20% above and below the assumed GREET value. The purpose of this *ad hoc* assignment of distributions was not to accurately assess the resulting uncertainty, but simply to determine if these values were important contributors to uncertainty. This approach allowed me to systematically ignore unimportant uncertainties from the analysis, and to identify those requiring further research.

In some cases, values used as constants in formulae in GREET are actually uncertain. To accommodate these in the stochastic simulation, the formulae were modified to refer to a cell rather than a constant value, and the cell was assigned a distribution based on the value originally used in GREET. This was done for the percent of CO_2 in lime (CaCO₃) that is emitted in the field after application. GREET assumed 100% emission, but there is evidence that this varies, and under come conditions can result in net CO_2 sequestration (Hamilton et al., 2007). Similarly, GREET assumes that Ammonia, Urea, and Ammonium Nitrate (AN) comprise 70.7%, 21. 1%, and 8.2%, respectively, of the N applied in feedstock production. For this analysis, I represented the first two fractions as triangular distributions ranging 4% above and below the values stated above, with the AN taking up the remainder.

I treat the distribution for the rate of soil N₂O emissions from applied nitrogen slightly differently than in GREET. Where GREET represented this rate using a triangular distribution with minimum, likeliest, and maximum values of 0.4%, 1.325%, and 4%, respectively, I modeled the individual components of the overall N₂O emissions rate based on the IPCC Tier I method, using the stated uncertainties for each, represented using lognormal distributions. To produce a distribution for use in GREET, I ran a separate Monte Carlo simulation to produce a frequency distribution for N₂O emission rate (figure 3.2) and then used Crystal Ball's curve fitting feature to find the best match. The resulting distribution was a lognormal distribution with mean of 1.65\%, standard deviation of 1.11\%, and location of 0.02\%.

For the global warming potentials for CH₄ and N₂O I assigned distributions based on IPCC guidance, which indicates $\pm 35\%$ representing a 90% confid 2-sigma around mean (Forster et al., 2007).

5.3.5 SCENARIOS CONSIDERED

For cellulosic ethanol pathways (differentiated into woody and herbaceous⁸ feedstocks in GREET), the overall GWI depends on two questionable assumptions: (i) production of biomass results in a large soil carbon sequestration benefit—112.5 kg CO_2 ton⁻¹ for woody biomass and 48.5 kg CO_2 ton⁻¹ for herbaceous biomass (Wu et al., 2006), and (ii) co-produced electricity displaces average US grid electricity.

The soil carbon sequestration in switchgrass production results from an assumption that 39% of the feedstock is grown on cropland. We note that competition with food for cropland would trigger

⁸Herbaceous biomass in GREET refers to switchgrass.

indirect land use changes which are not included in GREET. If switchgrass is grown instead on non-cropland (e.g., CRP land), ILUC would be avoided, but the soil sequestration benefit would be eliminated. Indeed, if the establishment of switchgrass involves tillage, sizable direct land-use conversion emissions would result.

To examine the sensitivity to these parameters, I adjusted the electricity displacement assumption to vary between (i) US grid average, (ii) natural gas combined-cycle (NGCC), and (iii) biomass integrated gasification combined-cycle (IGCC), and varied the soil carbon sequestration assumption between the default GREET value and zero. As depicted in figure 5.1, changing only these two parameters causes the GWI of ethanol from woody and herbaceous biomass to range from -13 to 12 g $CO_2 MJ^{-1}$, and 12 to 22 g $CO_2 MJ^{-1}$, respectively. (GREET considers only direct emissions, so ILUC is not included in these estimates.) The effect is larger on woody biomass because the carbon sequestration assumption is more than double that of switchgrass. Note that zeroing out the soil carbon sequestration flips woody biomass ethanol from net sequestration to net emissions, though still with a very low GWI.



Figure 5.1: Range of results for cellulosic biofuel GWI (g $CO_2 MJ^{-1}$) in GREET, varying assumptions of the type of electricity displaced and the amount of soil carbon sequestered. Indirect land-use change is omitted from these estimates. NGCC=natural gas combined-cycle; IGCC=integrated gasification combined-cycle.

5.4 RESULTS

5.4.1 UNCERTAINTY IMPORTANCE ANALYSIS

For each fuel pathway, fewer than 10 parameters contributed at least 1% of the total variance. In all cases, these parameters accounted for at least 85% of the variance. The 24 parameters and the pathways to which they contributed at least 1% of the variance are listed in table 5.4.

The contribution to variance for key parameters in the electricity, CARFG, woody and herbaceous cellulosic ethanol, and corn ethanol fuel pathways are illustrated in figures 5.2 through 5.7. For each fuel pathway, uncertainty importance was examined for GWI using 100-year global warming potentials for CH₄ and N₂O. The discussion below identifies parameters contributing at least 1% of the variance in each fuel pathway. For all fuel pathways examined, fewer than 10 parameters contributed 1% or more of the variance, and these parameters accounted for 85–90% of the total variance.

5.4.1.1 ELECTRICITY

Even with a modest spread—a triangular distribution representing a $\pm 10\%$ range—the EER contributed 72% of the variance in the EER-adjusted electricity life cycle for average California electricity (figure 5.2). Uncertainties related to natural gas (recovery and processing efficiency, global warming potential of CH₄) contributed an additional 13% of the variance. However, as illustrated in figures 5.8 and 5.9, the overall uncertainty in the GWI of electricity is low compared to biofuels.



Figure 5.2: Contribution to variance for EER-adjusted CA electricity. EER = energy efficiency ratio, NA = North America, NG = natural gas, GWP = global warming potential.

Table 5.4: Parameters contributing at least 1% of the variance in modeled fuel pathways. CG = conventional gasoline; LHV = lower heating value; CARFG = California reformulated gasoline; effic. = efficiency; EtOH = ethanol; N = nitrogen; GWP = global warming potential; EER = energy efficiency ratio; NA = North American; NG = natural gas; CA = California; C = carbon;

Parameter	Pathway	
CG LHV	CARFG	
CARFG refining effic.	CARFG	
Corn dry mill energy use	CARFG, Corn EtOH	
Crude recovery effic.	CARFG	
N fertilizer N ₂ O emission rate	CARFG, Corn and Switchgrass EtOH	
CG C ratio	CARFG	
CH ₄ GWP	CARFG, CA Electricity	
EER	CA Electricity	
NA NG recovery effic.	CA Electricity	
NA NG processing effic.	CA Electricity	
Coal C ratio	CA Electricity	
Farmed tree CO ₂ sequestration	Woody EtOH	
Type of electricity displaced by cellulosic biore- finery	Woody and Switchgrass EtOH	
Woody EtOH electricity production rate	Woody EtOH	
Farmed tree farming energy	Woody EtOH	
N ₂ O GWP	Woody, Switchgrass, and Corn EtOH	
Woody EtOH yield	Woody EtOH	
Switchgrass N application rate	Switchgrass EtOH	
Switchgrass CO ₂ sequestration	Switchgrass EtOH	
Switchgrass EtOH yield	Switchgrass EtOH	
Switchgrass EtOH electricity production rate	Switchgrass EtOH	
Switchgrass farming energy	Switchgrass EtOH	
Corn EtOH plant energy	Corn EtOH	
Corn N application rate	Corn EtOH	
Corn ILUC adder	Corn EtOH	

5.4.1.2 CALIFORNIA REFORMULATED GASOLINE (CARFG)

As illustrated in figure 5.3, the top contributors to variance in the GWI of CARFG are refining efficiency (33%) and in parameters describing the chemical characteristics of conventional gasoline (47%), including lower heating value (32%), density (13%), and carbon ratio (2%). An additional 4% is contributed by the GWP values for CH₄ (3%) and N₂O (1%). However, as discussed below and illustrated in figures 5.8 and 5.9, the overall uncertainty in the GWI of CARFG is relative low compared to biofuels, as over 80% of the GWI is attributable to the carbon in the fuel itself.



Figure 5.3: Contribution to variance for reformulated gasoline. CARFG = California Reformulated Gasoline, Conv. Gasoline = conventional gasoline, GWP = global warming potential.

5.4.1.3 Cellulosic ethanol

For cellulosic ethanol produced from farmed trees (figure 5.4), the overwhelming drivers of variance are the CO₂ emissions (sequestration, in this case) from land use change during feedstock production (63%), and the type of electricity displaced by co-produced electricity (17%). Electricity yield (kWh gal⁻¹) contributed 3% of the variance.

For switchgrass ethanol (figure 5.5), the main drivers of variance were N₂O emission rate (35%), nitrogen fertilization rate (26%), soil carbon sequestration (8%), ethanol yield (6%), N₂O global warming potential (5%), the type of electricity displaced (4%), and farming energy use (2%). In total, 66% of the variance relates to N₂O emissions.

5.4.1.4 CORN ETHANOL

The main drivers of variance in the corn ethanol life cycle (figure 5.6) relate to nitrogen fertilization: N₂O emission rate (53%), N fertilization rate (13%), and N₂O GWP (5%), together contributing 71% of the variance. Biorefinery energy use contributed 15%. Variables such as corn farming



Figure 5.4: Contribution to variance for ethanol from farmed trees. LUC = land use change.

energy, lime application rate, and the amount of corn displaced by DDGS contributed about 1% each to the overall variance.

5.4.1.5 CORN ETHANOL WITH INDIRECT LAND USE CHANGE

Although GREET does not include emissions from indirect land use change (ILUC), the CA LCFS does. To compare the relative importance of the (very approximate) uncertainty in ILUC with the uncertainties in the direct emissions estimated in GREET, I included a triangular distribution for ILUC ranging from 0 to 100 g CO₂e MJ⁻¹, with the most likely value set to the value adopted by CARB, 30 g CO₂e MJ⁻¹. Under these assumptions, (figure 5.7), the ILUC "adder" contributes 77% (100-year GWP) with nitrogen-related emissions dropping to 11–13% of the total.

5.4.2 UNCERTAINTY PROPAGATION

To propagate uncertainty, I ran a 2500-trial Monte Carlo simulation using the distributions described above. The distributions resulting from these runs are presented below in two forms: as box plots (figure 5.8, and as frequency distributions (figure 5.9). The greatest uncertainty is visible in the GWI for corn and switchgrass ethanol pathways, largely a result of nitrogen fertilization and resulting N₂O emissions. Farmed trees require less nitrogen per dry kg of biomass and thus are less affected by the uncertainty in the N₂O emission rate. In general, the interquartile ranges for the biofuel pathways were approximately 3–4 times broader than those of CARFG or EER-adjusted electricity. The GHG emissions from both corn and switchgrass ethanol show a very small probability of being greater than those of CARFG, however these distributions do not include indirect effects such as ILUC. It's also important to note that the corn ethanol pathway modeled here represents an efficient, natural gas fired dry-mill that dries only two-thirds of its distillers grains. Many other configurations—including several that produce higher GHG emissions—are possible.



Figure 5.5: Contribution to variance for switchgrass ethanol. N = nitrogen, GWP = global warming potential, NG = natural gas.

One topic that warrants discussion is the treatment of the co-product credit for electricity cogenerated by cellulosic ethanol facilities. I have framed this analysis as producing distributions for the default values for pathways used by a regulator such as CARB. The type of electricity displaced by these facilities will differ regionally by grid composition and by policies affecting competition among electricity generators, e.g., the existence of binding renewable generation requirements that treat cellulosic ethanol facilities as renewable electricity providers.

To bound the range of possibilities, I ran three Monte Carlo simulations for cellulosic ethanol, assuming the type of displaced electricity was US grid average (the assumption used by USEPA for RFS2), natural gas combined-cycle NGCC, and biomass IGCC. The results from these scenarios are shown in figure 5.10. The GHG displacement of woody ethanol pathway is more sensitive than the switchgrass ethanol pathway to the type of electricity assumed to be displaced since this prior contains more lignin and generates more electricity per ton of biomass.

As expected, fixing the type of displaced electricity caused different parameters to rise above the 1% threshold of uncertainty importance. For example, assuming electricity from woody ethanol production displaces the US grid results in a 1.7% contribution to variance from the efficiency of utility-scale coal boilers, and when NGCC electricity is assumed to be displaced, natural gas turbine efficiency rises to contribute 1% of the variance.

5.5 DISCUSSION AND CONCLUSION

The uncertainty around GWI for fossil fuel dominated pathways such as gasoline and electricity is much narrow than the uncertainty around biofuel GWI. This is true for corn ethanol and both cellulosic ethanol pathways examined. The GWI estimates for biofuels are highly uncertain even without considering ILUC.



Figure 5.6: Contribution to variance for corn ethanol. GWP = global warming potential, N = nitrogen, DDGS = dried distillers' grains with solubles.

As expected, relatively few parameters are responsible for most of the variance in the five pathways considered. Assumptions about electricity displacement and soil carbon sequestration are critical to the GWI of cellulosic ethanol. Parameters related to nitrous oxide emissions contributed much uncertainty to all biofuel pathways examined. The energy efficiency ratio (EER) dominates the uncertainty for electricity, but the overall uncertainty is small.

5.5.1 UNCERTAINTY IN ESTIMATING THE CLIMATE EFFECTS OF PETROLEUM FUELS

The uncertainty in estimates of the GHG emissions is much narrower for petroleum fuels than for biofuels. Approximately 80% of the life cycle GHG emissions of gasoline and diesel fuels result from the combustion of the carbon in the fuel (NETL, 2008), which is directly observable. Significant uncertainties remain in the smaller upstream fraction of emissions related to exploration, production, and refining. The main challenges are the variability of crude oil and lack of publicly-available data on oil production and refining processes (NETL, 2008). Finally, coproduct allocation among the slate of refinery products can be somewhat arbitrary. For example, the GREET model relies on a "rule of thumb", which allocates "60% of total refining process fuel use to gasoline production, 25% to diesel production, and the remaining 15% to other petroleum products" (Wang, 2008a). Analysts from the US National Energy Technology Laboratory (NETL) used a more sophisticated approach, allocating emissions from each major refinery process to the fuels that utilize that process. We note that the NETL estimates of the life cycle GHG emissions for gasoline and diesel are 101.6 and 100.3 g CO₂e MJ⁻¹ respectively, somewhat higher than the values of 95.9 and 94.7 g CO₂e MJ⁻¹ adopted by CARB in the LCFS. The NETL values are estimates for the US for 2005, while the CARB estimates are for fuel used in California in 2010.



Figure 5.7: Contribution to variance for corn ethanol, including emissions from indirect land use change (ILUC). iLUC = indirect land use change, N = nitrogen.

5.5.2 LIMITATIONS OF THIS ANALYSIS

Substantial model uncertainty remains related to the use of ALCA for policy purposes, and to the blending of ALCA and CLCA. For example, in an attributional analysis, the life cycle inventory includes the feedstock entering the biorefinery. In the LCFS, GWI protocol doesn't include differentiated corn farming emissions; rather, an average value is used. However, this value measures the wrong thing from a net GHG perspective: what matters are the emissions associated with the crops grown to replace whatever is displaced by corn ethanol—which may not even be corn, much less average corn. In the RFS2, EPA estimates the emissions from the net change in farming practices, which is quite different. Many more variables and model uncertainties are involved here, plus projections of these data to 2022.

For corn, GREET treats amount of urea, soybean, and corn displaced by DDGS, as well as a reduction in CH_4 emissions as uncorrelated variables. Clearly these are correlated, though they are treated as uncorrelated in this analysis.

As is the norm in GREET, this analysis did not consider the climate effects of aerosols and indirect GHGs.

GREET doesn't include a crop yield parameter. Rather, GREET includes farming energy use and application rates for fertilizer, pesticide, and lime per unit of crop harvested that are computed outside of GREET. If yield were explicitly represented, it would likely be of great significance to the GWI uncertainty since it is spatially and temporally variable. As noted in chapter 4, GREET would be improved by endogenizing farming energy calculations, allowing the regional averages and their underlying assumptions to be considered in an uncertainty analysis.



Figure 5.8: Box plots representing the GWI (g $CO_2 MJ^{-1}$, 100-year GWP) of five fuel pathways resulting from a 2500-trial Monte Carlo simulation of five fuel pathways in GREET. The blue boxes show the interquartile range; the line across the box indicates the median. The ends of the whiskers show the maximum and minimum values. The crossbars identify the 2.5 and 97.5 percentile values. *Note that these distributions do not include indirect effects such as ILUC*. EtOH = ethanol; Wood EtOH = ethanol from farmed trees; Herb. EtOH = herbaceous (switchgrass) ethanol; CARFG = California reformulated gasoline; CA elec. w/EER = California electricity, divided by energy efficiency ratio (EER).



Figure 5.9: Frequency distributions corresponding to the box plots shown in figure 5.8 *Note that these distributions do not include indirect effects such as ILUC*. EtOH = ethanol; Wood EtOH = ethanol from farmed trees; Herb. EtOH = herbaceous (switchgrass) ethanol; CARFG = California reformulated gasoline; CA elec. = California electricity, unadjusted; CA elec. w/EER = California electricity, adjusted by energy efficiency ratio (EER).



Figure 5.10: Monte Carlo simulation results for cellulosic ethanol assuming different displacement scenarios for co-produced electricity. *Note that these distributions do not include indirect effects such as ILUC.* EtOH = ethanol; Wood EtOH = ethanol from farmed trees; Herb. EtOH = herbaceous (switchgrass) ethanol; NGCC = natural gas combined-cycle; BIGCC = biomass integrated gasification combined-cycle.

Part III

UNCERTAINTY ANALYSIS OF INDIRECT LIFE CYCLE EMISSIONS

CHAPTER 6

UNCERTAINTY IN ESTIMATING EMISSIONS FROM INDIRECT LAND USE CHANGE

"Too large a proportion of recent 'mathematical' economics are mere concoctions, as imprecise as the initial assumptions they rest on, which allow the author to lose sight of the complexities and interdependencies of the real world in a maze of pretentious and unhelpful symbols."

John Maynard Keynes¹

6.1 PURPOSE AND SCOPE

This chapter catalogues the wide range of uncertainties inherent in the estimate of emissions from biofuel-induced indirect land use change. This chapter takes a purely qualitative approach; I do not attempt to quantify the uncertainties, I merely describe the limitations of our knowledge. The challenge of accurately quantifying the uncertainty in models of the emissions from indirect land use change (ILUC) provides the rationale for instead using a reduced-form model to examine ILUC uncertainty, presented in chapter 8.

This chapter includes some text adapted from O'Hare, Plevin, Martin, Jones, Kendall, and Hopson, 2009, "Proper accounting for time increases crop-based biofuels' greenhouse gas deficit versus petroleum", *Environmental Research Letters* 4(2).

6.2 OVERVIEW

When bioenergy crops displace food and feed crops, the displacement can trigger the conversion of lands, somewhere on the globe, from forest or grassland to cropping (Searchinger et al., 2008b; Dumortier et al., 2009; Hertel et al., 2010a; Al-Riffai et al., 2010). This result occurs because agricultural land is a constrained resource, and the demand for food and feed is highly inelastic (Kløverpris et al., 2008). This phenomenon is *market-mediated* in that the effects are transmitted

¹According to http://en.wikiquote.org/wiki/John_Maynard_Keynes, this quote is from Keynes' 1935 book "A General Theory of Employment Interest and Money", Book 5, Chapter 21, Section 3, pg. 298.

through global markets linked by commodity substitutability and competition for land (Laurance, 2007).

The combined social-ecological system through which indirect land use change (ILUC) operates is complex in the mathematical sense of involving non-linear relationships (e.g., feedbacks and thresholds) not all of which are well-understood or well-characterized by existing models (Costanza, 2003; Parker et al., 2008). Computable General Equilibrium (CGE) models are designed to capture these economic relationships as well as possible, however, economic effects are only one of several interacting drivers of land conversion (Geist and Lambin, 2002; Pfaff et al., 2007). In addition, many economists have questioned the theoretical underpinnings of these models, as discussed further in section 6.3. Even if the models were perfectly valid theoretically, practical issues of data quality and sectoral resolution limit our ability to precisely model land use changes. Estimates of changes in the demand for agricultural land are therefore uncertain, and the presence of substantial epistemic uncertainty limits our ability to calculate objective probability density functions (pdf) for these model outputs.²

Figure 6.1 illustrates the steps required to estimate the climate effects of biofuels expansion. In step a, an economic model projects changes in crop, pasture, and forestry areas resulting from expanded biofuels production. As most economic models are not spatially explicit, the changes in production areas must be mapped onto specific ecosystem types (step b). Next, we estimate the carbon fluxes from land use change in the identified ecosystems (step c). Finally, the LUC emissions are aggregated in some manner to compare these to the effects of the baseline petroleum-based fuel (step d).



Figure 6.1: Schematic of indirect land use change calculation

As described in sections 6.4.1 and 6.4.2, both the mapping of economic results to land cover types (step b) and the estimation of carbon fluxes from conversion (step c) are highly uncertain, owing to limitations in identifying land cover types and forest growth dynamics using remote sensing, as well as uncertainties in the estimation of ecosystem carbon stocks. The choice of

²See chapter 8 for a quantitative analysis of ILUC emissions resulting from corn ethanol expansion.

treatment of the different time profiles of emissions between biofuels and petroleum-based fuels involves stochastic, epistemic, and decision uncertainty O'Hare et al. (2009).

The following three sections describe the many uncertainties and subjective model choices embedded in the current generation of ILUC emissions models.

6.3 UNCERTAINTY IN ECONOMIC MODELING

Economic equilibrium models attempt to predict the effects on the global economy (in the case of general equilibrium) or a small number of sectors (in the case of partial equilibrium) resulting from a "shock" to an assumed starting equilibrium state. Jansen (1994) describes well some the uncertainties prevalent in this form of modeling:

"The factors that influence economic agents' decisions are so numerous and their interrelation is so complex that a full description is impossible. Therefore, economic models highlight a few salient factors and are used by economists to discover interrelationships. But since even the very choice of the variables influences the outcome, the perception of economic reality must be personal indeed. Economists are (or should be) aware of this and many agree that the world is best described through (subjective) probability. Apart from the uncertainty introduced by a subjective choice of reduction of the complex reality, we encounter problems in economic modelling because data are generally observed with error."

In addition to parameter uncertainty, CGE models involve model uncertainties that are difficult quantify, such as choice of functional form for production and demand functions, the degree of sectoral and regional aggregration, and the process used to build the underlying social accounting matrix (SAM), the choice of exogenous and endogenous parameters (the "closure"), the choice of baseline year, and the calibration of model parameters to that year. These uncertainties are not generally included in uncertainty analyses of CGE models, yet these choices can substantively affect model outcomes (Jansen, 1994; Roberts, 1994; McKitrick, 1998; Abler et al., 1999). Importantly, model uncertainty is difficult to quantify, because we cannot compare results to the real world to gauge the model's accuracy. More generally, all complex, open systems (including CGE models) in which processes are incompletely understood, and input data incompletely known, are fundamentally unverifiable (Oreskes et al., 1994). Discussing the issue of validation, Hertel (1999) writes:

"One question which consumers of AGE [applied general equilibrium] model results often ask is: 'Has the model been validated?' This is a reasonable question to expect from an analyst seeking advice on a policy reform which may end up shifting hundreds of millions of dollars around the economy. How can we be assured that the model bear any relationship to reality? The typical answer is that the AGE model, like any simulation model, has not been econometrically estimated and therefore cannot be subjected to the usual forecasting tests. To the extent that (a) the individual components of the system are based on plausible, perhaps even econometrically estimated, relationships, (b) the underlying social accounting matrix is accurate and reflects the best economy-wide data available, and (c) the equilibrium assumptions and macroclosure are plausible, then the assertion is that the results will indeed shed relevant light on what might actually happen if the proposed reforms were implemented.

Realistically, any such 'validation' effort will inevitably involve a certain amount of tinkering with the model in order to improve its performance. In this sense, such exercises are really a more elaborate method of calibration (but something short of formal econometrics) in which the model is fitted to multiple data points. In this sense they do not constitute proof that the model will perform well in future simulations. However, such efforts to compare model performance to economic history will go a long way to addressing the criticism that AGE models bear little or no relationship to reality." (Hertel, 1999)

"Shedding relevant light" is less challenging than the task of estimating ILUC emissions with confidence. Given the inherent complexity of the real world economy and human economic behavior, economic equilibrium models are necessarily coarse representations of the real world. Recounting the limitations of CGE models, Bewley (2007) cautions that "it would surely be unwise to elaborate the model in order to simulate an entire economy in detail with the hope of making accurate predictions." Owing to computational practicalities, data limitations and the exclusion of important aspects of the real economy in CGE models, Bewley counsels that "[s]uccessful simulations use reasonably simple models to give rough estimates" (Bewley, 2007).

Partial equilibrium (PE) models present some similar and distinct challenges. PE models generally offer greater resolution than do CGE models, as they focus on one or two sectors, but by definition, they lack linkages to other sectors (Kretschmer and Peterson, 2010). Biofuels obviously span the agricultural and energy sectors, and there are several less-obvious linkages between these: natural gas is the primary input to nitrogen fertilizer production; energy prices affect crop production costs; several biofuel pathways co-produce and export electricity; and cellulosic biofuel producers may compete with biomass electricity producers for resources. PE models can be more accurate when dealing with shocks that are not expected to have large impacts beyond the sector(s) modeled, but for larger shocks or dominant sectors, the isolation of the modeled sectors becomes a limiting factor in these models. PE models also frequently lack an explicit representation of land as a constrained resource, which of course prevents these models from examining the competition for agricultural land the occurs as biofuels scale up (Kretschmer and Peterson, 2010).

6.3.1 CRITIQUES OF ECONOMIC EQUILIBRIUM MODELS

Empirical models, including CGE models, represent three types of information: (i) *analytical*, including the basic theoretical underpinnings of the model, which identify critical parameters and

relationships functional; (ii) *functional*, which defines how the analytical information is represented in the model; and (iii) *numerical*, which defines the values of model parameters (McKitrick, 1998). CGE models have been criticized in all three areas (Harrison et al., 1993), raising fundamental questions about the predictive capacity of these models.

The following list summarizes some of the limitations of CGE models as described in the economic literature. These items reflect a range of uncertainties related to all three types of information noted above. When considering analyses of the uncertainty in CGE model results (including ILUC estimates), it's important to bear in mind that most, if not all, of these uncertainties are generally excluded from the analysis.

- 1. The fundamental notions that equilibrium obtains, or that the equilibrium predicted by the model is unique or stable are false (Ackerman, 2002; DeCanio, 2003; Scrieciu, 2007).
- The calibration approach limits CGE models to use functional forms "which embody restrictive assumptions about the structure of the industries being modeled" (McKitrick, 1998), and the choice of functional form is influential in CGE model performance (Roberts, 1994; McKitrick, 1998). Ackerman (2005) writes:

"Any modeling exercise involves simplification of reality. The question is not whether simplifications are involved, but whether those simplifications clarify or distort the underlying reality. Unfortunately, in the case of CGE models of international trade, it is all too clear that model structures and assumptions introduce unintended distortions into the results."

- 3. CGE models require strong assumptions (e.g. about optimizing behavior and competitive markets) that are typically violated in the real world (Bergman, 2005; Ackerman, 2005).
- 4. CGE models rely on the assembly of national accounts information in the form of a Social Accounting Matrix (SAM) (or the equivalent data in a database), including data from disparate sources that can be based on inconsistent assumptions (Grassini, 2007). The choice of data, and the manner by which the data are massaged to force the SAM into equilibrium are subjective decisions made by the analyst which can strongly influence model results (Shoven and Whalley, 1984; Mitra-Kahn, 2008).
- 5. Limitations imposed by the structure of the SAM, which are violated in real economies, restrict the range of model outcomes. Hertel (1999) writes:

"These SAMs detail all the basic accounting identities which must hold for the economy to be in equilibrium. Those who work with AGE models quickly recognize that these identities are as important as the behavioral assumptions. The fact that households cannot spend more than they earn, or that the same unit of labor, land or capital cannot be simultaneously employed in two different places, serves to tightly circumscribe the range of possible GE outcomes." 6. Parameter values used in functional forms are set in a process called "calibration", which ensures that these values are consistent with the base year data (Mitra-Kahn, 2008). CGE model parameters typically are calibrated to a single year's data. Given that any single year involves unique circumstances that may not generalize, the model is sensitive to the choice of baseline year (Shoven and Whalley, 1984; Roberts, 1994; McKitrick, 1998; Scrieciu, 2007). This is particularly the case for developing countries, as their economies are inherently less stable (Roberts, 1994). Shoven and Whalley (1984) write:

"A crucial point in using calibration is that because of the reliance on a single observation, the benchmark data typically do not identify a unique set of values for the parameters in any model. Particular values for the relevant elasticities are usually specified on the basis of other research, and these serve to identify uniquely the other parameters of the model along with the equilibrium observation. This typically places a lot of reliance on literature surveys of elasticities and, as many of the modelers have observed in discussing their own work, it is surprising how sparse (and sometimes contradictory) the literature is on some elasticity values. Also, although this procedure might sound straightforward, it is often exceedingly difficult because each study is different from every other and recognizing and taking account of these differences is necessary."

7. Elasticities are at the core of CGE models, yet estimating valid, generally-applicable elasticities is difficult. Kehoe et al. (2005) write:

"Many estimated parameters, including some of the elasticities, are not what Robert Lucas calls "deep" – invariant parameters of tastes and technology. This means that their estimates are subject to the Lucas critique that they are policyregime specific, so that values estimated with data from one regime cannot be used for analysis of data from a different regime. Even if the data are treated as representing an equilibrium, the restrictions on parameters that an equilibrium implies are rarely imposed in estimation.

•••

Often no estimates exist of required parameters, so they are guessed; or multiple estimates exist that are contradictory. In the econometric literature different estimation procedures, different data series, and different theoretical concepts are used, making it very difficult to use estimates drawn from the literature."

8. Every equation in a CGE model contains both an endogenous and exogenous variable, but the choice of which to endogenize is up to the modeler. The choice of endogenous and exogenous variables is called the "closure". The number of possible closures grows exponentially with the number of balancing equations in the model, and each closure potentially yields different results (Mitra-Kahn, 2008).

- 9. Sectors and regions are highly-aggregated, with a single price and elasticity assigned to each sector, despite often significant intra-sectoral heterogeneity (Hertel et al., 2007).
- 10. Static models lack any concept of time; all transactions effectively clear simultaneously (Grassini, 2007). Short-term transient price spikes cannot be represented in this framework, although these may trigger largely irreversible land use change³, as well as bankrupting businesses (Galbraith, 2008). So-called dynamic models are, in fact, "lurching" static models that move from one timeless equilibrium to the next, useful only for comparative static analyses, just as are static models (Grassini, 2007; Mitra-Kahn, 2008).

6.3.2 SUMMARY

Computable General Equilibrium models, in practice, are reduced-form models of theoretical representations of the economy, that diverge from reality in many ways, some important. The models represent a small number of homogenous commodity groups, regions, and actors, based on a social accounting matrix that has been adjusted to suit the requirements of the model, i.e. to ensure that all markets clear even though they didn't in the real world. The model's solution represents an instantaneous transition to an equilibrium state that exists only in theory, and may not be unique or stable in any case. The approaches used to shock the initial equilibrium produce side effects that are inseparable from the effect we wish to model, i.e. the expansion of biofuels production.

In summary, even CGE modelers recognize that it would be "unwise" (Bewley, 2007) to expect these models to offer more than coarse approximations that might "shed light" on policy outcomes (Hertel, 1999). CGE model results are influenced by a range of subjective choices on the part of the modeler, and the models are subject to model and parameter uncertainties that are generally excluded from sensitivity analyses due to computational and data limitations. Unfortunately, the model uncertainty cannot be quantified, as we have no better model to use as a benchmark, nor can we measure outcomes against the real global economy, in which *ceteris non paribus*. Many economists question the theory, assumptions, data, model form, and predictive capacity of CGE models.

Even if the models could reproduce recent history, the use of calibration to a specific data set and year leaves open the question of whether the same model can accurately predict deviations from that initial state. Given our inability to verify these models, we are faced with potentially large—and inestimable—model uncertainty.

Given regulations that require the assignment of life cycle GHG ratings to different fuel pathways, an important question is whether these models are capable of producing reasonably objective point estimates. Clearly, any model can be used to operationalize the estimation of the ILUC emissions for use in regulation, but without consideration of the uncertainty in these estimates, we don't

³For example, an anticipated large price increase in soybean price due to a shift from soybean to corn production in the US may trigger land use conversion to accomodate soybean production elsewhere, with attendant CO_2 emissions. Even if subsequent reduction in soybean price after markets adjust results in the release of the converted land, the CO_2 that was lost quickly will take years to be sequestered again in biomass, causing net global warming over any reasonable policy time horizon.
know how confident we can be that regulations based on these models will have their intended effect.

6.4 UNCERTAINTY IN ECOSYSTEM CARBON ACCOUNTING

The GHG emissions resulting from conversion to cropping vary with land cover types and across regions. Estimating ILUC emissions therefore requires assumptions about the specific land cover types converted as a result of biofuels expansion. As most economic models are not spatially explicit, other approaches must be used in conjunction with the economic model output to predict the land cover types affected. Given a specific land cover conversion, we can estimate the emissions that result from conversion. In this section, we explore the uncertainties in these components of the ILUC emissions model.

6.4.1 UNCERTAINTY IN PREDICTING AFFECTED ECOSYSTEMS

The translation of economic model output to carbon emissions, and the attribution of these emissions to a quantity of fuel, involve many additional uncertainties, including:

- 1. Error rates of 30–40% in recognizing specific land cover types in remote sensing based on satellite imagery (Harris et al., 2008). That is, the land cover type for 30–40% of the pixels is miscategorized, based on ground-truthing.
- 2. Extrapolation uncertainty in the assumption that past (gross) patterns of land use change are predictive of future land use changes.
- 3. Extrapolation uncertainty in the assumption that market-mediated land use changes follow the general pattern observed over time from all drivers of land use change.
- 4. Approximation uncertainty in the use of average carbon stocks to represent the carbon stocks of converted land (Houghton, 2005).
- 5. Variability in the estimation of above-ground carbon stocks.
- 6. Variability in the estimation of below-ground carbon stocks based on above-ground carbon estimates (Ramankutty et al., 2007).
- 7. Variability in the portion of above-ground carbon converted to CO₂ (and other GHGs) when land is cleared.
- 8. Variability in the quantity of carbon released from below-ground stocks when land is cleared, and in the rate of release of this carbon.

- Epistemic uncertainty in the quantity of fuel to which the ILUC emissions should be assigned. This turns on model choice parameters for the estimated biofuels production period, and projections of future crop and biorefinery yields.
- 10. Approximation uncertainty in the use of proxies in regions for which little data is available. For example, in the Woods Hole carbon accounting data underlying the Searchinger analysis (and our own analysis with GTAP), the region covering China, India, and Pakistan is assigned to a single ecosystem type based on the value for European grasslands.

6.4.1.1 CAUSES OF LAND USE CHANGE

In mapping economic model outputs to specific affected ecosystem types, the analyses performed to date are based on the assumption that a marginal increase in LUC in any region can be estimated from supply and demand functions for commodities and land. Agricultural extensification is recognized as a leading proximate cause of deforestation, however the underlying driving forces include social processes such as human population growth and migration, and national policies affecting agriculture, land use, and economic development (Geist and Lambin, 2002), as well as cultural, technological, and institutional issues, all interacting in complex relationships (Schaeffer et al., 2005). According to Geist and Lambin (2002), "[a]t the underlying level, tropical deforestation is also best explained by multiple factors and drivers acting synergistically rather than by single-factor causation, with more than one-third of the cases being driven by the full interplay of economic, institutional, technological, cultural, and demographic variables measures."

Deforestation is thus best understood as an emergent characteristic of a complex system, with a range of proximate and ultimate causes. Given this complexity, the ability to predict LUC from a single driver such as commodity price increases, may be quite limited, and thus a core assumption underlying ILUC modeling is called into question, resulting in model uncertainty that is difficult to quantify.

6.4.1.2 IDENTIFYING THE AGRICULTURAL FRONTIER

Even if the causal chain were well-characterized, economic models such as GTAP and FAPRI are not spatially explicit, and therefore cannot predict the specific land cover types affected by extensification.

The approach used in recent modeling efforts (e.g., Searchinger et al., 2008b; Harris et al., 2008) is to examine the history of land use change in each region to identify the agricultural frontier. All extensification induced by biofuels expansion is assumed to affect the same types of land cover as identified in the historical record in each affected region.

Although it is a reasonable first approximation, it is unclear whether the historical record has much predictive power. For many reasons, this may not be the case for large shocks and decadal time horizons. For example, changes in the proportion of each land type in close proximity to transportation networks or population centers, changes in laws regarding ecosystem protection, and distinct agronomic requirements for different crops, may alter these ratios. This approach also treats all forest-to-cropping LUC as equivalent, whether resulting from colonization and subsistence farming, or from timber harvesting followed by commercial agriculture. When colonists deforest for subsistence agriculture, they might burn the trees or field because it's cheap and they lack access to timber markets. When agribusinesses deforest, they might arrange clearing at no net cost by selling the wood. These two vectors are likely to affect different areas and have different GHG consequences, and the latter is arguably more likely to be induced by commodity price increases. Unfortunately, causality is not distinguishable from satellite imagery.

This approach includes both statistical uncertainty in the estimates of historical land use patterns as well as epistemic uncertainty regarding the predictive value of these historical patterns. The distributions of possible values for these parameters are not known.

6.4.1.3 WINROCK / USEPA APPROACH

In support of EPA's EISA rulemaking, Winrock International assembled emission factors for regions thought to be affected by biofuels expansion (Harris et al., 2008). Winrock relied on MODIS land cover data for the years 2001 and 2004 collected by NASA satellites.⁴ The areas showing land cover changes between the two years were categorized according to the "before" and "after" states to identify conversions to cropping and pasture from various prior cover types.

According to Winrock's report, land cover is correctly categorized (relative to ground-truthing) for only 60–75% of the pixels examined, across different continents, with North America offering the lowest accuracy (Table 6.1). While this clearly leaves considerable room for misidentification, the effect on carbon estimates it is not clear: identifying a savanna as shrubland would result in less error in terms of carbon emissions than, say, identifying a savanna as a forest.

Region	Accuracy Estimate (%)
Global	71.6
Africa	61.7
Australia & Insular Asia	71.9
Eurasia	67.8
North America	61.3
South America	75.4

Table 6.1: Accuracy of MODIS land cover classification for the globe and continental regions (Harris et al., 2008).

⁴MODIS data are available at http://edcdaac.usgs.gov/modis/mod12q1v4.asp

For the biofuels analysis, Winrock reclassified the original 17 land cover types available in MODIS into six more easily distinguished classes: cropland, forest, grassland, savanna, shrubland, and mixed. After reclassifying the data from 2001 and 2004, the data were compared to identify changes. Reclassification introduces additional approximation uncertainty as several land cover types in each region are combined into a single class and assigned one emission factor.

6.4.2 UNCERTAINTY IN ESTIMATING CARBON FLUXES

The carbon losses from conversion a specific ecosystem type to cropping or pasture will vary by location, land use history, and by the specific method of conversion. Since it is impossible to attribute a specific instance of deforestation to biofuels expansion, we can at best attempt to model the average effect of land use conversion for each ecosystem type.

In its "Good Practices Guidelines" for national GHG inventories, the IPCC provides default values for ecosystem conversions to cropland, including estimates of the uncertainty therein. These uncertainties, which reflect variation in field observations in different places and times of a phenomenon with intrinsic variation across locations, are in addition to the uncertainty in identifying affected land cover types.

Even if we knew that a specific type of forest was affected, the use of average carbon content of that forest type may be inappropriate since the processes underlying deforestation are unlikely to randomly select forest stands for removal; rather, selection criteria may include factors such as tree density and salability which may favor conversion of certain forest stands over others (Houghton, 2005). We have no data upon which to base estimates of this approximation uncertainty.

Figure 6.2 shows possible transitions following deforestation (Ramankutty et al., 2007). Comparing two satellite images of these different growth pathways will yield very different results depending on the stage captured in the image.

6.5 ACCOUNTING FOR TIME

6.5.1 PROJECTING TOTAL FUEL PRODUCTION

The GWI of fuels is typically measured in units of g $CO_2 e MJ^{-1}$. All of the preceding discussion has focused on estimating the numerator, the quantify of CO_2 emitted from induced LUC. We now turn our attention to the denominator, the quantity of fuel over which to attribute these emissions.

The study by Searchinger et al. (2008b) simply assumed 30 years of corn ethanol production at current yields, without allowing for any yield increases over that period. Projecting yield increases, however, is a matter of guesswork. Given the multi-decadal time frames under consideration, the feedstock, the conversion technology, and even the ultimate type of fuel produced can change in ways that are fundamentally unpredictable, other than the reasonable expectation of increasing fuel yield per unit area.

In a model that does allow for yield increases over time, one can either (1) hold *area* constant and assume that more fuel is produced per originally-displaced crop area, or (2) hold *fuel* output



Figure 6.2: Different pathways of carbon dynamics following deforestation. Depending on the land-use practices following deforestation, vegetation carbon can either remain at a lower level, or re-accumulate if the land is abandoned and allowed to regrow back into a forest. (Source: (Ramankutty et al., 2007).)

constant and assume that over time, land is "released" as higher crop and/or conversion yields result in the production of an equivalent quantity of fuel on smaller land areas. If the latter approach is used, the disposition of the "freed" land must be considered. For example, some fraction of the cropland might revert to a natural state, or the land might be used to grow other crops, thereby relieving pressure on natural lands somewhere else. In either case, the GHG fluxes associated with these assumptions could be considered in the model.

To demonstrate the effect of increasing yield on land requirements, we show the results of a simple model of ethanol production using a combination of corn grain and stover from the same land area. Table 6.2 lists the parameters of that model. Table 6.3 shows the combined effects of increasing starch and conversion yields, and the introduction of cellulosic conversion of stover over a 30-year period. By the end of this period, fuel yield more than doubles from about 450 to over 900 gal acre⁻¹, with the average yield in this period being over 700 gal $acre^{-1}$, an increase over the initial yield of nearly 60%. The land required to produce the initial annual quantity of fuel shrinks by approximately one-third over 30 years.

Table 6.2: Example parameterization of a simple model projecting fuel yield changes over time. These assumptions include guesses about the rates of improvement and deployment of seeds and conversion processes. Based on a 100 Mmgpy corn ethanol plant (denatured basis), with the addition of 25 Mmgpy stover-to-ethanol capacity. This configuration is similar to Poet's Emmetsburg plant.

Parameter	Value	Units
Starch ethanol capacity	1.0E+08	gal y ⁻¹
Cellulosic ethanol capacity	2.5E+07	gal y^{-1}
Time horizon	30	у
Corn yield increase	2.0	bu $ac^{-1} y^{-1}$
Starch yield increase	0.01	gal bu $^{-1}$ y $^{-1}$
Initial cellulosic yield	75	gal bdt $^{-1}$
Cellulosic yield increase	2.0	gal bdt $^{-1}$ y $^{-1}$
Stover collected	35%	

6.5.2 HANDLING DISTINCT EMISSION PROFILES OVER TIME

In most life cycle assessments, emissions of pollutants are summed without regard for when or where these emissions occur (Hellweg et al., 2003; Levasseur et al., 2010). For well-mixed greenhouse gases, it is appropriate to ignore the location of the emissions, as these are global pollutants. However, for long-lived pollutants, summing emissions over time masks potentially important differences among processes, especially if effects are measured at a fixed target date. In these situations, early emissions are in the environment longer relative to the target date, and thus cause greater environmental damage.

In the case of greenhouse gases (GHGs), global warming effects are usually aggregated by summing emissions of three gases (CO₂, CH₄, and N₂O) weighted by their respective global warming potentials (GWP). GWP is the measure of the cumulative radiative forcing (CRF) over a fixed time horizon (e.g., 20 or 100 years) of a pulse of some gas compared to the CRF of an equal mass of CO₂ over the same period (Forster et al., 2007). Most LCAs use the 100-year GWPs published by the IPCC (Forster et al., 2007).

In an LCA, it is appropriate to sum GWP-weighted GHG emissions for a process whose emissions are largely coincident with production and use. Summing GWP-weighted GHG emissions also makes sense in a national emissions inventory for a single year, because over the standard 100-year time horizon the specific release date *within* the inventory year is inconsequential to the total CRF. In both of these cases, emissions are implicitly summed or compared using a consistent

Table 6.3: Hypothetical fuel yield changes over time. As areal fuel yield increases, an initial unit of land can produce more fuel, or the same fuel yield can be achieved on less land. The following chart shows the results of increasing corn grain yields by 2 bu/ac/y, corn starch ethanol yields by 0.01 gal/bu/y, an initial cellulosic ethanol yield of 75 gal/bdt, increasing by 2 gal/bdt/y over 30 years. Until year 8, stover is assumed to be used for thermal energy in the grain ethanol process.

Year	Corn	Starch	Starch	Corn	Stover	Cellul.	Cellul.	Areal	Land
	Yield	Yield	EtOH	Area	used	Yield	Yield	Yield	Freed
	(bu/ac)	(gal/bu)	(gal/ac)	(ac)	(btd/ac)	(gal/bdi	(gal/ac)	(gal/ac)	(ha)
1	160	2.80	448	223,214	1.6	0	0	448	0
2	162	2.81	455	219,674	1.6	0	0	455	1,433
3	164	2.82	462	216,226	1.6	0	0	462	1,396
4	166	2.83	470	212,866	1.6	0	0	470	1,360
5	168	2.84	477	209,591	1.6	0	0	477	1,325
6	170	2.85	485	206,398	1.7	0	0	485	1,292
7	172	2.86	492	203,285	1.7	0	0	492	1,260
8	174	2.87	499	200,248	1.7	75	128	627	1,229
9	176	2.88	507	197,285	1.7	77	133	640	1,199
10	178	2.89	514	194,394	1.7	79	138	652	1,170
11	180	2.90	522	191,571	1.8	81	143	665	1,142
12	182	2.91	530	188,815	1.8	83	148	678	1,115
13	184	2.92	537	186,123	1.8	85	153	691	1,089
14	186	2.93	545	183,493	1.8	87	159	704	1,064
15	188	2.94	553	180,923	1.8	89	164	717	1,040
16	190	2.95	560	178,412	1.9	91	169	730	1,016
17	192	2.96	568	175,957	1.9	93	175	743	993
18	194	2.97	576	173,557	1.9	95	181	757	971
19	196	2.98	584	171,209	1.9	97	186	770	950
20	198	2.99	592	168,913	1.9	99	192	784	929
21	200	3.00	600	166,667	2.0	101	198	798	909
22	202	3.01	608	164,468	2.0	103	204	812	890
23	204	3.02	616	162,317	2.0	105	210	826	871
24	206	3.03	624	160,210	2.0	107	216	840	852
25	208	3.04	632	158,148	2.0	109	222	855	835
26	210	3.05	640	156,128	2.1	111	228	869	817
27	212	3.06	649	154,150	2.1	113	235	883	801
28	214	3.07	657	152,212	2.1	115	241	898	784
29	216	3.08	665	150,313	2.1	117	248	913	769
30	218	3.09	674	148,452	2.1	119	254	928	753

integration period.

Since LCAs are defined in terms of a functional unit (e.g., emissions per MJ of fuel) (ISO, 2006b,a), emissions from preparatory processes, such facility construction, must be allocated over the assumed lifetime of the facility to place these emissions in terms of the chosen functional unit (Canals et al., 2007). In practice, these amortized emissions are generally assumed negligible and ignored in LCA, resulting in a well-recognized "truncation error" (Guinée et al., 2006).

However, when considering indirect LUC caused by land-competitive biofuels, the assumptions that (i) emissions are largely coincident with production and use, or (ii) that preparatory emissions are negligible, no longer hold. The release of carbon from land cover conversion is fairly rapid. Most of the above-ground biomass is lost immediately (in the case of burning) or over a small number of years (Fargione et al., 2008). By some estimates, approximately 20% of the soil C is lost within about five years of the initial disturbance, with another 5% lost within about 20 years from the start of tillage (Houghton et al., 1991). The upfront iLUC emissions from land-competitive biofuels must be allocated over (that is, causally linked to) a quantity of fuel produced over decades, and the biofuel must be compared with a petroleum fuel with relatively small upfront emissions. When we compare processes with very different emission profiles over decades, the simple summation approach is no longer valid because it incorrectly sums the CRF of releases measured over overlapping, but distinct, integration periods. This is not the same as summing the CRF of these releases over a consistent, short time horizon during which all emissions occur. Discounting emission flows, as some have proposed, only compounds the error, since GWPs apply no discounting within their defined time horizon, and 100% discounting beyond the time horizon.

Several approaches have been proposed or used to account for the difference in emissions profiles over time, from simple amortization, to discounting emission flows, to models based on cumulative radiative forcing. In this section, we consider the ramifications of these alternatives.

6.5.2.1 STRAIGHTLINE AMORTIZATION

Several analysts have used straightline amortization to divide the up-front loss of carbon over an assumed 30 years of biofuels production, ignoring the time profile of emissions (Searchinger et al., 2008b; CARB, 2009a; USEPA, 2010b). This approach is generally justified on the basis of its simplicity, however, it underestimates the damages from biofuels that induce ILUC relative to fuels without large up-front emissions, as described in §6.5.2.4.

6.5.2.2 DISCOUNTING EMISSION FLOWS

Cost-benefit analyses for projects with long-lived costs and benefits are usually assessed using economic discounting to bring all costs and benefits back to a comparable present value (Boardman, 2001). Some analysts have proposed following this approach for GHG emissions, directly discounting physical GHG flows. However, discounting physical goods is an inappropriate application of a financial metaphor, and it is inconsistent with the physical reality (Marshall, 2009). Financial flows are one-time events, i.e. they have a "residence time" of zero. Greenhouse gases, in

contrast, have residence times measured in decades, causing continual social costs until the gases leave the atmosphere. Modeling GHG flows as though they were financial flows, and discounting each 'payment' ignores this non-zero residence time.

Using financial discounting for physical flows would be plausible if damages were a linear function of flow, in which case the physical and financial values would be interchangeable. But damages are a function of temperature change, which in turn depends on cumulative radiative forcing, which depends on the concentration of greenhouse gases (and other biogeochemical processes). The residence time of the gases is central to the problem, thus the analogy to financial flows breaks down.

Also unlike financial flows, the damages from a unit of CO_2 are a function of concentration, so the physical effects of a unit of CO_2 today and next year are not the same. Assuming increasing concentrations, the physical effect per unit CO_2 will increase over time, whereas discounting flows says the effect next year is reduced.

6.5.2.3 DISCOUNTING DAMAGES

More commonly, economists propose applying economic discounting to the economic damages resulting from emissions (Delucchi, 2003; Guo et al., 2006; Marshall, 2009). This approach incorporates additional epistemic uncertainties (most notably the social cost of carbon) and model choice parameters such as the discount rate and shape of the discounting function (Guo et al., 2006; Weitzman, 2007).

6.5.2.4 CUMULATIVE RADIATIVE FORCING

O'Hare et al. (2009) present a model and discussion of the cumulative radiative forcing from biofuel and gasoline GHG emissions, estimated using a simple model of atmospheric CO_2 decay, with and without economic discounting. This approach involves several policy choice parameters which materially affect the measured benefits (or disbenefits) of the biofuel compared to its petroleum alternative, such as:

- the biofuels production period,
- the analytic time horizon,
- the policy target date,
- whether to include reversion (see $\S6.5.2.5$) and over what timeframe, and
- whether to use discounting, and at what rate.

Based on this model, O'Hare et al. (2009) proposed an alternative metric, *fuel warming potential* (FWP), computed as the ratio of the CRF occurring over a given analytic horizon for the studied biofuel, relative to that of the baseline petroleum fuel. This approach inherits the structure and limitations of the IPCC's global warming potentials, rationalized to included emissions occurring at different times within a given analytic horizon. They show that for the parameter values assumed in the model, corn ethanol increases CRF by 15% compared to gasoline a 30-year analytic horizon, whereas using straightline amortization over 30 years would indicate that ethanol reduces GHG flows by 5%.

Levasseur et al. (2010) extend this approach to include the decay of CH_4 and N_2O , and suggest the use of a dynamic life cycle inventory that is a function of the time horizon examined. Applying their approach to the proposed rulemaking for RFS2, they conclude that "the lack of consideration for the temporal prole of the emissions in traditional LCA tends to underestimate the impact of LUC emissions."

6.5.2.5 REVERSION TO NATURAL STATE

Some models include the potential for land use conversions to revert to a natural state after the biofuels are no longer produced, e.g., (Delucchi, 2006). Land reversion could be included with any of these approaches to handling time, however, in the case of simple amortization, eventual reversion would cancel the effects of the initial land conversion. This result encourages the use discounting to avoid this apparently inappropriate outcome.

Other analysts suggest than any carbon benefits of post-biofuel land reversion should be credited to the future land use change, if and when such conversion occurs (Marshall, 2009). Whether, and to what degree, the LUC process is reversible is unpredictable. For one, any road-building associated with agricultural development not only reduces the cost of continuing to farm converted areas, relative to the cost of building roads elsewhere, the existence of the roads enables further deforestation (Kirby et al., 2006; Pfaff et al., 2007; NASA Earth Observatory, 2008). In addition, conversion of forests to pasture and soybean plantations causes drying (Butler, 2007b,a), which increases susceptibility to forest fires, in turn causing more drying.

Crediting reversion also implicitly assumes that the marginal reduction in land pressure, as mediated through markets existing when biofuels production ends will be equal to those estimated under current market conditions. This validity of assumption is impossible to predict.

6.6 CONCLUDING REMARKS

This chapter enumerated the many challenges and uncertainties associated with estimating emissions from biofuels-induced indirect land-use change. Differences in estimates of iLUC emissions result in part from the many subjective choices that must be made by modelers, e.g., the choice of modeling framework (economic or otherwise), technique for mapping economic results to affected land cover types, the emission factors assumed for land-use conversion, and the treatment of time. Given any combination of these subjective choices, many stochastic and epistemic uncertainties remain. A single point estimate from a single model of ILUC emissions cannot be shown to be more "correct" than another, which has led to the considerable conflict over these estimates the regulatory processes for the California LCFS and the RFS2.

CHAPTER 7 UNCERTAINTY ANALYSIS OF SEARCHINGER ET AL. ILUC MODEL

"It is better to be vaguely right than exactly wrong." *Carveth Read*.¹

7.1 PURPOSE AND SCOPE

In this chapter, I present a stochastic version of the Searchinger et al. (2008b) model of indirect land use change (ILUC) resulting from expansion of corn ethanol production. The underlying FAPRI economic model is not publicly available, and the authors of the model have not examined uncertainty, thus this analysis is limited by an inability to characterize the uncertainty in the economic model results. Nonetheless, it is instructive to understand the portion of the uncertainty in the post-economic-model portions of the ILUC emissions analysis.

A version of this analysis, co-authored with Andy Jones and Michael O'Hare, was submitted to and reviewed by *Environmental Research Letters*. I decided to pull the paper after the initial results from our analysis with Purdue University researchers indicated that the mean value from an analysis of the same phenomenon using the GTAP model was below the 2.5% certainty value from our analysis of the Searchinger et al. model—indicating that model uncertainty dominated the stochastic uncertainty examined here. Although we decided not to publish the paper, we subsequently used this stochastic version of the Searchinger et al. model with the results of Purdue's GTAP modeling for corn ethanol to produce uncertainty bounds around emission factors for use in the Systematic Sensitivity Analysis performed with GTAP (Hertel et al., 2010a).

7.2 INTRODUCTION

In this chapter, I employ Monte Carlo simulation, sensitivity analysis, and parametric analysis to help understand the possible range of emissions from indirect land use change. The model is based on the work of Searchinger et al. (2008b), the first peer-reviewed analysis to quantify the ILUC

¹This wonderful quote is often attributed to John Maynard Keynes, however, according to WikiQuotes (http://en. wikiquote.org/wiki/John_Maynard_Keynes) the posthumous attribution of this quote to Keynes is erroneous. They cite a book by Carveth Read, originally published in 1898, available at http://www.gutenberg.org/files/18440/18440-h/ 18440-h.htm.

emissions for corn ethanol. The Searchinger analysis employed a partial-equilbrium economic model of the US agricultural sector developed by the Food and Agricultural Policy Research Institute (FAPRI) to estimate market responses to increased ethanol production. In their base case, Searchinger et al. increased ethanol production by 56 billion liters above projected levels for 2016, applying estimates of carbon loss from the affected ecosystems and estimating the CO_2 that would be released from the LUC. (For a detailed description of that modeling effort, see Searchinger et al., 2008a,b).

7.3 Methods

7.3.1 Approach

I implemented a stochastic version of the carbon accounting model used in the Searchinger et al. (2008b) by adding probability distributions around all key point estimate assumptions and using Crystal BallTMto evaluate the model in a Monte Carlo simulation. All simulation runs in this study were performed using 4,000 iterations and Latin Hypercube Sampling (this sampling scheme provides better definition of the tails of the result distribution). This approach produced a probability distribution for the LUC-related emissions term, rather than a single point estimate.

In addition, I examined several alternative time horizons. Searchinger et al. assumed a 30year period for amortization of the loss of carbon, and for the foregone sequestration. There is no scientific basis for selecting this particular time horizon over any other, so we examined alternatives including 1 year (effectively no amortization), 20, 50, and 100 years.

7.3.2 UNCERTAINTY IN ECONOMIC MODELING RESULTS

The FAPRI model is not available to the public, nor did the Searchinger study quantify the uncertainty in the economic modeling results. (See section 6.3 for a discussion of the many factors contributing to uncertainty in these results.) The FAPRI model cannot easily be used in a Monte Carlo simulation, as it involved a suite of loosely connected models whose inputs and outputs are integrated manually by a team of researchers. Model evaluation is too slow (and too manual) to run hundreds or thousands of times. A single run to achieve equilibrium after a large shock can take a team of researchers up to three days to complete (Fabioso, 2007).

The FAPRI modeling effort results in a table of changes in acreage dedicated to each of nine crops (barley, corn, peanut, rapeseed, sorghum, soybeans, sugar, sunflower, and wheat) by country or region.² The Searchinger analysis sums these acreage changes across crops for each of the 42 countries / regions represented. These sums are further aggregated into acreage changes for

²The countries and regions represented are: Algeria, Argentina, Australia, Brazil, Bulgaria and Romania, Canada, China, CIS, Colombia, Cuba, Egypt, EU-25, Guatemala, India, Indonesia, Iran, Japan, Malaysia, Mexico, Morocco, Nigeria, Other Africa, Other Asia, Other CIS, Other Eastern Europe, Other Latin America, Other Middle East, Pakistan, Peru, Philippines, Rest of World, Russia, South Africa, South Korea, Taiwan, Thailand, Tunisia, Turkey, Ukraine, US, Venezuela, and Vietnam.

eleven larger regions, namely: Canada, Africa, Europe, Former Soviet Union, Latin America, North Africa and Middle East, Developed Pacific, China-India-Pakistan, Southeast Asia, United States, and Rest of World. The carbon flux calculations are then performed on these larger regions.

Parameter uncertainty includes statistical uncertainty in the estimation of historical values as well as epistemic uncertainty about how well historical values and model structure predict future values. As described above, equilibrium modeling includes a substantial amount of epistemic uncertainty, which is inherently difficult to quantify. As described in section 7.3.7, we applied probability distributions to the outputs of the FAPRI model, as we did not have access to the model to use it in a Monte Carlo framework.

7.3.3 UNCERTAINTY IN ESTIMATING AFFECTED ECOSYSTEM TYPES

To assign the acreage changes resulting from the economic analysis to specific ecosystems, Searchinger et al. assume that new land conversions will follow the pattern observed in the 1990s in each region. For many reasons, this may not be the case for large shocks and decadal time horizons. For example, changes in the proportion of each land type in close proximity to transportation networks or population centers, changes in laws regarding ecosystem protection, and distinct agronomic requirements for different crops may alter these ratios. Searchinger et al. estimate a global expansion of 10.8 M ha of cropland induced by a 56 billion liter per year expansion of ethanol production. This amounts to a 1% expansion relative to the amount of land classified by the FAO as arable or in permanent crops (FAO, 2007). Thus, given the moderate shock size and lack of stronger data, the historical pattern is a reasonable first approximation.

Reliance on historical patterns of land conversion for the present analysis involves both statistical uncertainty as well as epistemic uncertainty regarding the predictive value of these data. The distributions of possible values for these parameters are not known. However to include an approximation of these uncertainties in the simulation, we define a normal distribution whose mean is the historic fraction of conversion observed in each ecosystem type used in the study, by region, assuming a coefficient of variation of 25%. In each simulation run, the sampled percentages are multiplied by the new total in each region to produce adjusted proportional rates of conversion for each ecosystem type in each region, ensuring that the fractions sum to 100%.

7.3.4 UNCERTAINTY IN ESTIMATING CARBON FLUXES

Estimates of the carbon lost upon land conversion include uncertainties in several underlying quantities: the carbon in the above-ground biomass, the carbon in the below-ground biomass (generally estimated as a percentage of the above-ground biomass), the carbon in the soil, and the fraction of all of this carbon that is lost upon conversion. Estimates of the carbon lost from conversion of each ecosystem type reflect variation in field observations in different places and times of a phenomenon with intrinsic actual variation across locations. However, there is also uncertainty in how well these data represent the deforestation our analysis attempts to model. For example, the use of average carbon content of particular forest ecosystems (e.g. temperate evergreen forest) may be too coarse since the processes underlying deforestation are unlikely to randomly select forest stands for removal; rather, selection criteria may include factors such as tree density and salability which may favor conversion of certain forest stands over others (Houghton, 2005). We have no data upon which to base estimates of this uncertainty within ecosystem types, and our analysis does not incorporate this factor.

In addition, there are insufficient data on the carbon content of some ecosystems. For example, Searchinger et al. assume that the grasslands of the China-Pakistan-India region have the average carbon content estimated for the grasslands of Europe. It is difficult to quantify such epistemic uncertainty.

7.3.5 LOST FUTURE SEQUESTRATION

To estimate the sequestration that would have occurred had the land use conversion not taken place, Searchinger et al. divide the annual net carbon uptake by forests by total forest area by ecosystem in each region to produce a value denominated in tonnes carbon per hectare. These values are multiplied by 30, the assumed number of years of lost sequestration, and a weighted average is estimated for each region, per converted hectare. We recognize that the assumption that carbon uptake continues unabated for 30 years will not hold true in all cases, but as discussed in section 7.4.1, the number of years of carbon uptake by those regions assumed to be gaining carbon has relatively little influence on the LUC emissions term.

In the case of reforesting after a period of agricultural use, Searchinger et al. assume that 75% of initial 25% lost soil carbon is recovered. As shown in Table 1, we assume this 75% value has a triangular distribution ranging from 50% to 100%. This parameter, while uncertain, is not critical to the outcome of the analysis, as demonstrated in section 7.4.1.

7.3.6 The treatment of time

The release of carbon from ecosystem conversion is fairly rapid. By some estimates, approximately 20% of the soil C is lost within about five years of the initial disturbance, with another 5% lost within about 20 years from the start of tillage (Houghton et al., 1991). For simplicity, this loss of carbon is modeled by Searchinger et al. as an instantaneous change in stock. For a land use change term to be used in a regulatory context measuring the life cycle emissions of GHGs from biofuels, this stock change must be related to a unit of biofuel production, which is typically a megajoule of fuel, resulting in units of $g CO_2 MJ^{-1}$.

To compute the required numeraire, Searchinger et al. use straightline amortization over an assumed 30 years of biofuels production. This choice of divisor, however, is arbitrary; it is not uncertain, but rather a matter of modeling or policy choice O'Hare et al. (2009).

7.3.7 CORRELATED VARIABLES

Correlation among variables can increase or decrease the variance of functions of them. Generally, the variance of a sum or product of random variables is larger if they are positively correlated,

smaller if negatively. In the FAPRI model, uncertainty in some parameters may lead to positive correlations among land conversion estimates across regions (e.g. an increase in crop yields might reduce land conversion in all regions), while other parameters may lead to negative correlations across regions (e.g. a lower cost of production in one region may shift conversion to the region from others). To assign uncertainty to the output of the FAPRI model, I separately vary the total land conversion rate across all regions (inducing a positive correlation) as well as the fraction of conversion occurring in each region (inducing a negative correlation). Based on a prior simulation run, the total area changed was assigned a normal distribution with an 11% coefficient of variation.³ I assume a 25% coefficient of variation on the estimate of area converted indicated by the economic model. The regional changes were normalized by dividing each by the total area changed in each simulation draw, thereby converting the regional values into percentages. For each region, the percentage change is multiplied by the sampled value for total area change to produce the area change that is used subsequently in the model.

Clearly this approach is imperfect: while the normalization does capture the negative correlation between regional changes, our approach implicitly treats yield in all regions as equal since each region is made to compensate equally for other regions. More fundamentally, the 25% CV for each region has no scientific basis. The correct approach to modeling the uncertainty in the estimates of land conversion would be to introduce stochasticity into the parameters driving the economic model, ensuring that each set of regional area conversions is internally consistent. Unfortunately, this option was not available.

The estimates of ecosystem carbon also involve correlated variables. The Searchinger et al. model provides estimates of above- and below-ground carbon in land converted to agriculture from various natural conditions. I treat these as independent, however the above-ground and below-ground biomass (which is only a portion of the below-ground carbon) are positively correlated. Our results therefore likely underestimate the variance in ILUC emissions to some degree.

7.3.8 Assumed Probability Distributions

The most challenging aspect of many stochastic models is assigning probability distributions to parameters. This is especially the case when the uncertainty is largely epistemic, as is the case here, rather than statistical. This "meta uncertainty" (uncertainty about the variation) doesn't prevent us from exploring the model behavior, but it does prevent us from definitively quantifying the uncertainty in the LUC term.

Table 7.1 describes the probability distributions used in this model. It is important to recognize that most of these distributions are not parameters estimated by statistics of samples of random variables with specific, assumed or theoretically known, distributions in the classical statistical sense. They should be interpreted as intermediate distributions in a Bayesian sense, incorporating a variety of information about the true values and summarizing subjective probability judgments a reasonable person might hold on the basis of the reported values: "reasonable people" might

³In the sensitivity analysis, a 50% CV is applied to each region, resulting in a 23% CV for the total area.

disagree about these distributions.

The distributions are implemented by reference to meta-parameters that define the coefficient of variation for all parameters in each class listed in the table. Thus, the spreads can be adjusted to explore the impact on the output distribution due to our uncertainty about the input distributions.

Each parameter class defines a set of parameters describing the same phenomenon in different regions or ecosystems. The probability distribution is defined using the value from the Searchinger et al. model as the mean, and applying the coefficient of variation indicated in Table 7.1. Several distributions are taken from the IPCC's guidelines for national GHG inventories (Eggleston et al., 2006). The IPCC guidelines define default uncertainty levels, but they don't specify the shapes of these distributions, so I generally assumed lognormal distributions for non-negative parameters, and normal otherwise.

Parameter	Distribution	Value	$\mathrm{C}\mathrm{V}^{a}$	Min	Max
Regional area change (applied to eco- nomic model output)	normal		25%		
Total area changed	normal		$11\%^{b}$		
C in vegetation	lognormal		37.5% ^c		
C in soil to 1m	lognormal		$45\%^d$		
% Soil C lost to 1m	betaPERT ^e	$25\%^f$		0%	75%
Historic clearing by ecosystem	normal		50% ^g		
Forest area	triangle			-25%	+25%
Forest regrowing area	triangle			-25%	+25%
Uptake by regrowing forests	triangle			-25%	+25%
Fraction of lost soil C regained in re- growth (EU and FSU)	triangle	75% ^f		50%	100%

Table 7.1: Probability distributions used in the model

^a CV (coefficient of variation) is the ratio of the standard deviation to the mean.

^b Estimated in a prior Monte Carlo simulation using 25% CV around individual regional area changes.

^c IPCC (Eggleston et al., 2006, Section 5.3.1.5).

^{*d*} IPCC (Eggleston et al., 2006, Table 2.3).

^e The betaPERT distribution is bell-shaped and bounded on both extremes.

^{*f*} Searchinger et al. (2008b).

^g IPCC (Eggleston et al., 2006).

7.4 RESULTS

Figure 7.1 shows the results from the stochastic simulation of the model. The mean value for the LUC term is $110 \text{ g } \text{CO}_2 \text{ MJ}^{-1}$, with the 95% certainty interval around the mean ranging from 70 to 168 g CO₂ MJ⁻¹. Note that an ILUC term of 70 g CO₂ MJ⁻¹ would render corn ethanol from all current production methods worse than gasoline in life cycle GHG emissions (Plevin and Mueller, 2008). The ILUC emission distribution has a slight right tail as indicated by the asymmetric 95% certainty interval. The mean value of 110 g CO₂ MJ⁻¹ from the stochastic analysis is about 6% higher than the point estimate of 104 g CO₂ MJ⁻¹ from the same model.

As seen in Figure 7.2, about 95% of the total emissions are estimated to occur in five regions: Latin America (29%), United States (22%), Southeast Asia (21%), and China-India-Pakistan (13%), and Africa (9%). These results are a product of the area changed and the emissions rate per unit area for each region. The large contribution in total CO₂ emissions from Latin America is due to the large area impacted, whereas the large contribution from Southeast Asia is due to the high emissions rate. The United States has a moderately high emissions rate and area changed, resulting in high total CO₂ emissions.



Figure 7.1: Output distribution for Monte Carlo simulation of ILUC emissions term.



Figure 7.2: Percent of total estimated CO₂ emissions from ILUC by region.

7.4.1 ANALYSIS OF UNCERTAINTY AND SENSITIVITY

Ten parameters contribute about 80% of the total variance in the land use GHG term. Uncertainty in the total land area converted is the largest single contributor to variance, accounting for nearly one third of the total. Uncertainty in the assignment of regional area changes to specific ecosystems contributes another 20% of the variance. Uncertainty in estimates of the carbon in soil and vegetation accounts for nearly 40% of the variance.

7.4.1.1 The treatment of time

Table 7.2 shows the value of the ILUC emissions term for alternative values (1, 20, 30, 50, and 100 years) of amortization period. Note that the effect is not simply proportional with respect to the amortization period due to the uptake of carbon in some regions. Since sink capacity declines over time as the forest or grassland reaches maturity in the cases of the 50 and 100 year time horizons, we limited the uptake period to 30 years. The mean ILUC emissions term under 100-year amortization is about $30 \text{ g CO}_2 \text{ MJ}^{-1}$, which would indicate that expanding production of corn ethanol in the US using the most common process, natural gas-fired dry-milling, would produce a biofuel with approximately the same life cycle GHG emissions as gasoline (Plevin and Mueller, 2008).

Amortization Period (y)	$\begin{array}{c} \text{Mean} \\ (\text{g CO}_2 \text{ MJ}^{-1}) \end{array}$	2.5% value (g CO ₂ MJ ⁻¹)	97.5% value (g CO ₂ MJ ⁻¹)
1	3130	1960	4670
20	160	100	240
30	110	70	170
50*	65	40	100
100*	30	20	50

Table 7.2: The effect of amortization period on the LUC emissions term

*Forest uptake was limited ton 30 years for existing and regrowing forests.

7.4.1.2 Accounting for charcoal and forest products

In their analysis of biofuel "carbon debt", Fargione, Hill et al. (2008) estimate the portion of above-ground biomass that is *not* emitted as CO_2 during ecosystem conversion. Two categories considered are carbon left in the ground during charcoal production, and wood that remains in forest products for more than 50 years. Adding these carbon storage factors to our model for all tropical rainforests and grasslands reduces the LUC term by approximately 5 g CO_2 MJ⁻¹. Applying the default 90% oxidation factor from the IPCC's greenhouse gas inventory guidelines (Eggleston et al., 2006) similarly resulted in a decrease of about 5 g CO_2 MJ⁻¹ in the LUC term.

7.4.2 META-UNCERTAINTY ANALYSIS

A lack of data prevents making confident predictions of the probability density functions for most input parameters to this model. To address this, I perform a limited meta-uncertainty analysis to explore the effects on the output distribution of changes to key input distributions. Table 7.3 shows these results for two model parameters. Increasing the coefficient of variation of regional area change (an output from the economic model) from 25% to 50% increases the width of the 95% confidence interval of the land use emissions term from 90 to 140 g $CO_2 MJ^{-1}$, all else equal.

7.5 DISCUSSION

In addition to statistical and model uncertainties, this model of market-mediated LUC emissions is incomplete. For example, the parameter describing price-induced yield response affects the outcome because it reduces the amount of land required to replace displaced crops. On the other hand, crop yields are likely to decrease as agriculture expands into more marginal lands. There is uncertainty about the magnitude of each of these effects; Searchinger et al. simply assumed these

Parameter	\mathbf{CV}^{a}		LUC emissions term (g CO ₂ MJ ⁻			$(g \operatorname{CO}_2 \mathrm{MJ}^{-1})$
	Base case Alternate		Mean	95% prob. range		b. range
				Low	High	Width
Base case			110	70	160	90
Regional area change ^b	25%	50%	110	50	190	140
Gross uptake from re- growing forest	25%	50%	110	70	170	100

Table 7.3: Effects on mean and 95% certainty interval of LUC emissions term due to increasing various model parameter distribution standard deviations.

 a CV = coefficient of variation (standard deviation divided by the mean).

^b The CV of Total Area Change is changed from 11% to 23% for the alternate case.

effects roughly cancel out.

In addition to the limitations listed in section 7.3.7, several structural changes to the model could significantly affect the resulting ILUC emissions term. These include representing:

- 1. Marginal decreases in the productivity of land (increases ILUC term)
- 2. Higher relative weighting of near-term emissions (increases ILUC term)
- 3. Price-induced yield effect (reduces ILUC term)
- 4. Carbon recapture in post-conversion ecosystem (reduces ILUC term)
- 5. Albedo, especially snow on former forests (reduces ILUC term)
- 6. Other climate-related emissions such as SO_X , NO_X , and black carbon (variable)

Assumptions about land productivity and price induced yield improvements affect the magnitude and uncertainty of the total area converted, which in turn affects total CO₂ emissions. A stochastic economic model would permit us to further decompose total area converted into individual parametric and structural uncertainties that could be better characterized.

7.6 CONCLUDING REMARKS

These results are contingent on several key model choices such as the use of the FAPRI economic model and a 30-year straightline amortization schedule. Other economic models may predict more or less land use change in different regions (e.g., Dumortier et al., 2009; Hertel et al., 2010a; Al-Riffai et al., 2010; Tyner et al., 2010), and a different treatment of time (O'Hare et al., 2009) will

yield different results. Thus, although the present analysis captures several important parameter uncertainties, significant model uncertainties remain.

CHAPTER 8 REDUCED-FORM MODEL OF ILUC

"For some problems there comes a time when uncertainty is so high that conventional modes of probabilistic analysis (including decision analysis) may no longer make sense. While it is not easy to identify this point, investigators should continually ask themselves whether what they are doing makes sense and whether a much simpler approach, such as a bounding or order-of-magnitude analysis, might be superior."

Morgan et al. (2009)

8.1 **PURPOSE AND SCOPE**

In this chapter, I develop a reduced-form model of the emissions from indirect land use change (ILUC), parameterized from prior modeling ILUC studies, to examine the plausible bounds of uncertainty surrounding estimates of these emissions. I estimate that the bounding range for emissions from indirect land-use change (ILUC) from corn ethanol expansion is approximately 10 to 370 g CO₂ MJ^{-1} . Applying various probability distributions to model parameters, I find that the broadest 95% central interval, i.e., between the 2.5 and 97.5 percentile values, ranged from 24 to 151 g CO₂e MJ^{-1} . ILUC emissions from corn ethanol expansion thus range from small, but not negligible, to several times greater than the life cycle emissions of gasoline.

This analysis suggests that the ILUC emissions estimates of 30 g $CO_2 \text{ MJ}^{-1}$ by CARB and 34 g $CO_2 \text{e} \text{ MJ}^{-1}$ by USEPA (for 2022) are at the low end of the plausible range; a value five times as large is also plausible. The presence of epistemic uncertainty (ignorance) prevents the reliable estimation of a most likely value for ILUC emissions. The inherent challenge of modeling complex, global systems suggests that this range is unlikely to be narrowed substantially. Fuel policies that require narrow bounds around point estimates of life cycle GHG emissions are incompatible with current and anticipated modeling capabilities. Alternative policies that address the risks associated with uncertainty may more effectively achieve GHG reductions.

This chapter is based on a paper in review at ES&T as *Plevin RJ*, *O'Hare M*, *Jones AD*, *Torn MS*, *Gibbs HK*. The greenhouse gas emissions from market-mediated land use change are uncertain, but potentially much greater than previously estimated.

8.2 INTRODUCTION

To help mitigate the climate change impact of the transportation sector, new policies are being implemented in the US and Europe to reduce the so-called "carbon intensity" of road transportation fuels, presently dominated by petroleum-based gasoline and diesel. These regulations, including the US Energy Independence and Security Act (EISA) of 2007, California's Low-Carbon Fuel Standard (LCFS) (CARB, 2009a; USEPA, 2010b) and Europe's Renewable Energy Directive (RED) (European Parliament, 2009), promote greenhouse gas (GHG) reductions based on estimates of the life cycle GHG emissions from various fuels. At least twelve US states have committed to implementing low-carbon fuel standards similar to California's (Anon., 2009).

EISA defined life cycle GHG emissions to include "significant indirect emissions such as significant emissions from land use changes" (United States Congress, 2007a); the definition was subsequently adopted verbatim into the California LCFS (California Office of Administrative Law, 2010). Indirect land use change (ILUC) emissions are those that occur when grassland and forest is converted to additional cropland somewhere on the globe to meet the demand for commodities displaced by the production of biofuel feedstocks. ILUC emissions are potentially large compared to the direct global warming effects of processes in the biofuel supply chain, for any biofuel whose feedstock competes with food for land.¹ Indeed, these emissions may overwhelm the climate benefits of some biofuels as previously estimated without consideration of indirect effects (Searchinger et al., 2008b; Dumortier et al., 2009; Al-Riffai et al., 2010; Hertel et al., 2010a; USEPA, 2010b).

The challenge for policymakers is that estimating ILUC is a complex and inherently uncertain endeavor integrating global economic modeling with detailed accounting of ecosystem carbon (Delucchi, 2006; Kløverpris et al., 2008). Models of complex, global phenomena, especially for systems dominated by human behavior and whose operating parameters are changing over the time period comprising data sourcing and prediction period, are inevitably approximate.

Several studies that estimate ILUC emissions induced by the expansion of corn ethanol production in the US (e.g. Searchinger et al., 2008b; CARB, 2009a; Dumortier et al., 2009; USEPA, 2010b) or the EU (Al-Riffai et al., 2010) have applied the following sequence of modeling steps:

- 1. An economic equilibrium model (e.g., FASOM, FAPRI, GTAP, MIRAGE) is used to project the effects of increased biofuel production in the US on global land and commodity markets, including (i) how much additional land will be brought into production to compensate for land removed from other uses to produce biofuels and (ii) the approximate location of this land.
- 2. Land use changes projected by the economic model are mapped to specific land cover types based on historical patterns of land use change.
- 3. For each category of land cover conversion, the quantity and time profile of GHG emissions from land use conversion are estimated.

¹We note that other activities that compete with food for land, including other crops, roads, and development, also cause ILUC emissions. Our purpose here is to estimate the marginal ILUC caused by biofuels production.

4. To produce the desired GWI measure (e.g., grams of CO_2 -equivalent per MJ of biofuel), the emissions induced by the expanded biofuel production are attributed to the quantity of fuel produced over some designated time period.

Table 8.1 describes some of the uncertainties inherent in each of these modeling steps.²

8.2.1 PRIOR ESTIMATES OF ILUC EMISSIONS

Several studies have examined the ILUC emissions induced by expanding production in the US of corn ethanol. Table 8.2 describes the model, data, and regional focus of each of five studies. Table 8.3 compares the results from these studies, including ranges estimated (using various methods) by the authors of those studies.

Searchinger et al. (2008b) used a partial equilibrium model of the agricultural sector developed by the Food and Agricultural Policy Research Institute (FAPRI) and Center for Agriculture and Rural Development (CARD), and ecosystem carbon and land conversion data assembled by the Woods Hole Research Institute and estimate an ILUC emission factor of 104 g CO₂e MJ⁻¹, resulting from an increase of 56 billion liters of corn ethanol. This model uses straight-line amortization to distribute the LUC emissions across 30 years of fuel production³. Reducing the ethanol increment to 31 billion gallons reduced the ILUC factor by about 10 g CO₂e MJ⁻¹.

Dumortier et al. (2009) used the FAPRI model to explore the sensitivity of ILUC emission estimates to various assumptions regarding crop yield, the potential for deforestation in the US, lower direct emissions from the ethanol production life cycle, and of using an enhanced model which includes links the US ethanol and gasoline sectors. Results across these variants ranged from 21 to 118 g CO_2e MJ⁻¹ with 30-year amortization of ILUC emissions.

Hertel et al. (2010a) used the GTAP computable general equilibrium model, combined with the Woods Hole land cover and carbon accounting data taken from the Searchinger study, producing a point estimate of 27 g CO_2e MJ^{-1} , based on 30-year amortization. Sensitivity analysis of key economic parameters produced a range of 15 to 90 g CO_2e MJ^{-1} .

USEPA (2010b) used the forest and agricultural sector optimization model (FASOM) model (Beach and McCarl 2010) and the FAPRI model (CARD, 2009), combined with a satellite data analysis and model of LUC emissions developed by Winrock International (Harris et al., 2009). For each fuel pathway considered, USEPA examined the uncertainty in their ILUC emissions estimate resulting from land cover detection and land conversion carbon emissions. Table 3 shows the central 95% intervals for ILUC emissions from corn ethanol expansion in 2012, 2017, and 2022; the full range across years was 25 to 104 g CO_2e MJ⁻¹.

²Figure 2.1 presents the typology of uncertainty that was included in the version of this chapter submitted to ES&T.

³Assumed production period and therefore the quantity of fuel an initial ILUC discharge is amortized across is one of several important issues raised by fuels with differing time discharge profiles. These questions are not central to the present discussion–we use straight-line 30y amortization for comparison of models because it is widely familiar–and discussed further in O'Hare et al. (2009).

Component	Category	Description
Economic modeling	V	Elasticities Crop yields
	М	Type of model (partial or general equilibrium; other) Model resolution (number of regions and industrial sectors) Functional forms and choice of closure Choice of land classes to include
	D	Baseline year and analysis year
	Р	Values of exogenous parameters (e.g., oil price)
Mapping to land cover classes	V	Accuracy of land cover classification by remote sensing Reliability of land cover change detection
	М	Number and regional specificity of land cover classes Predictive power of historical patterns of LUC Reliability of land cover change detection
Estimating emissions for land cover conver- sion	V	Above- and below-ground carbon stocks Fraction of carbon emitted upon conversion Annual foregone sequestration Fraction of conversion through burning Non-CO ₂ emissions from burning Global warming potentials
	Μ	Use of average carbon stocks values as proxy for affected areas Global warming potentials
	D	Years of foregone sequestration assumed Which climate-affecting phenomena to include, (e.g., black carbon, albedo, evapotranspiration) Method of aggregating climate effects, e.g., combining regional and global phenomena
Estimating total fuel production	V	Temporal and spatial variability in biofuel feedstock yields Feedstock conversion yield
	М	Projected changes in crop yield over the production horizon Projected changes in biorefining yields Affects of climate change on crop productivity
	D	Assumed years of feedstock production following initial planting
Treatment of time	D	Analytic horizon over which to aggregate effects Whether to apply discounting, at what rate, and to what (e.g., emission flows, radiative forcing, temperature change, or economic damages) Assumed years of feedstock production following initial planting

Table 8.1: Uncertainties in modeling ILUC emissions. V = Variability, P = Parameter uncertainty, M = Model uncertainty, D = Decision uncertainty.

Study	Economic model(s)	Land cover change data	Emission Policy region factors
Searchinger et al.	FAPRI	Woods Hole (1990s)	Woods US Hole
Dumortier et al.	FAPRI	GreenAgSiM	IPCC US
Hertel et al.	GTAP	Woods Hole (1990s)	Woods US Hole
USEPA	FASOM, FAPRI	MODIS-5 (2001- 2007)	Winrock US Int'l
Al-Raffai et al.	MIRAGE	MODIS-4 (2001- 2004)	IPCC EU

Table 8.2: Models and data sources used to model ILUC emissions from corn ethanol expansion

Al-Riffai et al. (2010) from the International Food Policy Research Institute (IFPRI) used the MIRAGE computable general equilibrium model and a greatly modified GTAP-7 database to estimate the ILUC effects triggered by EU biofuel mandates. For LUC emissions analysis, they relied on the land cover change detection analysis produced by Winrock International (Harris et al., 2008) for USEPA⁴, combined with IPCC emission factors . Unlike the other studies described above, Al-Riffai et al include biofuel mandates in other countries (i.e., US and Brazil) in the baseline. They examined the results of modifying several key elasticity parameters and explored different scenarios describing alternative trade regimes, though results were not reported for all variants. The point estimates for the BAU and "full trade liberalization" scenarios were 54 and 79 g CO_2e MJ⁻¹, based on 20-year amortization. Converted to 30-year amortization for comparison to the other modeling results gives a range of 36 to 52 g CO_2e MJ⁻¹.

The range of results from these studies demonstrates the presence of substantial model uncertainty in estimates of ILUC emissions. Importantly, none of these studies examined the full range of uncertainties in the economic modeling, land cover detection, carbon accounting, and the treatment of emissions over time (Table 8.1). Where sensitivity analysis was performed in these studies, it was almost exclusively local, one-at-a-time (OAT) analysis, describing changes in model results caused by perturbations in individual parameters. In general, a *global* sensitivity analysis, i.e., one that allows for simultaneous changes in multiple parameters, is required unless a model has been proved to be linear. In non-linear models such as economic equilibrium models, sensitivity to any single factor, in general, depends on the state of other variables (Abler et al., 1999; Saltelli et al.,

⁴Note that Al-Riffai used the version of the Winrock International analysis produced for USEPA's proposed rulemaking for the US Renewable Fuel Standard. USEPA used an updated version of this analysis for its final rulemaking that relied on a higher-resolution data set and a longer time interval.

Table 8.3: Published estimates of ILUC emissions induced by expansion of corn ethanol in the US and EU. All studies amortized ILUC emissions over 30 years, except Al-Riffai et al, who use 20 years. We present the Al-Riffai normalized to 30 years for comparison. To normalize all values to 20-year amortization, add 50% to each.

Study	Target year	Shock size (10 ⁹ L)	ILUC factor (g $CO_2 e MJ^{-1}$)	Range (g CO ₂ e MJ ⁻¹)
Searchinger et al. (2008b)	2016	56	104	$20 - 200^{a}$
Hertel et al. (2010a)	2001 ^b	50	27	$15 - 90^{\circ}$
Dumortier et al. (2009)	2018/19	30	n/a	$21 - 118^d$
USEPA (2010b)	2012	7.5	81	$62 - 104^{e}$
USEPA (2010b)	2017	14	58	$43 - 76^{e}$
USEPA (2010b)	2022	10	34	$25 - 45^{e}$
Al-Riffai et al. (2010)	2020^{f}	0.47	36	$36 - 53^{g}$

^a Calculated from reported sensitivity results

^b Analysis was performed using the GTAP-6 database, based on 2001 data, but the results were adjusted *post facto* to account for the 10% greater average corn yield in 2010.

^c Range is based on a combination of high and low values for various uncertain economic model parameters.

d Range is based on evaluating alternative model assumptions.

 e Range is 95% CI around mean considering only the uncertainty in satellite data analysis and carbon accounting.

^{*f*} Analysis was performed using the GTAP-7 database, based on 2004 data, using the model to project out to 2020.

^{*g*} Effect of additional 106 GJ after meeting 5.6% mandate. Higher value is for greater trade liberalization. 2006). The range in results outlined by a global sensitivity analysis will generally be broader than that of a local sensitivity analysis.

8.2.2 CHARACTERIZING UNCERTAINTY

My analysis demonstrates that if we believe the input ranges are reasonable, the specific shape of the pdfs isn't important qualitatively: the choice of bounding values and the functional form drive the results. Some analysts caution that stochastic and epistemic uncertainty must be propagated separately in uncertainty analysis, using techniques such as probability bounds analysis (Ferson and Ginzburg, 1996). Others (e.g. Morgan et al., 2009; Aven, 2010) argue that subjective probabilities can be used to obtain a scientific judgment about unknown quantities. The result is likewise a subjective assessment of probability. In the present chapter, I characterize plausible boundaries around ILUC emissions using a simple and transparent model parameterized from the literature, assigning subjective probability distributions to all parameters and propagating these uncertainties through the model using Monte Carlo simulation. I employ several alternative sets of probability distributions to examine the possible size and shape of the frequency distribution for ILUC emissions, and we examine the contribution of each model parameter to the uncertainty in the result. My objective is thus not to define an objective probability distribution around ILUC emissions, but to characterize a plausible range of ILUC emissions that is robust to assumptions about the underlying distributions of key parameters, and to consider how this information can inform fuel GHG regulations.

8.3 Methods

8.3.1 REDUCED-FORM MODEL

To explore the range of ILUC emission estimates that can result from alternative model parameterizations, I use a *reduced-form model of ILUC* (hereafter, RFMI) based on the nine parameters described in the equations below and in Table 8.4. The net displacement factor for land (*land NDF*) is the ratio of (a) hectares of new agricultural land brought into production to replace agricultural production displaced by biofuel feedstocks, to (b) the hectares dedicated directly to additional biofuel feedstocks. The average emission factor (*AvgEmissionFactor*) is the average mass of CO₂ emitted per unit area for land converted to cropping. For the purposes of this model, I apply straight-line amortization of the ILUC emissions over the total biofuel production occurring over the presumed production period (*TotalFuel*) assumed to be associated with the initial ILUC emissions, although I recognize that this approach underestimates the relative warming caused by ILUC (O'Hare et al., 2009). Table 8.4 lists the parameters that are subjected to bounding analysis in the reduced-form model.

The CO₂ emissions resulting from land use conversion can be represented by the following

equation:

$$ILUC(g\ CO_2\ MJ^{-1}) = \frac{AreaConverted(ha) \times AvgEmissionFactor(Mg\ CO_2\ ha^{-1}) \times \ 10^6}{TotalFuel(MJ)}$$
(8.1)

Where

$$AreaConverted(ha) = \frac{FuelIncrement(MJ y^{-1})}{FuelYield(MJ ha^{-1}y^{-1})} \times NetDisplacementFactor$$
(8.2)

 $AvgEmissionFactor (Mg CO_2 ha^{-1}) = \sum_{i=f, g, w} EmissionFactor_i (Mg CO_2 ha^{-1}) \times Fraction_i$ (8.3)

where f is forest, g is grassland, and w is wetland.

$$TotalFuel (MJ) = AreaConverted (ha) \times FuelYield (MJ ha^{-1} y^{-1}) \times ProductionPeriod (y)$$
(8.4)

From the form of equation (8.1) we can see that if the terms in the numerator have wide error bars, and the denominator has relatively narrow error bars, the multiplicative form of the numerator will result in a right-skewed bounding range: the high bounding value will be further from the point estimate than is the lower bounding value. This is indeed the case, as demonstrated below.

RFMI is implemented in Microsoft ExcelTM. I use Monte Carlo simulation (implemented using the Crystal BallTMadd-in) to examine alternative probability distributions for model parameters and to support uncertainty importance analysis. Lacking empirical basis for assigning probability distributions to the model parameters, I explored the sensitivity of RFMI results to different probability distributions: uniform, triangular, betaPERT⁵, and lognormal. For the uniform, triangular, and betaPERT distributions, the maximum and minimum values were set to those shown in Table 8.4, with the central value for the triangular and betaPERT set to the midpoint of the range. For the lognormal case, lognormal distributions were assigned to the production period, average fuel yield, and three emission factors by setting the 2.5% and 97.5% values of the distributions to the ranges as shown in Table 4; the remaining parameters were assigned betaPERT distributions as described previously.

⁵Like a triangular distribution, a betaPERT distribution has fixed minimum and maximum values and a most probable value. However the betaPERT distribution has a bell shape which, relative to a triangular distribution, has more probability density in the center and less at the extremes (Vose, 1997).

To evaluate the relative contribution of each RFMI parameter to variance, I assigned all parameters uniform probability distributions ranging from their corresponding low and high values indicated in Table 8.4 and ran a 10,000-trial simulation, using Latin Hypercube Sampling. While the precise statistics of the output distribution are not meaningful, this approach allows us to estimate the contribution to variance for each parameter based on the normalized rank correlation of each parameter to the final amortized ILUC emissions value.

8.3.2 PARAMETER RANGES

Table 8.4 lists the bounding values assumed for each parameter in the present exercise, which apply to ethanol from US corn. In the following sections I explain the rationale and evidentiary basis for these ranges.

Parameter	Units	Low	High
Fuel yield	$MJ ha^{-1} y^{-1}$	3500	4500
Net displacement factor		25%	80%
Emission factor _{forest}	${ m Mg}~{ m CO}_2~{ m ha}^{-1}$	350	650
Emission factor _{grass}	${ m Mg}~{ m CO}_2~{ m ha}^{-1}$	75	200
Emission factor _{wetland}	${ m Mg}~{ m CO}_2~{ m ha}^{-1}$	1000	3000
Fraction _{forest}		15%	50%
Fraction:wetland		0%	2%
Fraction _{grassland}	1 – (forest +	wetland	d frac-
	tions)		
Production period	У	15	45

Table 8.4: Parameters and ranges explored using the reduced-form model for US corn ethanol.

8.3.2.1 AVERAGE FUEL YIELD

Initial ILUC emissions are a function of the areal biofuel yield (MJ $ha^{-1} y^{-1}$) at the time of expansion. Searchinger et al. (2008b) assumed an annual corn ethanol yield of 3766 L ha^{-1} ; Hertel et al. (2010a) assumed 3598 L ha^{-1} . In its final rulemaking for RFS2, the USEPA (2010b) assumed that corn ethanol yield will reach nearly 4423 L ha^{-1} in 2017 and 4692 L ha^{-1} in 2022.⁶

⁶The FASOM model, used by USEPA to estimate domestic LUC emissions, projects that in 2017, corn yield will be 174.5 bushels acre-1 (10.9 Mg ha⁻¹) in 2017 and 185.1 bu acre-1 (11.6 Mg ha⁻¹) in 2022, with a constant biorefinery

Our analysis uses a range of 3500 to 4500 L ha^{-1} for average fuel yield over the modeled time horizon.

8.3.2.2 NET DISPLACEMENT FACTOR

Land net displacement factor (NDF) reflects the number of hectares of new agricultural land projected to come into production per hectare of land used to meet the modeled increase in biofuels production. The NDF includes the combined effects of (i) price-induced yield increases, (ii) relative productivity of land converted to cropping, (iii) price-induced reductions in food consumption, and (iv) substitution by biofuel co-products such as distillers' grains.

The NDF is perhaps the most challenging parameter to estimate since it is a result of a worldwide economic system constantly seeking equilibrium and thus depends on many uncertain parameters and subjective choices in the economic models used. NDF is also the most influential parameter in the RFMI because the range of values from prior studies is quite broad.

Values imputed for NDF vary from 28% of land used to meet the modeled increase in biofuels production in the Hertel et al. (2010a) analysis, to 72% in the Searchinger et al. (2008b) analysis, and higher in the USEPA (2010b) analysis. The NDFs estimated from USEPA's published results⁷ for corn ethanol was 102% in 2012, 52% in 2017, and 29% 2022. However, as the full corn ethanol mandate is projected by USEPA to be met in 2016, I ignore the 2022 value, averaging the values for 2012 and 2017 to produce an estimate of 77%.

Our analysis thus uses a low value of 25% and a high value of 80% for NDF. I note this range reflects the very significant model uncertainty more than the parametric uncertainty inherent in the underlying models.

8.3.2.3 ECOSYSTEM CONVERSION FRACTIONS

The GHG emissions resulting from conversion to cropping vary with land cover type, cropping system, and across regions.

The studies reviewed here estimated ILUC by first estimating the fractions of specific land types converted as a result of biofuels expansion. As economic models are generally not spatially explicit, prior modeling efforts have used other approaches to predict the land cover types affected. Using this method, the predicted fraction of final LUC that occurs on prior forest, grassland, or wetland is a function of both economic modeling results and historical data on land use conversion. The economic models predict the countries (in the case of FAPRI) or agro-ecological zones (in the case of GTAP) in which amounts of land conversion will occur. These results are combined with historical data on land use conversion for the identified country or zone to determine the type of land cover likely to be affected. A weakness of this approach is that it assumes that LUC induced

yield across the modeling horizon of 2.71 anhydrous gal bu-1 (404 L Mg⁻¹) of corn.

⁷These results are for the FAPRI model only. See section 8.6 for an explanation of why I excluded the FASOM results.

through commodity markets has the same pattern of ecosystems and carbon stocks as does the undifferentiated average LUC observable in the historical record.

Searchinger et al estimate that 52% of the LUC resulting from corn ethanol expansion occurs on forested land, and 48% in grassland. Hertel et al estimate that 19% of the net conversion⁸ to cropland comes from forest, and 81% from pasture. I was unable to derive a corresponding division from the USEPA analysis.

I assume that the forest conversion fraction ranges from 15% to 50% of the total LUC induced by biofuels expansion. Given the high emission factor for wetland conversion, but lacking empirical data on the fraction of conversion from wetlands, I allow this fraction to range from 0% to 2%. The grassland fraction is computed as 100% minus the sum of the forest and wetland fractions, and thus ranges from 48% to 85%.

8.3.2.4 LAND CONVERSION CO₂ EMISSION FACTORS

I define a parameter representing the average CO_2 emissions associated with the conversion to cropland for each of three coarse land cover classes: forest, grassland, and wetland. The models used by CARB and USEPA use more land classes, with differentiated emission factors for forest and grassland subtypes. The coarse values used here for the three broad land cover classes represent area-weighted averages of emissions from these subtypes, and thus depend on assumptions of the occurrence of conversion for each of these subtypes.

Several challenges make it difficult to accurately estimate CO_2 emissions from land use changes across large regions. The carbon stocks in the original ecosystem must be estimated and our knowledge of these remains limited, particularly in the tropics (Gibbs et al., 2007). Forest inventories are often used to estimate carbon stocks, but as pointed out by (Houghton, 2005), inventories remain outdated and incomplete across the tropics. In regions where estimates do exist, there can be a wide range in estimates of total biomass, as well as disagreement as to the locations of the most and least carbon dense forests. In addition, Houghton notes that existing estimates are largely for undisturbed forests. Natural disturbances and human activities add further variability to these estimates. For example, it is not clear that the average carbon stock estimate for an ecosystem is representative of the carbon released by LUC (Houghton, 2005).

Estimating the carbon fluxes from land use conversion requires estimates of the above- and below-ground biomass and soil carbon stocks before and after the conversion, which are all both variable from place to place and uncertain even in a specific location (Guo and Gifford 2002; Gibbs, Brown et al. 2007; Ramankutty, Gibbs et al. 2007). Below-ground biomass is usually estimated using a "shoots-to-roots" ratio based on estimates of above-ground biomass, so this skewed uncertainty applies to below-ground biomass carbon as well.

Gibbs et al. (2008) estimate CO_2 emissions for conversion of various tropical land cover types to cropland, assuming a loss of all aboveground and belowground biomass and 25% of the carbon in the first 1m of soil. They estimate a loss of 334 to 897 Mg CO_2 ha⁻¹ for tropical forests across

⁸Net conversion includes a relatively small amount of reversion (15% of total area change) from pasture to forest.

all regions, with a range of 538 to 793 Mg CO_2 ha⁻¹ for the Americas, 202 to 482 Mg CO_2 ha⁻¹ for disturbed tropical forests across all regions, and 307 to 437 Mg CO_2 ha⁻¹ in the Americas. Fargione et al. (2008) estimate the "carbon debt" (the change in above- and below-ground carbon stocks 50 years after conversion) associated with the conversion of several land cover types to biofuel feedstock production. They estimate a carbon debt of 702 Mg CO_2 ha⁻¹ for lowland tropical rainforest in Southeast Asia, and 737 Mg CO_2 ha⁻¹ for Amazonian rainforest. Based on different economic models, but using essentially the same emission factors, Searchinger et al. (2008a) and Hertel et al. (2010a) estimated average emissions for forest conversion of 533 and 607 Mg CO_2 ha⁻¹, respectively. For the average emission factor for forest conversion, I assume a range from 350 to 650 Mg CO_2 ha⁻¹.

For conversion of US central grasslands to cropland Fargione et al. (2008) estimate a carbon debt of 134 Mg CO₂ ha⁻¹. Searchinger et al. (2008a) estimate the emissions for conversion of temperate grasslands to be 199 Mg CO₂ ha⁻¹; for tropical grasslands, they estimate 104 Mg CO₂ ha⁻¹. Gibbs et al. (2008) estimate a loss of 52 to 103 Mg CO₂ ha⁻¹ for tropical grassland, and 126 to 348 Mg CO₂ ha⁻¹ for tropical shrubland and savanna. The average values estimated by Searchinger et al and Hertel et al for grassland to cropland were 142 and 105 Mg CO₂ ha⁻¹, respectively. For the average emission factor for conversion of grassland to cropland, I use a range from 75 to 200 Mg CO₂ ha⁻¹.

The emission factor for conversion of moist tropical Southeast Asian forests from the Woods Hole data set is 1146 Mg CO₂ ha⁻¹. Fargione et al. (2008) estimate a carbon debt for conversion of peatland tropical rainforest in Southeast Asia to be 3452 Mg CO₂ ha⁻¹. Gibbs et al. (2008) estimate the total loss of 5876 Mg CO₂ ha⁻¹ over 120 years for the conversion of peat soils. For wetlands, I assume emissions range from 1000 to 3000 Mg CO₂ ha⁻¹.

8.3.2.5 **PRODUCTION PERIOD**

The RFMI treats all ILUC emissions associated with biofuels expansion as occurring instantaneously at the start of biofuel expansion.⁹ To include these emissions in fuel regulations that assign a GHG rating to each unit of fuel, the emissions must be attributed to each unit of fuel associated with the expansion. This, in turn, requires an estimate of the duration of this associated production. The simplest approach uses straight-line amortization to distribute the emissions evenly over some number of years of biofuels production. Searchinger et al. (2008b) assumed 30 years of biofuel production, a value which has subsequently been adopted by both CARB and USEPA in their respective rulemakings (CARB, 2009a; USEPA, 2010b). However, the 30-year assumption was not based on empirical data, but rather was chosen to avoid being criticized as too low (Searchinger, 2009). In contrast, the EU Renewable Energy Directive requires that land use change emissions be distributed evenly over 20 years of production (European Parliament, 2009, Annex V). Note that

⁹ I recognize this is a simplification of the actual emission profile and have written separately on this subject (O'Hare et al., 2009). However, for simplicity in the exposition of the present bounding analysis, I have ignored these complexities. The effect of this omission is to somewhat underestimate the GHG effects of biofuels relative to those of gasoline, but this effect is small relative to the uncertainty ranges examined here.

changing the assumed production period from 30 to 20 years increases the unit ILUC emissions value by 50%.

Some biofuels, especially those cheap or efficient to produce such as Brazilian cane ethanol, may be produced for longer than the 30 year "anchoring" value. Although the value for this parameter has been a model choice in practice, it can be treated as a variable whose most representative value is uncertain. I allow a range of 15 to 45 years.

8.4 **RESULTS**

Assumings parameter independence, plausible (in the range-of-possibilities sense used here) values for the ILUC factor based on interval analysis ranged from about 10 to 370 g CO_2e MJ⁻¹, as shown in Figure 8.1.



Figure 8.1: Parameter (panels a-d) and result (panel e) ranges for ILUC factor for US corn ethanol. Values identified as RFMI (red) combine to produce the highest result; values identified as rfmi (green) produce the lowest result. RFMI = Reduced Form Model of ILUC; EPA'12 = USEPA results for year 2012; EPA'17 = USEPA results for year 2017.

8.4.1 PLAUSIBLE FREQUENCY DISTRIBUTIONS

Figure 8.2 shows the output frequency distributions from Monte Carlo simulations based four alternative parameter distribution forms. Median values ranged from 60 to 66 g CO₂e MJ^{-1} . The widest 95% central interval (24 to 151 g CO₂e MJ^{-1}) resulted from using uniform parameter distributions; the narrowest (34 to 111 g CO₂e MJ^{-1}) resulted from using betaPERT distributions.

Maximum values were above 260 g $CO_2 e MJ^{-1}$ for the cases with lognormal and uniform parameter distributions.

Results for all choices of input distributions were qualitatively similar; the output distributions are approximately lognormal, with a prominent right tail. The parameter ranges result from many underlying uncertainties, and may not bracket the full range of plausible values for each parameter. However, if we believe that values within the chosen ranges are plausible given the uncertainties, and I assume the values are independent, then the extreme values possible from the model (10 to $370 \text{ g CO}_2 \text{ e MJ}^{-1}$) are also plausible.

The ranges here are wider than those presented by the cited studies because I combined ranges of input parameters derived from those studies. The bounding range produced by probabilistic combination of even the uniform distribution (Figure 3) is narrower than that produced using interval calculations (Figure 2) because the likelihood of all input parameters achieving their bounding values simultaneously in the Monte Carlo simulation is quite slim. If the number of trials were increased, the thin portion of the right tails in Figure 3 would extend toward the maximum value (370 g $CO_2e MJ^{-1}$) shown in Figure 2. While I chose to define the "plausible" range as the central 95% interval, it's important to recognize that the fat right tails of these distributions represent non-zero risk of very high ILUC emissions.

8.4.2 UNCERTAINTY IMPORTANCE ANALYSIS

The land net displacement factor accounts for about half the variance in the ILUC emission factor when the production period is allowed to vary from 15 to 45 years; the production period itself accounts for about 35% of the total variance. With the production period fixed at 30 years, the land net displacement factor accounts for three-quarters of the variance in the ILUC emission factor. Figure 8.3 shows the contribution to variance for each parameter under these two assumptions about production period.

The land net displacement factor, while represented as a single parameter in RFMI, is a derived result of economic models such as FAPRI and GTAP. As discussed earlier, it is unlikely that modelers will be able to greatly reduce the uncertainty in this parameter.

8.5 **DISCUSSION**

8.5.1 POSSIBLE BIASES

Factors not taken into account here may create a bias in the estimates of ILUC emissions. First I consider factors that increase our estimate of ILUC emissions, followed by factors that could reduce our estimate. Perhaps most importantly, many of these factors harbor considerable uncertainty, so including them in the analysis may increase the range of plausible results.

8.5.1.1 FACTORS THAT MIGHT CREATE A DOWNWARD BIAS IN ILUC ESTIMATES

Several considerations suggest the warming effect of ILUC may be higher than prior estimates.

First, owing to temporal asymmetries in the gain and loss of ecosystem carbon, the use of net area changes results in a systematic underestimate of emissions. When forests and grasslands are converted to cropland, or forests converted to pasture, carbon is released much more quickly than it is regained when the land reverts to a natural state. For example, clearing tropical forests by burning releases carbon essentially instantaneously, while it takes 100-150 years for a tropical forest to return to a carbon plateau. Economic models and satellite images estimate *net* land use changes at their highest resolution, which is inevitably somewhat coarse. Using net change numerically cancels gains and losses of cropland, despite the asymmetry in carbon flux. Emissions from shifting land uses below this level of resolution are therefore systematically underestimated.

Second, other known climate forcing effects induced by ILUC have not been included in estimates to date, including emissions of black carbon from biomass clearing, changes in albedo, and changes in evapotranspiration. Including black carbon would likely increase the warming effect of ILUC (Delmas, Lacaux et al. 1995; Bond and Sun 2005), whereas including albedo is likely to somewhat reduce the warming effect since trees tend to be darker than row crops (Thompson, Adams et al. 2009). Adding these effects would improve model completeness and reduce systematic error, but it would not reduce uncertainty.

Finally, competition among biofuel feedstocks and food crops results in higher food prices and a reduction in food demand. A flaw with an exclusive focus on GHG emissions is that a nutritional deficit induced by higher food prices is counted as a GHG benefit (Searchinger et al., 2008a). In their modeling of ILUC emissions from corn ethanol expansion, Hertel et al. (2010b) estimate that holding food consumption constant increases the ILUC factor by about 40%.

8.5.1.2 FACTORS THAT MIGHT CREATE AN UPWARD BIAS IN ILUC ESTIMATES

Several factors may cause ILUC emissions to be lower than estimated by prior studies. For example, yield on recently converted crop land may not be lower than average yield where supply is transportation bound. That is, high-productivity land may be available that is unused because of logistical constraints. As prices rise, these constraints may be overcome.

In some regions (e.g. Brazil), double-cropping results in higher yield elasticity than if only single-cropping is assumed. That is, if prices increase, farmers may plant more than one crop per season, without requiring additional land.

The baseline emissions of methane (CH_4) from wetlands is eliminated when these are converted to cropping. This avoided emission of CH_4 reduces the emission factor estimated if considering only CO_2 emissions.

In general, the models and thus the parameters I derive from them assume the continuation of existing policies. If, instead, policies were implemented to steer land conversion toward already-disturbed land, lower emissions than those estimated would result.

Trees have generally darker than cropland, as noted earlier, so conversion of forests to crops
increases surface albedo and produces local cooling (Thompson et al., 2009).

8.6 Comments on the USEPA analysis for the Renewable Fuel Standard

In their regulatory impact analysis for RFS2, USEPA combined the results of two economic models—FASOM for domestic emissions and FAPRI for foreign emissions—to estimate the net change in global emissions associated with different fuel pathways. After reviewing USEPA's analysis, I chose to draw parameters for RFMI from the FAPRI model rather than from the integrated FAPRI-FASOM results. There are three reasons for this decision. First, I was unable to reconstruct the reported integrated results based on the spreadsheets and documents made available by USEPA. The results from the FAPRI model, in contrast, were quite easy to extract. Second, the FAPRI international model uses the output of the FAPRI US model—not the output of the FASOM model—and differences between these two US models grow over the modeling horizon to produce a notable gap by 2022. Third, the large carbon sequestration benefit estimate by FASOM in 2022 appears to be an artifact of the model which I suspect could disappear if the carbon accounting were handled more realistically in FASOM.

I discuss these issues in more detail below.

8.6.1 MODEL INTEGRATION ISSUES

The FASOM model estimates the changes in agricultural and forestry production resulting from a change in biofuels production, and endogenously calculates net GHG fluxes using emission or sequestration factors associated with each activity. Changes in soil GHG fluxes are calculated using factors developed with the DAYCENT model and incorporated into FASOM.

The FAPRI modeling system estimates the changes in agricultural production resulting from a change in biofuel production. As FAPRI doesn't include GHG accounting, emissions from changes in crop and livestock production are estimated externally to FAPRI using emission factors for fuels and agricultural inputs from GREET, and LUC emission factors developed by Winrock International.

Since the FASOM model estimates changes in emissions for the US, USEPA subtracts the estimated land use changes in the US from the FAPRI results, resulting in a "foreign" emission estimate that can be added to the FASOM results.

Although USEPA attempted to bridge the gap between the two models, the models cannot produce the same result even with identical assumptions. For example, FASOM includes the forestry sector and models switchgrass production, while FAPRI does neither. Although the two models predict similar area change in the US in 2012, by 2022 their projections have diverged significantly, with FASOM estimating more than double the domestic land use change estimated by FAPRI (Figure 8.4 and Figure 8.5) Since FAPRI doesn't include switchgrass, when modeling switchgrass ethanol, USEPA subtracted the area projected by FASOM to be planted in switchgrass from the available area in FAPRI and re-equilibrated FAPRI to produce results for the analysis outside the US. However, in the case of corn ethanol, the corn-only case (i.e., reducing corn ethanol from the RFS2 level to the baseline level) results in a loss of corn acreage, and as a side-effect, a loss of corn stover collection. In place of stover, FASOM projects that 2.8 million tons of switchgrass would be produced to meet the cellulosic mandate in RFS2. However, in this case, USEPA did not adjust the FAPRI US model to account for the production of switchgrass.

Because of this interaction between corn grain and stover, the USEPA emission estimate for corn (grain) ethanol is meaningful only *in the context of the RFS2 cellulosic biofuel requirement*. If, say, cellulosic ethanol comes to market more slowly than anticipated and Congress modifies the RFS2 mandate, the projected planting of switchgrass would be incorrect, and a new value would need to be calculated for corn ethanol.

8.6.2 QUESTIONS ABOUT GHG ACCOUNTING

8.6.2.1 GHG BENEFITS OF REDUCED TILLAGE

There is mounting evidence that the assumed carbon sequestration benefit of no-tillage over conventional tillage may be an artifact of shallow sampling depth (Baker et al., 2007; Gál et al., 2007; Blanco-Canqui and Lal, 2008; Yang et al., 2008; Batlle-Bayer et al., 2010). Baker et al. (2007) conclude that while "there are other good reasons to use conservation tillage, evidence that it promotes C sequestration is not compelling."

FASOM incorporates from DAYCENT emission factors for soil GHG fluxes. The specifics of these factors and where exactly they are applied has not been documented by USEPA. Six et al. (2004) conclude that conversion to no-till can increase N_2O emissions for decades, resulting in a net increase in global warming potential—even assuming no-tillage results in carbon sequestration—yet it's unclear whether FASOM accounts for this. The large CO₂e benefit FA-SOM assigns to conversion to no-till seems to indicate that this N_2O effect is not included.

8.6.2.2 FOREST CARBON SEQUESTRATION

The FASOM projections published by USEPA show large swings in forest carbon sequestration and release over the time-steps modeled. For example, for corn ethanol in 2022, FASOM predicts that non-combustion GHG emissions are net negative: 74 million tonnes of CO₂ are sequestered domestically as a result of corn ethanol expansion. The single largest factor is "C in afforested forest above-ground biomass (w/o Litter)", with projected sequestration of 99 million tonnes of CO₂. In addition, "C in cropped and pasture ag soil" accounts for sequestration of 29 million tonnes CO₂. On the emission side, "C in continuous and afforested forest soils" and "C in continuous forest above-ground biomass (w/o Litter)" account for the release of 14 million and 38 million tonnes CO₂, respectively. The FASOM total includes a few categories of much less consequence. The 99 million tonnes sequestered through afforestation results from the increased sequestration in the corn case of 115 M tonnes CO_2 versus the sequestration of 19 M tonnes CO_2 in the baseline case. The changes projected by FASOM at the 5-year time-steps are illustrated in Figure 8.6. The 99 M tonnes sequestered in 2022 represent a strong departure from the trend otherwise apparent in the model results. Figure 8.6 shows the changes in carbon in biomass associated with afforestation. The corn-only case (blue line) shows a very sharp peak in 2022, while the baseline case (red line) showed a sharp drop, resulting in a large sequestration benefit for corn ethanol (green line).

The only year in which FASOM projects sequestration of CO_2 from afforestation is 2022; all other years register net emissions. In years subsequent to 2022, the sequestration is reversed, with relatively large positive emissions for 30 years following the end of the RFS2 program.

FASOM tracks the annual flows of carbon into and out of various biomass and soil categories. Sequestration in biomass and soil is assigned a negative value, and emissions to the atmosphere are assigned a positive value. These flows are summed in each time period, treating emissions and sequestration as equivalent—regardless of the duration of the sequestration. The capture of one ton of carbon in a tree results in a full sequestration benefit credited in the year in which it occurs, even if the carbon is released the following year.

Accounting for flows without regard to the atmospheric residence time of CO_2 or the reversibility of sequestration in natural systems overstates the value of temporary sequestration and understates the cost of re-release.¹⁰ The large sequestration registered in 2022 is mostly reversed in 2027, suggesting that the sequestration value of that temporarily captured CO_2 is very small. Considering a 100-year time horizon, Moura Costa and Wilson (2000) conclude that CO_2 must be sequestered for 55 years to reach equivalence with avoiding emission of the same quantity of CO_2 , given the residence time of CO_2 in the atmosphere. This suggests that giving full equivalence to CO_2 stored for only 5 years overstates the value of the sequestration by a factor of 10.

8.7 CONCLUDING REMARKS

Several critics of ILUC modeling have suggested that the uncertainty inherent in estimates of ILUC emissions should disqualify these estimates from fuel regulatory efforts such as California's LCFS and the US renewable fuel standard (e.g. Greenwood, 2008; Simmons et al., 2008). This perspective views uncertainty as a flaw in the modeling process that must be corrected before policy can be developed (van der Sluijs et al., 2005). For example, an amendment attached to the American Clean Energy and Security Act of 2009 (H.R. 2454) in the US House of Representatives would excise international ILUC emissions from the GHG accounting protocol in the renewable fuel standard, and require a five-year National Academies of Science study to determine whether models can project international LUC emissions "with reliability, predictability, and confidence"

¹⁰Many farmers who have used Monsanto's Roundup herbicide (glyphosate) for years are now plowing up fields previously managed without tillage, in an effort to eradicate glyphosate-resistant "super weeds" (Neuman and Pollack, Neuman and Pollack). Plowing these fields reverses any sequestration benefits from no-tillage.

(Peterson, 2009). As these terms are left undefined, the awkward implication of ignoring ILUC because of uncertainty is that estimates of the *direct* emissions from fuel life cycles may also be inadmissible for policymaking, as considerable parameter and model uncertainties are present in all life cycle assessments (Finnveden, 2000; Björklund, 2002).

Ignoring ILUC emissions is equivalent to assigning a value of zero to this effect. If estimates of the effect were (i) centered symmetrically (ii) at zero—that is, if the *most likely* and *expected* values were zero—and (iii) if the cost of error were symmetrical across zero, it might be reasonable to ignore ILUC emissions. However, our analysis and the modeling studies discussed herein suggest that ILUC emissions for corn ethanol are *not* best approximated by zero, whatever estimator is used. Several studies have projected significant ILUC emissions associated with other food-competitive feedstocks such as soybeans, rapeseed, sunflower, wheat, palm oil, and switch-grass (CARB, 2009a; Al-Riffai et al., 2010; USEPA, 2010b). The estimates of ILUC emissions for corn ethanol of 30 g CO_2 MJ⁻¹ by CARB and 34 g CO_2 e MJ⁻¹ by USEPA (for 2022) are at the low end of the plausible range; a value at least five times as large is also plausible. Excluding ILUC from these regulatory efforts provides only specious precision, and could result in perverse policy outcomes.

The presence of irreducible and broad uncertainty in estimates of the life cycle GHGs from biofuels highlights the limitations of performance-based regulations based on point estimates. Given these limitations, policies that deal explicitly with the risk posed by potentially high ILUC emissions might be more appropriate. Consideration of these risks has led to calls to slow the expansion of biofuels until these risks can be reduced (Gallagher, 2008; Florin and Bunting, 2009). One clear way to narrow the uncertainty and reduce the risk of large ILUC emissions would be to discourage biofuel feedstocks that compete with food for land, and to encourage others such as wastes, residues, and certain algae production systems. However, even these can have indirect effects that must be considered (Brander et al., 2009).



Figure 8.2: Frequency distributions for four Monte Carlo simulations of ILUC emissions for US corn ethanol using (i) betaPERT, (ii) triangular, (iii) lognormal, and (iv) uniform distributions for model parameters. The green boxes in the upper half show the interquartile range; the line across the box indicates the median. The ends of the whiskers show the maximum and minimum values and the crossbars identify the 95% central interval, i.e., the 2.5 and 97.5 percentile values. The blue curves in the lower half show the shape of the same frequency distributions.



Figure 8.3: Contribution to variance of reduced-form model parameters. The top bar shows the results for a fixed 30-yr production period, while the bottom bar shows results with production period varying from 15 to 45 years, with all parameters represented by uniform distributions.



Figure 8.4: Estimates of land use change (LUC) from corn ethanol expansion under RFS2, based on the FASOM model for the US and the FAPRI model for the rest of the world.



Figure 8.5: Estimates of land use change (LUC) from corn ethanol expansion under RFS2, based on the FAPRI model.



Figure 8.6: Changes in "C in afforested forest above-ground biomass (w/o Litter)" as projected in FASOM for RFS2. Positive values indicate emissions to the atmosphere; negative values indicate sequestration in biomass. Note that "corn only" represents meeting all RFS2 mandates *except* that corn ethanol is produced at the lower baseline level. (Source: Author's calculations from FASOM results spreadsheet in the USEPA's RFS2 docket.)

Part IV Conclusion

CHAPTER 9

UNCERTAINTY IN THE SCIENCE-POLICY INTERFACE

"Management and regulatory agencies would be far better off, and far more transparent, were they to acknowledge, consider, and document these value-based judgments than to pretend that the decision making framework is objective and value-free."

Gregory et al. (2006)

9.1 PURPOSE AND SCOPE

A frequent response to concerns about uncertainty in LCA-based regulations is that "all regulations involve uncertainty." Although true, this statement denies potentially important differences in the magnitude and nature of uncertainty. In the first section of this chapter, I examine the nature of the uncertainty in several environmental regulations to determine whether LCA-based regulations present a similar or greater challenge. In the second section, I present several (abstract) strategies for coping with uncertainty and explore how these strategies have been applied in the regulatory process of the LCFS.

9.2 UNCERTAINTY IN PERFORMANCE-BASED REGULATIONS

All regulations involve some degree of uncertainty, however the nature of uncertainty varies widely among regulations. Performance-based regulations are based on an assumption that controlling a given performance metric will achieve a desired regulatory outcome. Thus with performance-based regulations there can be uncertainties both in the estimate of the performance metric, i.e., *metric uncertainty*, as well as in the accuracy with which the metric represents the effect the policy is intended to address, i.e. *proxy uncertainty*.

Here I use the examples of several well-known environmental policies to contextualize the uncertainty in LCA-based fuel policies.

9.2.1 ACID RAIN PROGRAM

GOAL. Reduction of acid rain.¹

PERFORMANCE METRIC. Tons of SO₂ and NO_X emitted by the electric power sector.

METRIC UNCERTAINTY. The quantity of interest is observable from smokestacks and measurable in real-time using continuous emission monitoring systems, or in some cases using approved emission estimation methods (discussed further under *Treatment of uncertainty*). Regulated sources report hourly emissions of SO_2 , NO_X , and CO_2 . Estimation uncertainty involves measurement error and temporal variability.

PROXY UNCERTAINTY. Proxy uncertainty is low since the mechanisms causing acid rain are wellunderstood and the magnitude of the effect is directly related to the quantity of SO_2 and NO_X emitted. Coal-fired power plants are responsible for two-thirds of SO_2 emissions.

TREATMENT OF UNCERTAINTY. Continuous emission monitoring systems are considered reasonably accurate. Estimation procedures apply assumptions believed to generally overestimate actual emissions, thereby incorporating the additional uncertainty associated with estimation (Napolitano et al., 2007).

9.2.2 CLEAN AIR ACT: PARTICULATE MATTER

GOAL. Reduction of damage to human health from inhalable coarse particles 10 microns and smaller (PM_{10}) and fine particles 2.5 microns and smaller $(PM_{2.5})$.²

PERFORMANCE METRIC. Sources are numerous and mobile, thus particulate matter is regulated via ambient air quality standards, with maximum (average) levels for 24-hour and 1-year intervals. For example, the 2006 update to the standard requires that the 3-year average of the weighted annual mean PM_{2.5} concentrations from single or multiple community-oriented monitors must not exceed $15\mu g$ m³, and the 3-year average of the 98th percentile of 24-hour concentrations at each population-oriented monitor within an area must not exceed $35\mu g$ m³.

METRIC UNCERTAINTY. Particulate matter concentrations are observable and measurable, and subject to measurement error, as well as temporal and spatial variability. Average measurements depend on the location and frequency of measurement, and thus may vary from the concentrations actually experienced by the population.

PROXY UNCERTAINTY. The Clean Air Act requires EPA to set air quality standards that protect public health with "an adequate margin of safety." Specific ambient pollution levels at which "adequate safety" is achieved are uncertain, and concentration-response relationships vary across individuals. Particle concentration may not be the best proxy for harm since different chemical species can have different human toxicological properties.

¹See http://www.epa.gov/airmarkets/progsregs/arp/basic.html for information on the Acid Rain Program.

²See http://www.epa.gov/oar/particlepollution for more information.

TREATMENT OF UNCERTAINTY. Uncertainty in the metric is addressed by using the 98th percentile of 24-hour concentrations as the estimator, rather than using a central estimator such as mean or median. Safety margins were established based on a cost-benefit analysis that incorporated sensitivity analysis and Monte Carlo simulation based on expert elicitation of probability distributions, e.g., for concentration-response relationships.

9.2.3 KYOTO PROTOCOL

GOAL. The goal of the Kyoto $Protocol^3$ (KP) is the avoidance of "dangerous anthropogenic interference" in the earth's climate system, as stated in the United Nations Framework Convention on Climate Change.

PERFORMANCE METRIC. Nations listed in Annex I of the KP must reduce their net direct emissions of "aggregate anthropogenic carbon dioxide equivalent emissions of the greenhouse gases". In practice, carbon dioxide equivalence means that the net emissions of each regulated gas is weighted by its 100-year GWP value.

METRIC UNCERTAINTY. Emissions other than from agriculture are dominated by CO₂, most of which results from the combustion of fossil fuels and is thus relatively certain (Rypdal and Winiwarter, 2001; USEPA, 2009b). The main uncertainties involve estimating emission factors and activity levels for heterogenous sources across large geographic areas. Emissions from natural processes, e.g., CH₄ and N₂O from agriculture, and biotic carbon fluxes, are highly variable spatially and temporally. For the GHGs included in the KP, the IPCC assigns $\pm 35\%$ uncertainty (defining a range of ± 2 standard deviations) to GWP values. For inventories dominated by CO₂ emissions, GHG inventory uncertainty is relatively low. For example, for the US, in which CO₂ comprises about 85% of total GHG emissions, the 95% confidence interval for the 2007 national GHG inventory (net of sources and sinks) was estimated to be -3% to +7% (USEPA, 2009b, p. 1-15). Uncertainties in emission trends are estimated to be $\pm 4 - 5\%$ (Rypdal and Winiwarter, 2001).

PROXY UNCERTAINTY. GHG inventories are based on political boundaries, and thus subject to leakage to non-Annex I countries. The set of emissions regulated under the KP does not include known climate-active emissions such as aerosols or changes in biogeophysical effects such as albedo. The GWP method masks trade-offs between emissions with stronger long- or short-term forcings (Jackson, 2009), and truncates CO_2 effects at the end of the chosen time period, though much of the gas lingers in the atmosphere for centuries (Archer et al., 2009).

TREATMENT OF UNCERTAINTY. Parties to the agreement are encouraged, but not required, to propagate uncertainty through their national GHG inventories. To date, uncertainty is not factored into compliance monitoring or emission trading mechanisms. The issue of uncertainty in national GHG inventories has long been discussed in the literature (e.g., Parkinson et al., 2001; Gupta

³See http://unfccc.int/resource/docs/convkp/kpeng.html.

et al., 2003; Nahorski and Horabik, 2008), and there are ongoing international forums focused on bringing this information into the KP and any successor agreements.

9.2.4 LOW-CARBON FUEL STANDARD

GOAL. Reduction of climate change impacts from the transportation sector.

PERFORMANCE METRIC. Life cycle emissions of three GHGs: CO_2 , CH_4 , and N_2O , aggregated to CO_2 -equivalents using 100-year GWP values defined by the IPCC. In the case of RFS2 and the California LCFS, "life cycle emissions" is defined to include indirect emissions such as those from ILUC.

METRIC UNCERTAINTY. For direct emissions, metric uncertainties includes those identified for the Kyoto Protocol, plus uncertainty related to identifying all components of the supply chain. By including indirect emissions, we add all the uncertainties associated with economic modeling and projections into the future. Results are highly variable, unobservable, and require estimation of potentially large, very uncertain indirect effects. The difference in estimates of life cycle GHGs for individual fuels may be larger than the change a policy like the LCFS is attempt to induce.

PROXY UNCERTAINTY. Proxy uncertainties include those of the Kyoto Protocol. In addition, the need to convert an up-front stock change from ILUC emissions into a per-MJ flow, requires more complex time accounting than does an annual GHG inventory. Retaining a simple sum-of-emissions approach with time-varying emissions creates proxy bias in favor of biofuels (O'Hare et al., 2009). The size of biofuel programs violates the *ceteris paribus* assumptions underlying attributional LCA, creating additional proxy uncertainty. Fuel substitutions are subject to leakage (particularly reshuffling and the petroleum rebound effect) that is not captured in the performance metric.

TREATMENT OF UNCERTAINTY. Uncertainty is not addressed in this regulation.

9.2.5 COMPARISON OF POLICIES

As these examples demonstrate, LCA-based regulation of fuels is more complex and uncertain than other forms of environmental regulation. So while it's true that all of these policies involve uncertainties, LCA-based fuel policies involve greater uncertainty both in estimating the performance metric and in the relevance of the metric to the policy goal.

Table 9.1 presents subjective estimates of the levels of metric and proxy uncertainty in the four policies considered. Proxy uncertainty is medium for the Kyoto Protocol since it regulates CO_2 -equivalent flows, while climate forcing is a function of atmospheric stock, thus the path to final reductions matters but is not captured by the KP. Uncertainty is relatively low for the Acid Rain Program, which targets immediate, measurable concentration levels related to current emissions (Pizer, 2005), and strong scientific evidence links SO_2 emissions with acid rain. The LCFS and RFS2 share these uncertainties, but in addition, agricultural systems affected directly and indirectly by biofuel feedstock production involve effects such as changes in albedo and evapo-transpiration

that are not captured in the proxy. This is also be true under the KP, but this limitation applies mainly to nations whose predominant GHG emissions are from agriculture and natural systems, however the (Annex I) countries regulated under the KP are more developed countries whose emissions are mainly from the combustion of fossil fuels.

Fuel GWI—the 100-year CO_2 -equivalence of the life cycle emission of three gases—is poorly known, owing to pervasive data, parameter, and model uncertainty associated with the *post facto* reconstruction of the supply chain and the estimation of indirect effects. Metric uncertainty is therefore higher for LCFS and RFS2 than for policies relying only on direct measurements. In addition, the adequacy of this proxy (even if it were perfectly known) is uncertain as the proxy includes only a portion of the climate-forcing effects of fuel production and use, and the specific climate forcing, temperature change, and damages associated with each fuel would be uncertain even if the proxy were perfectly known.

Additional uncertainties affects both the RFS2 and LCFS proxies. In the RFS2 case, USEPA has chosen to regulate near-term biofuels based on projected 2022 improvements (USEPA, 2010b). Based on USEPA's own estimates, near term fuels have much higher GWI ratings than they are projected to have in 2022, thus the ratings used are not only uncertain, but clearly biased downward (Plevin, 2010). In the LCFS case, the performance metric mixes attributional and consequential approaches, ignores several non-negligible indirect effects that are included in the RFS2 analysis, and fails to account for substantial leakage.

To comply with the "safety margin" required by the Clean Air Act, USEPA estimates particulate concentrations using the 98th percentile value rather than the mean or median value. Despite the demonstrably greater uncertainty in estimating the climate effects of fuels, neither the RFS2 nor LCFS include any safety margin, implicitly treating estimates of fuel GWI as precise. CARB (2009a, p. ES-32) writes that AB 32—the law under which the LCFS is authorized—requires that emissions reductions be "real, permanent, quantifiable, verifiable, and enforceable." It's hard to make the case that the LCFS meets these requirements.

Policy	Metric uncertainty	Proxy uncertainty
Acid rain program	Low	Low
PM _{2.5} standards	Low	Medium
Kyoto Protocol	Low	Medium
RFS2	High	High
LCFS	High	High

Table 9.1: Comparison of uncertainties in performance-based environmental policies. Values represent author's subjective appraisals.

In contrast to the metrics used in the other performance-based environmental policies discussed

above, LCA methods are recognized as being incapable of establishing the objective truth about the environmental performance of products as complex as transportation fuels (Finnveden, 2000; ISO, 2006b). Uncertainty is indeed a common feature of environmental regulation. However, the degree of uncertainty differs widely among environmental performance measures. As a result, policies differ in their robustness to uncertainty.

9.3 STRATEGIES FOR COPING WITH UNCERTAINTY

The deep uncertainties such as those prevalent in estimates of biofuel GWI can blur categories that are usually considered distinct—knowledge versus ignorance, objective versus subjective, facts versus values, prediction versus speculation, science versus policy—creating "monsters" in the science-policy-interface (van der Sluijs, 2005). The scientific community (including policymakers relying on scientific judgement) can respond to these monsters using a variety of coping strategies. Van der Sluijs identifies four styles of treating uncertainty: *monster exorcism, monster adaptation, monster embracement*, and *monster assimilation*. Here I review how these coping strategies have been used in the public review processes for the LCFS and RFS2.

MONSTER EXORCISM. This style views science as capable of producing unambiguous truths. In this context, uncertainty is an aberration that should be expelled, and the focus of research should be to reduce uncertainties. Examples of this perspective were evident related to the LCFS and RFS2. In 2008, a group of biomass and biofuel researchers wrote to CARB chairwoman Mary Nichols to recommend that CARB leave ILUC emissions out of the LCFS protocol. Simmons et al. (2008) wrote:

We propose that a sound policy approach would be to base the initial LCFS on existing data sets that possess scientific consensus. These include the direct impacts of renewable biofuels production. The scientific and economic communities can then take advantage of the necessary time over the next five years to fully understand, gather, and validate the indirect impacts of biofuels production with empirical evidence that will enable the implementation of a sound policy that can address any indirect impacts.

From this perspective, a more "sound" policy would be achieved when uncertainty has been reduced or vanquished, and "scientific consensus" has been achieved. Similarly, US House of Representatives agricultural committee chairman Colin Peterson proposed a climate bill amendment requiring a five-year National Academies study that would study whether models existed that could "project with reliability, predictability, and confidence" the emissions from international ILUC induced by biofuels (Peterson, 2009). Until such time, international ILUC emissions would be excluded from the RFS2 analysis.

In fact, this approach is consistent with the general practice in LCA of excluding highly uncertain climate effects such as those of black carbon, sulfates, indirect GHGs, biogeophysical effects, and indirect economic effects (Delucchi, 2010). Unfortunately, willfully ignoring uncertain effects provides only the illusion of certainty. In fact, the existence of these uncertain effects indicates that our knowledge of the climate costs or benefits of many fuel alternatives is uncertain; ignoring these effects doesn't make it otherwise

Van der Sluijs notes that regulators may choose to hide or downplay uncertainty out of fear that the explicit recognition of uncertainty would leave them liable to legal challenges. This points to the implicit burden-of-proof borne by the regulator: in the US, products are generally considered "innocent" unless proven "guilty". Doremus (2005) writes that appeals to precaution must start with openly conceding the uncertainties in the existing science. She writes:

"Conservationists have been loathe to admit to uncertainty. Perhaps they would be more willing to take that plunge if they understood that doing so would enhance their ability to appeal to precaution without ceding the political power of their claim to be seeking scientifically legitimate regulatory decision making."

A more precautionary approach would reverse the burden of proof, as does the European Community's Registration, Evaluation, Authorisation and Restriction of Chemical substances (REACH) regulations on industrial chemicals.⁴ REACH requires that manufacturers of industrial chemicals evaluation and demonstrate that their products do not pose undue risks to health or the environment. When there is high uncertainty, the party bearing the burden-of-proof is placed at a disadvantage. For example, if biofuel producers were required to demonstrate the avoidance of ILUC, they would face precisely the same uncertainties currently confronting CARB and USEPA.

MONSTER ADAPTATION. This style attempts to transform the monster so that it fits better in existing categories, typically by quantifying uncertainties. If there is no objective, empirical basis for quantifying uncertainties, subjective estimates are used. This approach may also attempt to draw clear distinctions between knowledge and ignorance, for example by creating subjective scenarios within which a model based on "objective science" can be evaluated. Some "adapters" are uncomfortable with even this much ambiguity, requiring that probabilities be assigned to scenarios to allow their combination into a single distribution describing the phenomenon of interest.

Examples of this approach abound. The IPCC recommends the quantification of uncertainty in its GHG inventory guidelines (IPCC, 2000). EPA guidelines recommend quantification of uncertainty in regulatory environmental modeling (USEPA Science Advisory Board, 2006; NRC, 2007). The LCA standard, ISO 14040, recommends quantification of uncertainty in life cycle analysis (ISO, 2006b). Underlying these guidelines is the assumption that uncertainty can be meaningfully rendered into probability distributions.

MONSTER EMBRACEMENT. This approach includes using uncertainty to deny the reality of environmental risks, and is frequently used to avoid regulation by framing uncertainty as a failure of science (Doremus, 2005). This strategy was prevalent in stakeholder responses to the estimation of ILUC emissions in both the LCFS and RFS2 processes. Strategic embracement of uncertainty has certainly been a main strategy of climate change deniers.

⁴See http://ec.europa.eu/environment/chemicals/reach/reach_intro.htm for more information on REACH.

MONSTER ASSIMILATION. This style assimilates uncertainty into the management of environmental risks, for example by recognizing that consensus about the truth of complex environmental risks is unlikely. In the case of fuel policy, if we were to recognize that uncertainty in LCA often precludes clear determination of the relative environmental effects of different fuels, we might consider regulatory approaches that focus on risk, perhaps using qualitative assessments rather than relying solely on quantification.

Recognizing the high level of uncertainty in estimating ILUC emissions, the Gallagher review of the indirect GHG emissions from biofuels (Gallagher, 2008) for the UK Renewable Transport Agency concluded that "the balance of evidence shows a significant risk that current policies will lead to net greenhouse gas emissions and loss of biodiversity". Gallagher (2008) recommended slowing down the expansion of biofuels until a better understanding was developed, and promoting biofuels that avoided competition with food to limit the risk of high ILUC emissions. Florin and Bunting (2009) concur, suggesting that given the high level of uncertainty, governments should "take their foot off the accelerator" to provide time to better understand and fully consider the risks of expanding biofuel production.

9.4 Adapting fuel standards to uncertainty

Fuel climate policies can incorporate uncertainty in GWI either by (i) revising standards such as the LCFS and RFS2 that were designed without regard to uncertainty, or (ii) designing new policies that respect the limits of our ability to estimate GWI. Sections 9.4.1 and 9.4.2 present two approaches to incorporating uncertainty into regulations that currently rely on point estimates of GWI. Section 9.5 considers alternative regulatory approaches that recognize that we can't accurately quantify the GWI of many fuel pathways.

9.4.1 POLICIES USING THRESHOLD TESTS

Policies that require a comparison of a performance metric against a threshold (or baseline) can incorporate uncertainty most simply by propagating uncertainty through the computation of the performance metric and using a probabilistic comparison rather than comparing point estimates. This approach immediately raises the question of how certain we need to be of meeting a given threshold. For example, if the median value from the output distribution of the performance metric just meets the threshold, there is a 50% chance that performance fails to meet the threshold. This may not be deemed adequate assurane of policy outcomes. Increasing the required level of certainty reduces Type I errors (i.e., reduces the chance of assigning unwarranted climate benefits) while increasing Type II errors (i.e., increasing the chance of rejecting valid climate benefits.) Requiring any level certainty greater than 50% provides incentives to reduce the penalty associated with uncertainty (Gupta et al., 2003).

The choice of certainty level is a value-based judgment about which reasonable people will disagree. Gupta et al. (2003) reviews several judicial interpretations of uncertainty levels (table

9.2, derived from Weiss 2003) to suggest that requiring a minimum certainty of 67% would be appropriate for compliance with the Kyoto Protocol, and consistent with legal reasoning.

Percentage of probability	IPCC "scien- tific" uncer- tainty	Juridical description of uncertainty	Legal action that requires this level of probability	
99%	Virtually certain	Beyond reasonable doubt	Criminal conviction	
90–99%	Very likely	Clear and convincing evidence	Quasi-penal civil actions	
80–90%	Likely	Clear showing	Granting temporary in- junctions	
67-80%	Likely	Substantial and credible evidence	Evidence for impeachment	

Table 9.2: Judicial interpretation of uncertainty levels (Source: Gupta et al., 2003).

9.4.1.1 INCORPORATING UNCERTAINTY IN THE LCFS AND RFS2

In both the LCFS and RFS2, fuel GWI is computed as a point estimate using assumed best estimates of values for all model parameters. For the RFS, compliance for each fuel pathway is based on a comparison of (i) the point estimate GWI for the fuel and (ii) the designated reduction from the 2005 petroleum fuel baseline, e.g., the GWI of cellulosic ethanol must not exceed 40% of the GWI of 2005 gasoline. Compliance is *binary*; there is no additional benefit for exceeding the requirement.

In the LCFS, fuel pathways are likewise assigned a point estimate GWI rating, however, compliance is determined by comparing to a designated target the AFCI (Average Fuel Carbon Intensity, i.e., the energy-weighted average GWI) of fuels sold by each regulated party. Thus, compliance with the LCFS is also based on a binary test of AFCI versus a threshold. However, in the LCFS, we can incorporate uncertainty either at the fuel pathway level or the AFCI level.

To incorporate uncertainty, the threshold comparison can be handled by computing a probability distribution representing the likelihood that the threshold has been met. For example, in a Monte Carlo simulation it would be possible to compute $\frac{GHG_{biofuel}-GHG_{gasoline}}{GHG_{gasoline}}$ and then determine the portion of the distribution below the reduction threshold of, say, 60%.

Finally, to be meaningful, this approach requires inclusion of all major uncertainties in the output frequency distribution. Otherwise, the distribution will be unrepresentative of the actual uncertainty and any conclusions drawn from will be misleading. For example, in its regulatory

impact analysis for RFS2, USEPA (2010b) compared frequency distributions for biofuels with the required reduction thresholds, but these distributions included only uncertainties in the remote sensing and carbon accounting portions of the model (Plevin, 2010). Figure 9.1 is taken from the Regulatory Impact Analysis for RFS2, showing a frequency distribution for the percentage reduction in corn ethanol GWI versus the required 20% reduction threshold. As demonstrated in chapter 8, uncertainties in the economic modeling dominate the uncertainty in estimates of ILUC emissions, yet these uncertainties were not included in USEPA's fuel GWI distribution. As a result these distributions are not appropriate for the purpose of determining the probability of compliance.



Figure 9.1: Distribution of 2022 corn ethanol GWI reduction relative to 2005 gasoline (for natural gas fired facilities producing 63% dry and 37% wet DGS, with fractionation). (Source: USEPA, 2010b, PDF p. 480).

9.4.2 POLICIES USING ABSOLUTE RATINGS

Some policies require assigning specific values to the climate effects or benefits of projects or products. Examples include (i) the LCFS, (ii) the Kyoto Protocol's Clean Development Mechanism (CDM), by which Annex I countries can offset their emissions through the purchase of emission reduction credits from certified projects in non-Annex I countries, and (iii) the REDD program, discussed earlier, which offers similar credits for the protection of forests.

Uncertainty can be incorporated into performance absolute ratings by applying the "conservativeness approach" to ratings (UNFCCC, 2006; Mollicone et al., 2007; Grassi et al., 2008). Under this approach, project performance is estimated probabilistically, and an environmentally conservative value is chosen from the uncertainty distribution. In the context of REDD, conservativeness means that "when completeness or accuracy of estimates cannot be achieved, the reduction of emissions should not be overestimated, or at least the risk of overestimation should be minimized" (Mollicone et al., 2007). For policies rating fuel GWI, such as the LCFS, a conservative value would be a high one. If the baseline petroleum fuel were treated as uncertain, a low value would be conservative.⁵ Using a conservative estimate financially penalizes uncertainty, thereby encouraging better data collection (Brown, 2002; Grassi et al., 2008).

A straightforward way to incorporate uncertainty into the LCFS would be to estimate the GWI of each fuel probabilistically, rating each fuel at its, say, 75th percentile value.⁶ This approach implicitly places a higher value on reducing GHG emissions than on minimizing costs of compliance, as the use of higher percentile values may result in the elimination of some climate change mitigating options, requiring the use of more expensive alternatives. The cost-benefit tradeoffs of different estimators for the LCFS would be technically difficult to analyze, as it would require a sophisticated techno-economic model and would be burdened with all the uncertainties noted herein as well as those related to the economics of climate change.

9.5 Assimilating uncertainty into fuel climate policy

A challenge to using either of the approaches described above in fuel GHG policies is the requirement to produce a single frequency distribution describing fuel GWI. While this is fairly straightforward for national GHG inventories, which count historical, observable, direct GHG emissions, life cycle estimates of fuel GWI involve future, unobservable, indirect emissions, rendering these estimates highly scenario-dependent and subject to epistemic uncertainty. To produce a single frequency distribution we can therefore either model one out of possibly many plausible scenarios, or we must somehow aggregate distributions produced for multiple scenarios into a single distribution. The choice of scenarios and aggregation method are necessarily highly subjective. As a result, both the frequency distribution and the choice of estimator are likely to generate as much debate as have point estimates of ILUC emissions.

An alternative to policies requiring accurate quantification or even production of reliable fre-

⁶This idea is explored in more detail in §10.5.1.1.

⁵It is not useful treat the baseline as uncertain in the LCFS or RFS2. Both policies use a fixed baseline (2005 for RFS2, 2010 for LCFS) against which reductions must be achieved. If the alternative fuels in question were replacing the baseline fuel, the GHG benefit of using the alternative fuel would be the difference between the emissions from that fuel and the baseline fuel, net of the rebound effect, as per equation 10.2. However, since the baseline is fixed, and the policies require reductions out to 2020 (LCFS) and 2022 (RFS2), the alternative fuels do not replace the designated baseline fuel. Moreover, in both policies, the GWI of the baseline fuel serves only to establish an arbitrary performance target (e.g., a 10% reduction relative to 2010 fuels for the LCFS), so precision in the estimation of the baseline GWI is of little relevance.

quency distribution of GWI, would be to distinguish biofuels qualitatively. Biofuels that compete with highly demand-inelastic good like food and feed pose a substantial risk of causing higher GHG emissions than do petroleum fuels (and contribute to increasing global food prices.) One approach to reducing this risk would be to *replace* food-competitive biofuels with lower-GWI, second-generation biofuels as technologies to process lignocellulose become commercially viable. This is distinguished from RFS2, which expands both corn-based ethanol and advanced biofuels.

Besides replacing higher-risk biofuels with lower-risk ones, this approach can avoid two problems associated with supply-side fuel policies, namely the petroleum rebound effect and market reshuffling. As detailed in chapter 10, increasing domestic biofuel supplies reduces domestic petroleum demand, which results in a slight decline in the global price of petroleum and thereby causes an increase in consumption relative to a no-biofuels scenario; these market-mediated GHG emissions are conceptually no different those from ILUC and should thus counted when estimating the benefits of a fuel GHG policy. Under incomplete regulation, market reshuffling, i.e., merely displacing rather replacing high-GWI fuels, can reduce or negate the apparent gains from the LCFS.

Replacing existing corn ethanol with low-GWI cellulosic biofuels would offer a number of benefits:

- 1. Fuel could be produced from wastes and residues, freeing up land currently producing corn for ethanol.
- 2. Some of the newly-available land could be used to produce higher-yielding cellulosic feedstocks, resulting in soil carbon sequestration as well as reductions in nitrogen fertilization and reduced leaching to waterways.
- 3. By replacing an existing fuel, rather than expanding fuel supply, the rebound effect would not be induced.
- 4. By replacing an existing fuel, the corn ethanol would not simply be reshuffled to noncompliant markets. This, however, would require that corn ethanol production be phased out, much like leaded gasoline and MTBE.

I recognize this to be a political nonstarter given the financial interests involved, as well as the political interest in producing alternatives to petroleum to enhance energy security. This tension highlights the climate-versus-security tradeoff surrounding the production of high-GWI fuels (including those derived from oil sands, oil shale, and coal, as well as some biofuels). These tradeoffs are largely absent for demand-side solutions. Reducing overall transportation energy use—whether through behavior changes, mode shifting, or energy efficiency—reduces GHG emissions (with pollution reduction co-benefits) while increasing energy independence.

9.6 PROSPECTS FOR REDUCING UNCERTAINTY

Policy robustness can potentially be improved by reducing uncertainty. More precise estimates of soil GHG fluxes and biomass carbon are possible in principle, though to capture the fine spatial

heterogeneity (e.g., of soil N₂O emissions) would require an enormous effort. In any case, while N₂O emissions and carbon fluxes can be measured or modeled for a specific field, economic models underlying ILUC estimates disagree on the *continents and countries* in which LUC occurs, thus the type of ecosystems affected are highly uncertain. GHG fluxes are highly variable spatially, so this uncertainty renders precise field-based measurements of little added value. Since ILUC dominates the analysis of crop-based biofuels, we cannot accurately estimate GWI for these fuels.

As with long-term weather prediction, I believe we will have to simply accept our very limited ability to accurately predict the behavior of complex systems.

CHAPTER 10 ESTIMATING GHG REDUCTIONS FROM THE CALIFORNIA LCFS

"Unless science is targeted toward evaluating the effects of uncertainty on the design and components of management alternatives, more and better science will not necessarily lead to better information for decision makers. Even with well-targeted research there will be residual uncertainties, often ones that are significant. What is important to decision making is both the quality of the uncertainty judgments themselves and the ability of stakeholders and decision makers to understand them, particularly when judgements are contradictory."

Gregory et al. (2006)

10.1 PURPOSE AND SCOPE

This chapter examines whether the Low-Carbon Fuel Standard is likely to produce reductions in GHG emissions. Projecting the effect of the LCFS on net GHG emissions is a non-trivial exercise—one that, to my knowledge, has not been attempted to date. Indeed, this is an important area for future research.

To understand the efficacy of the LCFS, we would want to estimate the difference in net GHG emissions between (i) a world with the LCFS and (ii) a world without the policy, including whether this difference is statistically meaningful given uncertainty. To examine policy robustness we would like to understand how policy efficacy varies across plausible scenarios. Unfortunately, these analyses are beyond the scope of this dissertation. Rather, this chapter explores several of the analytical issues associated with such an analysis. Although I focus on the LCFS, a few of the issues relate to the Renewable Fuel Standard (RFS2) as well. These instances are noted as appropriate.

10.2 INTRODUCTION

The life cycle assessment protocol employed in the California LCFS generates a global warming intensity (GWI) rating for each fuel pathway, in units of g CO_2e MJ⁻¹. To comply with the LCFS, petroleum blenders must achieve an average fuel "carbon" intensity (AFCI) at or below the target,

which by 2020 ratchets down to 90% of the 2010 state-wide baseline AFCI for on-road fuels. The state has set separate targets for gasoline and diesel fuels and their respective substitutes. The LCFS is an intensity standard: a fuel use increase could overwhelms the AFCI decrease, resulting in a net increase in GHG emissions. However, the increase would, in principle be smaller than without the standard.

10.2.1 ANALYTIC BOUNDARIES OF THE LCFS

Although CARB has jurisdiction only within California state boundaries, the use of an LCA-based performance metric allows the agency to extend its reach to wherever emissions occur, whether in the supply chain or as a result of price effects. CARB justifies the LCFS by describing the damage climate change will cause on the state. These damages are reduced only if the LCFS reduces the warming effects that would have occurred absent the policy, net of leakage and all indirect effects. The LCFS proposal starts with this (CARB, 2009a):

In this rulemaking, the Air Resources Board (ARB/ Board) staff is proposing to reduce emissions of greenhouse gases (GHG) by lowering the carbon content of transportation fuels used in California. The regulation is referred to as the California Low Carbon Fuel Standard (LCFS). The LCFS will reduce GHG emissions from the transportation sector in California by about 16 million metric tons (MMT) in 2020.

The boundaries of this analysis are not clearly identified. On the one hand, CARB writes that the LCFS will reduce emissions of GHGs (location unspecified) by lowering the carbon content of fuels used in California. Subsequently CARB writes that the LCFS "will reduce GHG emissions from the transport sector in California", but it's unclear if "in California" modifies "transport sector" or "GHG emissions". If the LCFS is intended only to reduce GHG emissions within the state, then it would be inappropriate to use a life cycle framework, as this approach includes out-of-state emissions.

Presumably, the intended meaning is that the LCFS will reduce GHG emissions *globally* by reducing the carbon intensity of fuels used in California. This implies a need to account for policy leakage. CARB (2009a, p. ES-33) also states that the LCFS "will provide overall societal benefits by reducing GHG emissions from the transportation fuel pool", however societal benefits do not accrue unless *global* emission reductions are achieved, net of leakage.

10.2.2 LEAKAGE

Climate policies with less than global scope can displace GHG-emitting activities to areas beyond the scope of the policy. This general phenomenon is known as *leakage* (Barker et al., 2007; Weber and Peters, 2009; Chen, 2009). Schwarze et al. (2002) identify four distinct types of leakage: *activity, market, life cycle*, and *ecological*.

ACTIVITY SHIFTING. An emitting activity can relocate from a regulated to an unregulated jurisdiction. For example, with national boundaries on GHG inventories under the Kyoto Protocol, the relocation of a high emitter from one country counts as an emission reduction. If the activity relocates to another regulated (i.e., Annex I) country, those emissions are accounted for, but if the new location is a non-Annex-I country, the emissions are "lost".

A closely-related type of leakage is *reshuffling*, which occurs when regulations cause a reorganization of a market such that compliant goods are sold in regulated markets and non-compliant goods are displaced to unregulated markets (Bushnell, 2008). This could be thought of as "virtual" activity shifting.

- MARKET EFFECTS. Price changes resulting from a policy can trigger an increase or decrease in emissions elsewhere. ILUC is one such market effect. Another market effect that is often singled out is known as the *rebound effect*, which occurs when efficiency improvements or emission reduction strategies result in lower prices that, in turn, cause an increase in consumption (and thus emissions) relative to the business-as-usual scenario (Sorrell and Dimitropoulos, 2008; Barker et al., 2009; Stoft, 2010).
- LIFE CYCLE EFFECTS. Increasing or decreasing an activity can cause emission changes up and down the supply chain. Given the LCA basis of the policies considered herein, this leakage is inherently part of the GWI calculation.
- ECOLOGICAL EFFECTS. Finally, changes in practices in one area can trigger increased or decreased emissions in adjacent areas. For example, a reforestation project might introduce a pathogen that adversely affects a neighboring forest. Alternatively, protecting a forest might buffer another forest from degradation that would otherwise occur.

Fuel substitution policies are susceptible to both reshuffling and rebound effects, thus any estimate of GHG reduction benefits must take these into account. These two types of leakage are discussed below.

10.3 LCFS MAY SIMPLY RESHUFFLE BIOFUEL MARKETS

In its rulemaking for the LCFS, CARB noted that incomplete policy coverage could result in market reshuffling, resulting in "little or no net change in fuel carbon content on a global scale" (CARB, 2009a, p. ES-29). However, CARB concluded that "leakage is not expected" as a result of the LCFS (CARB, 2009a, p. ES-34). This conclusion may have been based on the 2007 examination of the LCFS by researchers at UC Berkeley and UC Davis (Farrell et al., 2007). That study raised the prospect of market reshuffling in the context of the then-current renewable fuel standard (now known as RFS1), but concluded that RFS1 would result in lower-GWI renewable fuels only "coincidently" since higher-GWI renewable fuels were less expensive to produce (Farrell et al., 2007, p. 10). Importantly, RFS1 included a biofuel mandate, but no GHG performance standards, thus the dependence on "coincidence" to lower fuel GWI. However, in December 2007, five months after the UC Study was completed, RFS2 was enacted under the Energy Independence and Security Act, augmenting the volume mandate with a GHG performance standard. This raises the question of whether RFS2 provides sufficient low-GWI fuel to meet the proposed low-carbon fuel standards in California and eleven other states.

10.3.1 LOW-GWI BIOFUELS REQUIRED TO MEET A 12-STATE LCFS

On December 30, 2009, eleven northeastern US states signed a memorandum of understanding to develop a low carbon fuel standard (LCFS) (Anon., 2009). These states, together with California, which adopted its LCFS in April of 2009, together accounted for 29% of the motor gasoline and ethanol consumed in the US in 2008¹. The total motor gasoline and fuel ethanol consumed in these twelve states in 2008 is shown in Table 10.1.

Assuming that these eleven states adopt a policy similar to California's, and assuming that the only LCFS compliance strategy employed is the blending of low-GWI biofuels, the entire demand for these fuels in the LCFS states can be met by the cellulosic biofuels mandated for 2020 by RFS2 (Figure 10.1). If all the RFS2-compliant fuel were ethanol, this quantity of biofuel would comprise 23% by volume of the blended gasoline consumed in the LCFS states. Assuming that all LCFS states adopt E10 as the standard fuel, approximately 5 billion gallons of ethanol would need to be sold in the form of E85. If so-called "drop-in" fuels that are fungible with petroleum-based fuels become available, then the ethanol blend-wall would cease to be a concern.

Low-GWI fuels will be more valuable in LCFS markets than in unregulated markets. All else equal, low-GWI fuels mandated by RFS2 will be attracted to LCFS markets, displacing the higher-GWI corn ethanol currently in use to unregulated states or countries.

10.3.2 DIFFERENCES IN GWI UNDER LCFS AND RFS2

The approach to calculating the GWI of transportation fuels developed by CARB differs in important ways from the approach adopted by USEPA for RFS2 (CARB, 2009a; USEPA, 2010b). Some of these differences are listed in table 10.2. For example, CARB relies on the GREET model, adapted to the California context. GREET is a (mostly²) attributional LCA model, and therefore relies on average data. CARB uses the 2010 fuel slate as the baseline against which reductions are measured, and analyzes all fuels in the present. For crop-based biofuels, CARB adds an estimate of emissions from indirect land use change (ILUC), based on the a global equilibrium model (GTAP), using a 2001 database, with a *post hoc* adjustment for higher crop yields in 2010 (Hertel et al., 2010).

For RFS2, USEPA developed a novel consequential LCA modeling system, projecting changes in emissions in 2022 with and without the RFS2, assuming a range of crop yield and technology im-

¹Based on 2008 EIA data available at http://www.eia.doe.gov/emeu/states/_seds_updates.html

²GREET is based primarily on attributional (static) analysis, but in some instances it handles co-products via the displacement method, which is a consequential (change-based) approach.

State/Region	Motor gasoline	Iotor gasoline Fuel ethanol	
California	360,261	23,683	6.2%
Connecticut	35,791	2,875	7.4%
Delaware	10,465	802	7.1%
Maine	15,607	1,169	7.0%
Maryland	64,257	4,371	6.4%
Massachusetts	67,214	5,028	7.0%
New Hamp- shire	17,188	1,055	5.8%
New Jersey	102,677	7,801	7.1%
New York	134,206	9,827	6.8%
Pennsylvania	119,724	8,575	6.7%
Rhode Island	9,561	944	9.0%
Vermont	7,865	502	6.0%
12-state total	944,816	66,632	6.6%
United States	3,233,378	226,567	6.5%

Table 10.1: 2008 motor gasoline and fuel ethanol use for transportation in twelve LCFS states and US, 2008 (thousand bbl). Source: EIA



Figure 10.1: Year 2020 fuels mandated by RFS2 compared to low-GHG fuel required by 12 LCFS states to meet a 10% reduction in GWI, assuming that cellulosic fuels (blue bar) achieve a 60% reduction under the LCFS rating system.

provements occur by that date. To estimate emissions, USEPA combines land cover change emission factors with the results of two economic partial equilibrium models (FASOM and FAPRI).

Congress mandated that USEPA apply a 2005 petroleum baseline. USEPA estimated the GWI of 2005 gasoline as 98,205 g CO_2e MMBtu⁻¹ (USEPA, 2009c, PDF p. 487), which is equivalent to 93 g CO_2e MJ⁻¹. CARB uses a 2010 baseline for California reformulated gasoline, including 10% Midwestern corn ethanol with a GWI rating of 96 g CO_2e MJ⁻¹(CARB, 2009a).

Although the two regulatory systems measure different phenomena and thus produce incommensurable ratings, for the present analysis, I assume that the advanced and cellulosic biofuels mandated under RFS2 would achieve a 50% reduction in GWI in the CARB LCFS. Note that in the RFS2 system, 4.5 billion gallons of advanced and 15 billion gallons of cellulosic biofuels must be used by 2020, the final LCFS target date. These fuels must achieve a 50% (advanced) or 60% (cellulosic) reduction in GWI relative to the 2005 petroleum fuel baseline. If other fuels (e.g., elec-

Table	10.2: Methodological	and data differen	ces in global wa	arming intensity ca	lculations in Cali-
fornia	LCFS and US RFS2				

Attribute	CARB / LCFS	USEPA / RFS2
LCA framework	Attributional (static, uses average data)	Consequential (dynamic, uses marginal data)
Models used	GREET, GTAP	FASOM, FAPRI, ASPEN, others
Indirect effects consid- ered	ILUC	ILUC, changes in methane from livestock and rice, changes in on-farm energy use and fertilization
Temporal framework	2010 fuel baseline, 2010 fuel analysis, 2001 ILUC analysis with <i>post hoc</i> yield adjustment	2005 petroleum baseline, 2022 biofuel and ILUC analysis, including pro- jected yield and technology gains
Fuels considered	Gasoline, diesel, natural gas, biogas, hydrogen, bio- fuels, electricity	Gasoline, diesel, biofuels



Figure 10.2: Similar to Figure 10.1 except assuming that the average of advanced and cellulosic biofuels achieves a 50% reduction under the LCFS rating system. Demand for low-GWI ethanol in 12 LCFS states can still be met by the RFS2 mandate (blue and red bars together).

tricity, natural gas, hydrogen) are deployed to comply with the LCFS, the demand for biofuels in LCFS markets will be reduced, and even less RFS2-mandated fuel will be required to meet LCFS targets.

Assuming that the RFS2 mandates are met, the atmosphere may see no greater reduction with these low carbon fuel standards than without them, at least in the light-duty vehicle market. While RFS2 mandates only a small quantity of renewable diesel fuel (1 billion gallons by 2012), the RFS2 does not preclude advanced and cellulosic *diesel* fuels. So some or all of the diesel AFCI reduction could be met with RFS2 fuels as well, especially if "drop-in" fuels are commercialized.

Thus, in the context of RFS2, the benefit under the CA LCFS of vehicle electrification is much greater than the benefit of using these low-GWI biofuels since the biofuels will be used in any case (though perhaps elsewhere) and their supply is likely sufficient to meet LCFS targets. Reductions achieved through vehicle electrification are more likely additional since current federal policy doesn't mandate vehicle electrification. The LCFS, however, gives equal incentives to both compliance strategies based on their life cycle GHG emissions, even though one likely achieves real reductions and the other may be achieved through reshuffling, with no net reduction in GHG

emissions.

10.3.3 INTERNATIONAL LEAKAGE UNDER A NATIONAL LCFS

One potential benefit of the California LCFS, despite leakage, may be to provide an example for other jurisdictions to implement similar policies, thereby increasing policy coverage. In theory, expanded policy coverage reduces the opportunity for reshuffling.³ However, just as a limited LCFS within the US may result in reshuffling domestically, a national LCFS is likely to drive high-GWI petroleum fuels to unregulated regions (Kueter, 2009). An analysis by the US Energy Information Administration of a 5% federal LCFS indicated that most of the reduction registered using national accounting boundaries would be offset by international leakage as high-GHG fuels (e.g., oilsands) are shipped to unregulated markets (Difiglio, 2009). Figure 10.3 shows the results of that analysis: the US achieves a reduction in CO₂ emissions of approximately 165 million tonnes, but reshuffling causes an increase of about 130 million tonnes of CO₂ in international markets, offsetting nearly 80% of the measured domestic reductions.

10.3.4 LCFS AS BACKSTOP AGAINST WEAK RFS2 PROTOCOL

The LCFS will induce production of lower-GWI fuels if demand for these fuels exceed the level mandated by RFS2, for example, if the LCFS GWI ratings are stricter than those of RFS2. In an amendment to the American Clean Energy And Security Act of 2009 (H.R. 2454), agricultural committee chairman Collin Peterson of Minnesota required the USEPA to drop international ILUC estimates from its calculations of GWI (Peterson, 2009). If this amendment were to become law, there would be no guarantee that fuels complying with RFS2 would achieve real reductions. The international ILUC values in RFS2 for corn ethanol and soybean biodiesel are 31 and 43 g CO₂e MJ⁻¹, respectively (Table 10.3): the ILUC factors for these fuels are 169% (corn ethanol) and 95% (soybean biodiesel) of the required reduction relative to the baseline ratings for petroleum-based gasoline and diesel. Therefore, without ILUC, corn ethanol that meets the mandated reduction requirement under the (modified) RFS2 could easily generate net *increases* in GHG emissions, and biodiesel may produce increases or reductions—uncertainty prevents us from knowing for sure.

If the international ILUC values are stripped from the RFS2 rule, more stringent state-level programs become much more important. The California LCFS includes ILUC emissions, and the 11 Northeast states have indicated an intention to do the same (Anon., 2009). Therefore, if the Peterson amendment becomes law, the LCFS may indeed force production of lower-GWI fuels and not simply reshuffle fuel produced under the RFS2 mandate.

³We must be careful not to attribute long-term GHG reductions that might be achieved under greater policy coverage to the near-term implementation of an LCFS with only partial coverage. Near-term policies that are less susceptible to leakage, e.g., *in situ* GWI reductions or electrification, would be a good complement to these longer-term policies.



Figure 10.3: Net CO₂ reduction under a federal LCFS. Large reductions registered in the US (blue region) are largely offset by increases outside the US (green region) resulting in a much reduced net reduction (red region). (Source: Difiglio, 2009)

10.4 Petroleum rebound effect

An increase in the production and use of renewable fuels in the US leads to a decrease in domestic crude oil demand. This decrease in US oil demand causes a decline in the world oil price, which, all else equal, spurs increased oil consumption abroad relative to the baseline without the additional biofuels (Rajagopal et al., 2007; Rajagopal and Zilberman, 2010). This price-induced increase in consumption—known as the global petroleum rebound effect (Stoft, 2010)—partially offsets the GHG reduction benefits of substituting for petroleum (USEPA, 2010b, p. 512).

As with all projected baselines and counterfactual scenarios, the estimate of the rebound effect is uncertain. Estimation of the effect is further complicated by the challenge of predicting OPEC behavior in the face of the competition and price effects from biofuels and other alternatives to petroleum Stoft (2010). However, inclusion of the rebound effect clearly reduces estimates of the GHG reductions from fuel substitution. Based on a *post facto* analysis of several modeling studies, Stoft (2010) estimated a global petroleum rebound effect of between 29% and 70%. Using parameters derived from modeling for USEPA in support of RFS2, Stoft estimates a rebound effect of 32%, meaning that 1 MJ of biofuels displaces only 0.68 MJ of petroleum (Stoft, 2010). Barker

	Corn Ethanol	Soybean Biodiesel	Corn Stover Ethanol	Switchgrass Ethanol
Int'l ILUC emissions	31	43	3	15
Baseline fuel rating	92	91	92	92
Required reduction (%)	20%	50%	60%	60%
Required reduction (g CO_2e MJ^{-1})	18	46	46	46
Int'l ILUC as % of reduction	169%	95%	6%	27%

Table 10.3: Baseline fuel ratings, international indirect land use change emission factors, and required GHG reductions (g CO₂e/MJ). (Source: USEPA, 2010b, author's calculations).

et al. (2009) estimate a rebound effect for efficiency policies in the transport sector ranging from 36% for the 2020 timeframe and 52% for 2030, with similar values for the overall economy.

10.4.1 INCLUDING THE REBOUND EFFECT IN ESTIMATES OF GHG BENEFITS

Virtually all biofuel LCA studies and some policy analyses (notably those of USEPA for RFS2 and CARB for LCFS) simply assume no price effects, which is equivalent to assuming that oil producers respond to increases in biofuel production by reducing oil production to match the additional quantities of biofuels. Typical of LCA, Guinée et al. (2009) ignore price effects to define the GHG reduction achieved by bioenergy as:

$$Reduction_{nominal}(\%) = \frac{GHG_{fossil} - GHG_{bio}}{GHG_{fossil}} * 100$$
(10.1)

The EU Renewable Energy Directive specifies the same approach to calculate the GHG savings from biofuels (European Parliament, 2009, Annex V).

For a biofuel with GWI of 70 g CO₂ MJ⁻¹ and gasoline with GWI of 100 g CO₂ MJ⁻¹, *Reduction_{nominal}* = $\frac{100-70}{100}$ = 30%. Equation 10.2 includes the rebound effect, *R*, expressed as the percentage of a unit of fossil fuel used above the baseline, induced by the price reduction afforded by expanding fuel supply.

$$Reduction_{rebound}(\%) = \frac{(1-R) \times GHG_{fossil} - GHG_{bio}}{GHG_{fossil}} * 100$$
(10.2)

Assuming a 32% rebound effect for petroleum as estimated by Stoft (2010), and assuming the

same biofuel and gasoline ratings as above, $Reduction_{rebound} = \frac{(1-0.32)*100-70}{100} = \frac{68-70}{100} = -2\%$, meaning a 2% net *increase* in GHGs. In general, alternative fuels with a nominal GWI reduction (as per equation 10.1) less than *R* result in a net increase in emissions when the rebound effect is included.

In its analysis of the GHG reductions and economic benefits of the RFS2 program USEPA (2010b) applied equation 10.1, assuming MJ for MJ replacement of petroleum fuels by biofuels, despite including the rebound effect in their analysis of the program's energy security benefits. Similarly, CARB (2009a) estimated the GHG emissions from various LCFS compliance scenarios using a linear scaling of the life cycle GHG emissions from each pathway as estimated in the CA-GREET model (plus ILUC values for biofuels), ignoring both leakage and rebound effects.⁴

10.4.2 NOT ALL GWI REDUCTIONS TRIGGER THE REBOUND EFFECT

The LCFS allows producers to reduce AFCI four ways: (i) improving the GHG efficiency of production processes, (ii) substitution of high-GWI fuels with low-GWI fuels, (iii) buying credits from overcomplying firms, or (iv) using banked credits from prior years (CARB, 2009a). Reducing the GWI of fuels in use does not trigger a rebound effect unless it reduces the price of fuel. Fuel substitution, however, does trigger the rebound effect, since petroleum fuels not used in the LCFS market become available in other markets. For this reason, reductions achieved through *in situ* efficiency gains provide greater GHG reductions than do nominally-equivalent reductions achieved via fuel substitution. Including the rebound effect in an LCFS would provide incentives to develop "better biofuels before more biofuels", to borrow a phrase from the late Alex Farrell (2008).

Because fuels differ in their indirect effects, ignoring these, or including only some of them (e.g., ILUC) creates biases in a competitive system such as the LCFS. For example, neglecting the petroleum rebound effect creates a bias toward fuel substitution over *in situ* improvements in GWI such as increasing energy conversion efficiencies. Similarly, neglecting the uncertainties in our understanding of the net GHG benefits of biofuels creates a system that prefers a fuel with a lower mean but a long right tail due to ILUC, over another with a slightly higher, but much more certain mean.

10.4.3 REBOUND EFFECT INTERACTION WITH ALTERNATIVE FUEL GWI

The quantity of substitute fuel required to achieve a given reduction in AFCI is inversely and nonlinearly related to the average GWI of the substitute. Figure 10.4 shows the blend level (by energy) required (*Y*-axis) for biofuels with a given GWI (*X*-axis), assuming blending with a baseline fuel rating 100 g CO₂e MJ⁻¹ to achieve a target of 90 g CO₂e MJ⁻¹. Increasing a biofuel's GWI from 0 to 40 g CO₂e MJ⁻¹ increases the required blend level (by energy) from 10% to 17%, whereas increasing GWI from 40 to 80 g CO₂e MJ⁻¹ increases blend level from 17% to 50%.

⁴Note that if LCFS compliance is achieved through reshuffling fuels mandated under RFS2, the rebound effect for those fuels would be more appropriately attributed to the RFS2 rather than to the LCFS.

Figure 10.5 shows the relationship between alternative fuel GWI and the rebound effect. Although the nominal target AFCI (in this case, 90 g $CO_2e MJ^{-1}$) is met for all four biofuel ratings (*X*-axis), lower GWI ratings require a greater quantity of biofuel (blue segment) and thus induce a greater rebound effect (green segment.) Assuming a 32% global rebound effect, nominally meeting an AFCI of 90 g $CO_2e MJ^{-1}$ using a biofuel rated at 68 g $CO_2e MJ^{-1}$ would induce a rebound effect that eliminates any reduction in AFCI. Using a biofuel rated above 68 g $CO_2e MJ^{-1}$ results an increase net emissions.

The implication of this analysis is that the LCFS should account for the rebound effect to provide additional incentives for (i) *in situ* improvements, which don't incur any rebound penalty, and for (ii) very low-GWI substitutes, which minimizing the quantity of petroleum displacement and thus minimize the rebound penalty. Note, however, that minimizing the rebound penalty means simultaneously minimizing the energy security benefits of the LCFS, given a definition of energy security based on the quantity of petroleum consumed.



Figure 10.4: Required alternative fuel blend level at different global warming intensities, assuming a baseline fuel with a GWI of 100 g CO_2e MJ⁻¹ and a 10% reduction target.

10.4.4 GHG REDUCTIONS UNDER THE LCFS DEPEND ON THE PRICE OF PETROLEUM

The net effect on GHG emissions achieved by the LCFS depends in part on the relationship between the price of petroleum and the price of the marginal biofuel required to meet the regulation (Rajagopal and Zilberman, 2010). Under high petroleum prices, the energy-equivalent price of alternative fuels rises to the gasoline price. The additional biofuels extend total fuel supply, suppressing the global petroleum price somewhat from what it would be in the absence of biofuels. This



Figure 10.5: Relationship between alternative fuel GWI and rebound effect, assuming a baseline fuel with a GWI of 100 g CO_2e MJ⁻¹, a 10% reduction target, and 32% petroleum rebound effect.

results in additional consumption of petroleum above the BAU scenario.⁵ Under low petroleum prices, the mandated GWI reduction under the LCFS or RFS2 forces the use of relatively expensive biofuels, increasing the price of fuel, and inducing reductions in fuel use in the regulated market relative to BAU, tempered somewhat by the rebound effect in unregulated markets which enjoy greater supply than under BAU.

The GHG reductions from an LCFS are therefore contingent on the projected relative prices of petroleum and alternative fuels. This sensitivity should examined using scenarios.

⁵Holland et al. (2009) show that an LCFS behaves like a tax on fuels with GWI above the standard and a simultaneous subsidy of fuels with GWI below the standard. This subsidization results in increased consumption of fuels compared to a tax on all fuels based on their GWI.
10.5 MODELING THE LCFS

The effect of the LCFS on GHG emissions is the difference in GHG emissions in the world with the policy versus those in the world without the policy. This type of change-based analysis is consistent with the consequential LCA framework. The California LCFS, however, is based on the GREET model, with an added term for ILUC emissions induced by biofuels. While the ILUC emissions term captures one important difference between the two worlds, other important differences are absent from the CARB LCA protocol, e.g., changes in methane from livestock and rice production; changes in tillage and on-farm energy use—factors that are captured in the USEPA analysis for RFS2. In addition, actual GHG reductions depend on the magnitude of the rebound effect and on market reshuffling. Therefore, the performance measure driving policy differs fairly substantially from a reasonable measure of policy effects. The divergence between these creates the possibility of undesirable policy outcomes.

If we adopt Stoft's estimate of the rebound effect, crop-based biofuels must achieve a minimum 32% reduction in life cycle GHG emissions—including indirect effects—just to achieve parity with gasoline on a point estimate basis. In addition, owing to the skewed distribution for total GHG emissions—resulting from uncertainty in N₂O emissions as well as ILUC—the probabilistic mean for biofuels GHGs is certainly higher than the point estimate, requiring further reductions to ensure parity. Finally, if our goal is to ensure reduction, we should be relatively certain that our chosen mitigation strategy actually achieves reductions commensurate with the cost of their implementation and the opportunity cost of more certain strategies that we have forgone. Using a mean value is insufficiently robust for this task. We could instead require, say, 90% certainty that an emission reduction is achieved. This would in effect require a reduction of at least 50%, including our best estimate of indirect emissions, just to gain a reasonable assurance that *some* reduction was achieved.

The 10% reduction aimed for by the LCFS is not robust if it is achieved through the use of large quantities of moderately low-GHG biofuels, especially given the likelihood of leakage. For example, if the CA fuel mix included 50% biofuels that offered a 20% reduction (including ILUC), the net effect, including Stoft's estimate of rebound effect, would be an *increase* in emissions. However, even without leakage, no rebound effect, and certainty about ILUC emissions, meeting a shallow (e.g., 10%), near-term intensity reduction target may increase the cost of meeting a steeper (e.g., 50% or 80%) reduction by mid-century. This is because increasing the use of biofuels—the preferred option of petroleum companies—may suffice as a strategy to meet a 10% reduction, but this strategy does not appear to put us on the path toward steeper reductions. In an examination of alternative scenarios for meeting steep (50% and 80%) GHG reductions in the transportation sector, McCollum and Yang (2009) conclude that:

[E]ven a small increase in average biofuel lifecycle carbon intensity due to LUC (e.g., +15 g $CO_2e MJ^{-1}$) would double the carbon intensity assumed in this study, eliminating much of the GHG reduction potential in the scenarios. In sum, if supplies of low-GHG biofuels are signicantly constrained for the reasons mentioned here, then a

multi-strategy future with considerable penetration of electric-drive vehicles and decarbonized energy carriers (i.e., H_2 and electricity) may be the only real option for making emission reductions across all of transport. In this case, deep transport-wide reductions on the order of 80% may be unachievable, though less stringent targets may still be attainable.

There are several reason for this conclusion: (i) potentially large GHG emissions from ILUC render the GHG benefits of first-generation (crop-based) biofuels very uncertain; (ii) non-cropbased biofuel feedstocks (e.g., waste and sustainably harvestable residues) are too limited in supply to achieve a 50% reduction across the fuel sector; (iii) fuel alternatives such as hydrogen (when used in fuel cells) and electricity require 10–15 years of lead-time to deploy large numbers of vehicles capable of using these fuels. The uncertain reduction in GWI achieved with biofuels may come at the cost of delaying the deployment of lower-GHG alternatives. Of course, biofuels are not mutually exclusive with options such as plug-in hybrid vehicles.

The requirement of a 50 or 60% GHG reduction under RFS2 should ensure that advanced and cellulosic fuels achieve actual reductions (assuming iLUC remains included), but this is true only if the policy is binding and these GHG thresholds are met. If petroleum prices are high enough that biofuels are profitable, then production will be limited only by feedstock, blending, and distribution limitations, regardless of GHG rating, since RFS2 doesn't prohibit high-GHG fuels. And since RFS2 defines floors rather than cielings, high petroleum prices would spur increases in corn ethanol production as well as increased production of second generation biofuels. In this sense, the main problem with RFS2 is not the specific rating system, but that the rating system is relevant only if the mandate is binding.

10.5.1 A SOPHISTICATED MODEL

To estimate the GHG reductions achieved by the LCFS would require a model of the global economy that includes the agriculture, forestry, power, and fuel sectors (at a minimum). The model would ideally include a representation of atmospheric GHG loading and decay, current and anticipated biofuel and land-use policies, and projected trends in food demand. The model would need enough technological and carbon accounting resolution to capture the interplay between fuel GWI ratings and the LCFS credit price, allowing producers to maximize profit by investing in GWI-reductions technology to increase the premium paid for their low-GHG fuels—or simply by shuffling. The model would need to incorporate rebound effects as well, which implies some representation of anticipated fuel demand, petroleum depletion, and OPEC behavior. This type of model is beyond the scope of this dissertation, but it is worth considering to understand what would be required to capture the important features of this problem.

Uncertainty in GHG ratings is a central issue in this policy, so uncertainty analysis would need to be a central component of the model. Given the many epistemic uncertainties, large-scale scenario analysis is probably more appropriate than Monte Carlo simulation (Lempert et al., 2003; Morgan et al., 2009). Table 10.4 lists some of the parameters affecting estimates of ILUC emissions. Other important modeling decisions include the choice of emission factors for LUC, the

method for allocating ILUC emissions to each megajoule of fuel (e.g., straightline amortization or fuel warming potential, with or without discounting). Additional factors that affect LCFS compliance are the availability and GWI rating of advanced and cellulosic ethanol, and the availability of electric vehicles. The actual GHG reductions induced by the LCFS will vary with the compliance scenario that emerges from the distributed decisions of regulated parties.

To understand the robustness of the LCFS to all these uncertainties, we would want to evaluate our model with many combinations of these (and other) parameter assumptions and modeling choices. Within each scenario, variability and parameter uncertainty could be modeled stochastically to produce a probability distribution for GHG reductions relative to BAU. Each scenario could then be graded by the probability of meeting a decrease in actual GHG emissions. Given sufficient economic resolution, we could also estimate the total cost for each compliant scenario relative to BAU. This model would allow an examination of the circumstances under which the LCFS would be likely to deliver GHG reductions, net of shuffling and leakage—and the scenarios in which it would not. This, in turn, would provide guidance on alternative of complementary policies that would increase the likelihood of achieving policy goals.

Parameter		Possible values	
Oil price	Low	Med	High
Years of production	15	30	45
Land use policies	None	Weak	Strong
Climate agreement	None	Developed world	Global
Crop yields	Below trend	Historic trend	Above trend
Food reduction	Treat as GHG benefit		Prevent in model
Scale of analysis	National biofuels	Global biofuels	Global biomass
Type of model	General equilibrium	Partial equilibrium	Agent-based

Table 10.4: A sampling of parameters affecting estimates of ILUC emissions

10.5.1.1 APPLYING THE CONSERVATIVENESS PRINCIPLE

One question we might ask of our model is how rating fuels conservatively (e.g., using the 75th percentile GHG value rather than the mean as an estimator) would affect the performance of the regulation in terms of GHG reductions and net social cost. Using a high-percentile estimator for fuel GWI penalizes uncertainty and raises the cost of meeting the regulation. Since both emissions and the social cost of carbon are uncertain (and especially if they both have right tails) the product

of multiplying these might be high enough that social cost would be minimized by avoiding the riskiest, food-competitive biofuels.

In the case of fuels for which a reliable probability distribution for GWI cannot be generated (e.g., for fuels with potentially large indirect effects), a subjective estimate of these effects could be used, though any value chosen would be challenged by some stakeholders. I note that, given the broad uncertainty in ILUC emissions, the decisions taken by the regulator to define the GWI calculation protocol itself amounts to a subjective determination of ILUC—with the ensuing controversy. The suggestion made here differs only in that the subjectivity would be openly acknowledged, rather than hidden behind the imposing edifice of an economic model.

Given the uncertainty, we face a trade-off between risking rating fuels too high and foregoing potentially cheaper mitigation alternatives and raising the social cost of compliance, or rating fuels too low and risking causing more harm than necessary, even to the extent of causing more harm than BAU without the policy. Using high-percentile estimators would result in larger risk penalties for fuels with less certain GWI, such as biofuels, and smaller penalties on fuels with more certain GWI, such as fossil fuels. As a result, some biofuels would be of no value in the LCFS, but the 10% reduction would still need to be met the next best option (from the blender perspective), which is presumably somewhat more expensive than the first choice. Thus, the certainty that the policy goal was met would increase, though presumably at a higher cost. A similar result obtains under the RFS2: the mandate must be met by compliant fuels: under stricter ratings, meeting the standard requires greater certainty, either through using well-characterized fuels or fuels with very low (mean) reductions, which provide headroom against uncertainty. Therefore, stricter rating systems result in increased likelihood of meeting the standards, but at increased cost since low-GWI biofuels such as those from cellulose and algae are presently more expensive than current commercial biofuels.

10.5.2 A SIMPLE MODEL INCORPORATING REBOUND AND RESHUFFLING EFFECTS

Although the model outlined above is beyond the scope of this dissertation, a simple model can serve to highlight the importance of including rebound and reshuffling effects.

To rate fuel pathways in the California LCFS, CARB uses attributional LCA (in GREET) to estimate direct emissions. For crop-based biofuels CARB adds to this of ILUC emissions based on the GTAP model. These ratings are summed, weighted by energy content to produce an average fuel carbon intensity (AFCI) value for each regulated entity. Assuming the LCFS is binding, we can expect the total statewide AFCI to exactly meet the nominal 10% reduction in 2020. However, AFCI measures a reduction in fuel carbon intensity for fuels used in California. To estimate the *global* change in GHG emissions resulting from the LCFS⁶, we need to account for reshuffling and rebound effects.

⁶The change in emissions is the product of the megajoules of transportation fuel used and the AFCI value. We can express the global change in terms of GWI if we assume the demand for megajoules of transportation energy is constant in California for the target year. This simplifying assumption lends clarity to this exposition without affecting the qualitative results of the analysis.

The LCFS can achieve nominal AFCI reductions using three methods: *in situ* improvement, induced new production, and reshuffling. As discussed earlier, *in situ* improvements, such as increasing the efficiency of a boiler used in a fuel production process, does not trigger the petroleum rebound effect. These improvements are "real" in the sense that the nominal improvement in AFCI represents an actual improvement. The LCFS can also induce production of new, low-GWI biofuels that would not have been produced under the business-as-usual scenario (i.e., under RFS2). However, while these fuels may offer a real reduction in GWI relative to petroleum fuels, the production of these fuels increases overall fuel supply and thus incurs a rebound penalty. Finally, fuels that would been used elsewhere in the BAU scenario may simply be sold in CA and thus counted toward AFCI even though relocation does not reduce net GHG emissions. In fact, to the extent that reshuffling incurs greater transportation emissions, the use of these fuels in California could somewhat increase GHG emissions.

METHODS. The question we would like to answer is how the *actual* emissions compare to the BAU case. That is, what is the net effect of the LCFS on GHG emissions? To examine this, I implemented a simple stochastic spreadsheet model that makes the following assumptions:

- On average, *in situ* improvement reduces the GWI of some set of biofuels from 100 to 75 g CO₂e MJ⁻¹. The fraction of in-state biofuels from these "improved" pathways is represented by a uniform distribution ranging from 0–20%.
- The GWI of fuels reshuffled into the LCFS market is represented by a uniform distribution from 10–40 g CO₂e MJ⁻¹.
- The GWI of new biofuels induced by the LCFS is represented by a uniform distribution from $10-40 \text{ g } \text{CO}_2 \text{ e } \text{MJ}^{-1}$. This value represents the GWI that is used in the AFCI calculation. A separate parameter allows for undercounting in ILUC emissions, represented by a uniform distribution ranging from 0–60 g CO₂e MJ⁻¹. This parameter is added to the GWI parameter for the purposes of estimating actual GHG changes. The fraction of in-state biofuels from this new production is represented by a uniform distribution from 0–30%. The fraction of in-state biofuels resulting from reshuffling computed as 1 minus the sum of the *in situ* and new production fractions, and thus ranges from 50–100%.
- The rebound effect is represented by a uniform distribution ranging from 20–50%.
- For the purposes of this exercise, I assume the biofuel has the same heating value as gasoline.

RESULTS. In the calculation of actual percent change, I assume that (i) the change in GHG emissions associated with reshuffling is zero, (ii) the net change associated with new fuel production is discounted by the rebound effect as per equation 10.2, and (iii) the net change for *in situ* improvements are treated as "real", as noted above.

Running a 50,000 trial Monte Carlo simulation produced the output distribution for the actual percent change in GHGs shown in figure 10.6. The 95% confidence interval ranges from -1.9%

to +0.6%, meaning that 97.5% of the time, the actual emission reductions achieved were 1.9% or lower. Moreover, 16% of the time there was a (small) net increase in GHG emissions. The median change was -0.5%. i.e., essentially unchanged from BAU.



Figure 10.6: Frequency distribution for actual reductions in GWI (g $CO_2 e MJ^{-1}$) for LCFS, including new production, reshuffling, and rebound effects, allowing for the possibility of undercounting ILUC emissions.

The 95% confidence interval for the fraction of the fuel base from biofuels ranges from 12–18%, which is reasonably consistent with the scenarios considered by CARB, which range from 16–20% ethanol.

The contributions to variance of the parameters to this model are illustrated in figure 10.7. The GWI contribution of undercounted ILUC emissions contributes 39% of the variance. The fraction of biofuels undergoing *in situ* improvement contributes 26%. The rebound effect contributes 21% of the variance, and the GWI of new production induced by the LCFS contributes 11%. The fraction of biofuels from new production contributes 3%, and the GWI of reshuffled fuel contributes 1% of the variance.

Although the distributions used in this model are contrived, the analysis demonstrates that when the rebound effect and reshuffling are taken into account, along with uncertainties in ILUC emissions, the actual benefits from the LCFS appear to be small to negligible. The outcome in terms of net GHG flows will be determined by the extent to which to LCFS is met by reshuffling, new fuel production, and *in situ* GWI reductions. Although this outcome is uncertain, it appears quite possible that much of the nominal reduction in AFCI can be achieved through reshuffling



Figure 10.7: Contribution to variance of parameters in simple model of LCFS.

RFS2-mandated fuels.

A more complete model as described above would support a more refined analysis, though many of the parameters therein would remain speculative. The more complex model, however, would provide the basis for a robustness analysis, i.e., examination of a wide range of scenarios to understand the conditions under which the policy resulted in desirable or undesirable outcomes.

CHAPTER 11

CONCLUSION

"Point estimates of uncertain risk comparisons offer a simplicity that makes decisions easier but makes wrong decisions well-nigh inevitable. Rather than either blinding ourselves to the numbers or letting the numbers usurp all our power to discern and choose, we should start fresh with Schopenhauer's apt advice: "the value of what one knows is doubled if one confesses to not knowing what one does not know."

Adam M. Finkel (1995)

11.1 MAIN FINDINGS

This dissertation makes the following argument:

- 1. Life cycle assessment suffers severe methodological and data limitations and is incapable of definitive estimates of environmental outcomes such as net climate effects.
- 2. Point estimates of life cycle global warming intensity (GWI) describe only one plausible scenario, and many scenarios may be equally plausible. Point estimate GWI estimates are therefore necessarily subjective.
- 3. Indirect effects (especially for biofuels) can strongly determine LCA results, but these effects are unobservable and estimates of their magnitude are unreliable.
- 4. As a consequence of the above observations, GWI for many biofuels is highly uncertain and subjective.
- 5. The climate benefits of performance-based regulations based on GWI are uncertain and difficult to assess.
- 6. Our inability to predict the climate effects of biofuels calls for policies that explicitly address uncertainty, risk, and societal values.

The first generation of life-cycle-based fuel regulations were drafted before the challenges of estimating ILUC emissions were clear. As discussed herein, the GHG emissions due to ILUC depend on projections decades into the future of several important parameters such as crop yields, technological change, petroleum price, and other aspects of the global economy. Estimating ILUC emissions therefore necessarily involves many subjective assumptions, stochastic uncertainty, and considerable epistemic uncertainty. In short, there is not—and cannot be—a definitive, objective estimate of the GHG emissions from indirect land use change induced by expanding biofuel production.

The uncertainties surrounding ILUC emissions, soil N_2O emission, soil carbon sequestration, and co-product credits render the fuel-cycle GWI rating for biofuels highly uncertain, raising serious questions about the appropriateness of fuel GWI as regulatory performance metric. Regulators faced with laws requiring the quantification of fuel-cycle GHG emissions will inevitably have to defend subjective choices in defining the protocol used to estimate GWI. These regulations can and should take account of the quantifiable uncertainties, which will differ across pathways. Uncertainties can be propagated through the model so that a point estimate for fuel-cycle emissions can be derived from the resulting output distribution. An argument has been presented for using a high-percentile value to ensure compliance, though this increases the cost of compliance. This trade-off between cost and certainty of emission reductions should be addressed openly.

Probabilistic comparisons do not entirely solve the problem, since model uncertainty and data gaps cannot be represented probabilistically (Finnveden et al., 2000). Scenarios can be used to compare methodological alternatives, but these results cannot always be meaningfully combined into a single probability distribution.

Market-based policies like the LCFS can minimize the cost of meeting a defined target, however, since the climate effects of fuel alternatives are so uncertain, the policy may not reduce emissions at all. Rather than building a complex, market-based system on highly-precise quantification of an unobservable, subjective, and uncertain measure like life cycle GHG emissions, we should recognize the limits of scientific analysis and develop policies that observe these limits. One approach would be to recognize, on a qualitative basis, that some fuel alternatives bear substantial risk of making matters worse rather than better, and thus should be avoided.

Despite the uncertainty, evidence indicates that in at least some cases, policies promoting the expanded use of biofuels will fail to achieve any near-term reduction in radiative forcing. If we consider (i) market-mediated effects such as ILUC, (ii) properly treating the time profile of ILUC emissions, (iii) uncertainty in the N_2O emission rate from feedstock production, (iv) that existing models treat reduced food consumption as a climate benefit, and (v) the global petroleum rebound effect, crop-based biofuels appear to offer little, if any, climate benefit—and present a risk of large disbenefits. In addition, the expansion of crop-based biofuels will incur other social costs, such as increasing food prices, water consumption, water pollution, and eutrophication, and reducing biodiversity (Fargione et al., 2010). These costs might be justified if crop-based biofuels offered strong climate change mitigation potential, or strong energy security benefits. However, the high end of the plausible range of net emissions from these fuels is quite high, suggesting that as an environmental policy, crop-based biofuels most likely incur a net social cost. Weighing these envi-

ronmental costs against energy security benefits is a value-based exercise about which reasonable people will disagree.

11.2 TOPICS FOR FUTURE RESEARCH

During the course of my dissertation research, I encountered several topics that are worthy of further research. I list them briefly here.

- Consequential LCA of electricity used and displaced in various fuel production pathways
- Consequential LCA of the effects of biofuel production on the production of petroleum fuels
- Effect on GWI of including black carbon, organic carbon, sulfates, NO_X, and CO
- Effect of ILUC emissions of including black and organic carbon for biomass burning
- Methodological study of combining attributional and consequential elements in a single LCA
- Robustness analysis of the 12-state LCFS using a moderately-sophisticated model

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APPENDIX A

,

SOURCE CODE FOR CRYSTALBALL-GREET MODULE

```
' CBG: CrystalBall-GREET
,
' Reads GREET Dist_Spec data and sets up CB to run simulation
,
' Rich Plevin
' March 6, 2009
Option Explicit 'require variable declarations
Const CbgMajorVersion As Integer = 1
Const CbgMinorVersion As Integer = 5
Const CbgDistSheetName As String = "Distributions"
Const CbgFirstDistRow As Integer = 3
Const CbgTrials As Integer = 10
Const CbgUnknownDist As Integer = -1
Const CbgForecast As Integer = 99
Const CbgTagsCol As Integer = 1
Const CbgSheetCol As Integer = 2
Const CbgRangeCol As Integer = 3
Const CbgDistCol As Integer = 4
Const CbgName1Col As Integer = 5
Const CbgValue1Col As Integer = 6
Const CbgName2Col As Integer = 7
Const CbgValue2Col As Integer = 8
Const CbgName3Col As Integer = 9
```

```
Const CbgValue3Col As Integer = 10
Const CbgNameCol As Integer = 11
' where the name of the target workbook is stored
Const CbgTargetWorkbookCell As String = "E1"
Dim CbgCallingWorkbook As Workbook
Const Debugging As Boolean = True
,
' Utility function
Private Function SheetExists(sName As String, wb As Workbook) As Boolean
    ' Returns True if sheet exists in the specified workbook
   Dim x As Object
    On Error Resume Next
    Set x = wb.Sheets(sName)
    If Err.Number = 0 Then SheetExists = True Else SheetExists = False
End Function
' Returns True if the workbook is open
Private Function WorkbookIsOpen(wbName As String) As Boolean
    Dim x As Workbook
    On Error Resume Next
    Set x = Workbooks(wbName)
    If Err.Number = 0 Then WorkbookIsOpen = True _
Else WorkbookIsOpen = False
End Function
' Utility function to get the target workbook name from the designated cell.
Private Function TargetWorkbook() As String
    Dim ws As Worksheet
    Dim wbName As String
    If Not SheetExists(CbgDistSheetName, CbgCallingWorkbook) Then
        MsgBox "The worksheet '" & CbgDistSheetName & _
            "' was not found in workbook '" & _
```

```
CbgCallingWorkbook.name & "'"
        TargetWorkbook = ""
        Exit Function
    End If
    Set ws = CbgCallingWorkbook.Worksheets(CbgDistSheetName)
    wbName = ws.Range(CbgTargetWorkbookCell).Value
    If Debugging Then Debug.Print "Target workbook is '" & wbName & "'"
    If (wbName = "") Then
        MsgBox "A target workbook must be specified in cell " &_
 CbgTargetWorkbookCell & _
            " of the " & CbgDistSheetName & " sheet"
        TargetWorkbook = ""
        Exit Function
    End If
    TargetWorkbook = wbName
End Function
' Run a GREET macro.
Private Function RunGreetMacro(macro As String) As Boolean
    Dim wbName As String
    RunGreetMacro = True ' not sure if Run returns a status...
    wbName = TargetWorkbook()
    Application.StatusBar = "Running GREET macro " & macro
    Application.Run "'" & wbName & "'!" & macro
End Function
' Count the number of distributions for use with the status indicator.
Private Function countDistributions(ws As Worksheet) As Integer
    Dim row As Integer
   row = CbgFirstDistRow
    ' Terminate when the worksheet column is empty.
    Do While Not IsEmpty(ws.Cells(row, CbgSheetCol))
```
```
row = row + 1
   Loop
    countDistributions = row - CbgFirstDistRow
End Function
' Update the progress status line to display the percent completed.
' Remembers the wbName to use on subsequent calls if not provided.
Private Sub updateProgress(percent, wbName As String)
    Application.StatusBar = "Setup " & wbName & ": " &
 Format(percent, "0\%") & " complete..."
End Sub
,
' Clear the progress indication
Private Sub removeProgress()
    Application.StatusBar = False
End Sub
' See if a list of tags includes the given tag
Private Function MatchTag(tag As String, tagString As String) As Boolean
    Dim tags As Variant
    Dim i As Long
    tags = Split(tagString, ",")
   MatchTag = True
   For i = 0 To UBound(tags)
       If tags(i) = tag Then Exit Function
    Next i
    MatchTag = False
End Function
,
' Interpret a Dist_Spec parameter tag as a Crystal Ball constant
' for use with CB.DefineAltParms
Private Function ConvertParameter(name As String) As Integer
    Dim code As Integer
```

```
Select Case LCase(name)
Case "minimum ="
    code = CbParmMinimum
Case "maximum ="
    code = CbParmMaximum
Case "likeliest ="
    code = CbParmLikeliest
Case "5th percentile ="
    code = CbParmPercentile + 5
Case "10th percentile ="
    code = CbParmPercentile + 10
Case "20th percentile ="
    code = CbParmPercentile + 20
Case "50th percentile ="
    code = CbParmPercentile + 50
Case "80th percentile ="
    code = CbParmPercentile + 80
Case "90th percentile ="
    code = CbParmPercentile + 90
Case "95th percentile ="
    code = CbParmPercentile + 95
Case "alpha ="
    code = CbParmAlpha
Case "beta ="
    code = CbParmBeta
Case "scale ="
    code = CbParmScale
Case "standard deviation ="
    code = CbParmStDev
Case "mean ="
    code = CbParmMean
Case "mode ="
    code = CbParmMode
Case "location ="
    code = CbParmLocation
Case "shape ="
    code = CbParmShape
Case "rate ="
    code = CbParmRate
Case Else
```

```
code = CbParmNone
   End Select
   ConvertParameter = code
End Function
' Convert a string distribution name (or "forecast") into an integer
' value for Crystal Ball. Return the code if successful, or
' CbgUnknownDist otherwise.
Private Function DistributionCode(name As String) As Integer
   Dim code As Integer
   Select Case LCase(name)
   Case "normal"
       Case "lognormal"
       code = cbDfaLogNormal ' mean, stdev
  Case "triangular"
                              ' min, likeliest, max
       code = cbDfaTriangular
  Case "uniform"
                              ' min, max
       code = cbDfaUniform
  Case "beta"
                      ' alpha>0.3, beta>0.3, max, min (alpha+beta<1000)
       code = cbDfaBeta
  Case "betapert"
                              ' max, min, likeliest
       code = cbDfaBetaPert
  Case "weibull"
                              ' location, scale>0, shape >0.05
       code = cbDfaWeibull
  Case "gamma"
                              ' location, scale>0, shape >0.05, <1000
       code = cbDfaGamma
                              ' mean, scale>0
  Case "logistic"
       code = cbDfaLogistic
  Case "extval", "minextreme" ' likeliest, scale>0
       code = cbDfaMinExtreme
  Case "maxextreme"
                             ' likeliest, scale>0
       code = cbDfaMaxExtreme
  Case "exponential"
                            ' rate
       code = cbDfaExponential
 Case "discrete"
                             ' minimum, maximum
       code = cbDfaDiscreteUniform
  ' "forecast" is a special case folded into distribution definitions
```

```
Case "forecast"
        code = CbgForecast
 Case Else
        code = CbgUnknownDist
    End Select
    DistributionCode = code
End Function
,
' Define a single assumption from the given parameters.
Private Function DefineAssumption(row As Integer, tag As String, _
    tagstr As String, targetWb As Workbook, _
    sheetName As String, rangeName As String, distName As String, _
    n1 As String, p1 As Variant, n2 As String, p2 As Variant, _
    n3 As String, p3 As Variant, _
    name As String) As Boolean
   Dim ws As Worksheet
    Dim dist As Integer
    Dim rng As Range
    DefineAssumption = False
    If Not SheetExists(sheetName, targetWb) Then
        MsgBox "CBG: Sheet '" & sheetName & "' not found in workbook " & _
        targetWb.name
        Exit Function
    End If
    Set ws = targetWb.Worksheets(sheetName)
    ws.Select
    On Error Resume Next
    Set rng = ws.Range(rangeName)
    If Err.Number <> 0 Then
        MsgBox "CBG: Specified range " & sheetName & "!" & rangeName & _
" is invalid (row " & row & ")"
        Exit Function
```

```
End If
    rng.Select
    If Not (tagstr = "all" Or MatchTag(tag, tagstr)) Then
        If Debugging And tagstr <> "" Then
            Debug.Print "tagstr '" & tagstr & "' doesn't match tag '" & tag & _
 "' (row " & row & ")"
        End If
        Cb.ClearDataND ' remove any previous distribution definition
        DefineAssumption = True
        Exit Function
    End If
    dist = DistributionCode(distName)
    If dist = CbgUnknownDist Then
        MsgBox "Unrecognized distribution type '" & distName & _
"' was specified (row " & row & ")"
        Exit Function
    End If
    If dist = CbgForecast Then
        ' "forecast" is a special case folded into distribution definitions
        Dim displayAuto As Boolean
        Dim displayWhileRunning As Boolean
        Dim units As String
        units = p1
        If p2 = 0 Then displayAuto = False Else displayAuto = True
        If p3 = 0 Then displayWhileRunning = False _
Else displayWhileRunning = True
        Cb.DefineForeND name, units, displayAuto, displayWhileRunning
        DefineAssumption = (Cb.MacroResult = cbErrNone)
        Exit Function
    End If
    If dist = cbDfaDiscreteUniform Then
        Cb.DefineAssumND dist, p1, p2, , , , name, , 0
        DefineAssumption = True
```

```
Exit Function
    End If
    ' Define the distribution according to the given parameters
    Dim parm1 As Integer, parm2 As Integer, parm3 As Integer
    Dim alt As Integer
    parm1 = ConvertParameter(n1)
    parm2 = ConvertParameter(n2)
    parm3 = ConvertParameter(n3)
    alt = Cb.DefineAltParms(dist, parm1, parm2, parm3)
    If (alt = -1) Then
        MsgBox "CBG: Failed to define alt params for " & distName & _
" (row " & row & ")"
        Exit Function
    End If
    Cb.DefineAssumND alt, p1, p2, p3, , , name, , 0
    If Cb.MacroResult = cbErrNone Then
        DefineAssumption = True
    Else
        MsgBox "CBG: " & Cb.MacroResultDetail.Msg & " (row " & row & ")"
    End If
End Function
' Read the distribution descriptions from the "Distributions" sheet
' and create the corresponding CB assumtions.
Private Function DefineAssumptions(tag As String)
    Dim ws As Worksheet
    Dim targetWb As Workbook
    Dim wbName As String
    Dim rng As Range
    Dim row As Integer
    Dim calc As XlCalculation
    Dim iter As Boolean, events As Boolean
    Dim maxiter As Integer, maxchg As Integer
```

```
With Application
        calc = .Calculation
        maxchg = .MaxChange
        maxiter = .MaxIterations
        iter = .Iteration
        events = .EnableEvents
        .ScreenUpdating = False
        .Calculation = xlCalculationManual
        .Iteration = True
        .MaxIterations = 20
        .MaxChange = 0.001
        .EnableEvents = False
    End With
    DefineAssumptions = False
    On Error GoTo QUIT
    If Not SheetExists(CbgDistSheetName, CbgCallingWorkbook) Then
        MsgBox "CBG: The sheet '" & CbgDistSheetName & _
"' was not found in the current workbook."
        Exit Function
   End If
    Set ws = CbgCallingWorkbook.Worksheets(CbgDistSheetName)
    wbName = ws.Range(CbgTargetWorkbookCell).Value
    If Debugging Then Debug.Print "Target workbook is '" & wbName & "'"
    If Not WorkbookIsOpen(wbName) Then
        MsgBox "CBG: Target workbook '" & wbName & _
"' must be open prior to running CB-GREET"
        GoTo QUIT
    End If
    Set targetWb = Application.Workbooks(wbName)
    targetWb.Activate
    Dim rows As Integer
    rows = countDistributions(ws)
    Call updateProgress(0, wbName)
```

```
' skip headings
    row = CbgFirstDistRow
    ' Terminate when the worksheet column is empty.
    Do While Not IsEmpty(ws.Cells(row, CbgSheetCol))
        Dim tagstr As String, sheetName As String
        Dim rangeName As String, distName As String
        Dim p1 As Variant, p2 As Variant, p3 As Variant
        Dim n1 As String, n2 As String, n3 As String
        Dim name As String
        tagstr = ws.Cells(row, CbgTagsCol).Value
        sheetName = ws.Cells(row, CbgSheetCol).Value
        rangeName = ws.Cells(row, CbgRangeCol).Value
        distName = ws.Cells(row, CbgDistCol).Value
        p1 = ws.Cells(row, CbgValue1Col).Value
        p2 = ws.Cells(row, CbgValue2Col).Value
        p3 = ws.Cells(row, CbgValue3Col).Value
        n1 = ws.Cells(row, CbgName1Col).Value
        n2 = ws.Cells(row, CbgName2Col).Value
        n3 = ws.Cells(row, CbgName3Col).Value
        name = ws.Cells(row, CbgNameCol).Value
        If name = "" Then name = sheetName & "!" & rangeName
        If Debugging And row = 162 Then Debug.Print "Row 162: range is " _
         & rangeName
        If DefineAssumption(row, tag, tagstr, targetWb, _
sheetName, rangeName, distName, _
  n1, p1, n2, p2, n3, p3, name) = False Then GoTo QUIT
        row = row + 1
        Call updateProgress((row - CbgFirstDistRow) / rows, wbName)
    Loop
    'If Debugging Then Debug.Print wbName & " has been updated."
    DefineAssumptions = True
```

```
QUIT:
    removeProgress
    If Debugging And Not Err.Number = 0 Then Debug.Print "Error: " &_
 Err.Description
    'CallingWorkbook.Activate
    With Application
        .MaxChange = maxchg
        .MaxIterations = maxiter
        .Iteration = iter
        .Calculation = calc
        .EnableEvents = events
        .ScreenUpdating = True
    End With
End Function
Public Sub SetupSim()
    If Not Cb.CBLoaded() Then Cb.Startup
    ' we handle errors ourselves
,
   Cb.AlertOnMacroResultError False
,
    Cb.AlertOnArgumentError False
    Cb.ResetND
    Cb.RunPrefsND cbRunMode, cbRunNormalSpeed
    Cb.RunPrefsND cbRunSaveAssumptionValues, True
    Cb.RunPrefsND cbRunUserMacros, False
    ' Cb.SetCBWorkbookPriority (10)
                                          ' call user-defined macros first
    Set CbgCallingWorkbook = ActiveWorkbook
    If DefineAssumptions("CornEtOH") Then
        MsgBox "CBG: Simulation has been set up"
        ' Cb.Simulation CbgTrials
    Else
        MsgBox "CBG: Simulation set-up failed"
    End If
    CbgCallingWorkbook.Activate
                                    ' restore prior active workbook
End Sub
```

APPENDIX B Key GREET DISTRIBUTIONS

GREET is programmed to perform analyses in user-selected target years from 2005 to 2020. Key LCA parameters that are anticipated to change over time are represented in GREET in time series tables (e.g., in the Fuel_Prod_TS and EF_TS worksheets). To allow the specification of probability distributions while accommodating variable target years, when the "stochastic analysis" option (Inputs!B7) is chosen, a macro finds all cells in the spreadsheet of a particular green color, and if the cells in the next row of the same column is yellow, the value is assumed to represent a time series. The macro then finds all references to the green cell and rewrites these to scale the value selected during the Monte Carlo simulation by the value in the yellow cell (the point estimate for the selected year) and the mean value for the distribution. The distributions shown in the following tables are the distributions used in GREET *before scaling*.

Cell	Distribution	Parameter1	Value1	Parameter2	Value2	Parameter3	Value3	Description
\$B\$20	TRIANGULAR	Minimum =	0.158	Maximum =	0.375	Likeliest =	0.283	Ammonia production share of NG as fuel
\$B\$22	TRIANGULAR	Minimum =	24.3	Maximum =	30.67	Likeliest =	27.49	Ammonia total production energy
\$B\$23	TRIANGULAR	Minimum =	22.46	Maximum =	30.28	Likeliest =	26.37	Ammonia production natural gas
\$C\$45	TRIANGULAR	Minimum =	27.24	Maximum =	7173	Likeliest =	3600.2	Ammonia process CO emissions
\$F\$22	TRIANGULAR	Minimum =	1.68	Maximum =	2.86	Likeliest =	2.27	Urea production total energy
\$F\$23	TRIANGULAR	Minimum =	1.464	Maximum =	2.816	Likeliest =	2.14	Urea production NG input
\$G\$47	TRIANGULAR	Minimum =	53.118	Maximum =	147.55	Likeliest =	100.33	Urea production PM10
\$H\$66	TRIANGULAR	Minimum =	66.7%	Maximum =	74.7%	Likeliest =	70.7%	Fraction of N applied as ammonia
\$1\$66	TRIANGULAR	Minimum =	17.1%	Maximum =	25.1%	Likeliest =	21.1%	Fraction of N applied as urea
\$J\$46	TRIANGULAR	Minimum =	549.3	Maximum =	998.8	Likeliest =	774.1	Nitric acid production NOx
\$J\$51	TRIANGULAR	Minimum =	1648	Maximum =	14183	Likeliest =	7916	Nitric acid production N2O
\$U\$22	TRIANGULAR	Minimum =	2.1	Maximum =	7.17	Likeliest =	4.64	Phosphoric acid production energy
\$U\$23	TRIANGULAR	Minimum =	1.546	Maximum =	6.8	Likeliest =	4.173	Phosphoric acid production NG
\$C\$131	BETA	Alpha =	2	Beta =	4	Scale =	0.0763	VOC from NG SC turbine
\$C\$144	BETA	Alpha =	7	Beta =	4	Scale =	0.0763	NOx from NG CC turbine
\$H\$157	BETA	Alpha =	1.0745	Beta =	4.548	Scale =	11.865	PM2.5 from coal boiler
\$H\$209	BETA	Alpha =	19.845	Beta =	1.1485	Scale =	0.3402	SOx from biomass IGCC turbine: Woody
\$AL\$168	TRIANGULAR	Minimum =	55%	Maximum =	55%	Likeliest =	55%	Fraction of biomass for EtOH; rest for power and electricity
\$C\$111	TRIANGULAR	Minimum =	0.992	Maximum =	0.992	Likeliest =	0.992	Corn displaced by 1 unit DDGS
\$C\$112	TRIANGULAR	Minimum =	0.306	Maximum =	0.306	Likeliest =	0.306	Soybean meal displaced by 1 unit DDGS
\$C\$113	TRIANGULAR	Minimum =	0.022	Maximum =	0.022	Likeliest =	0.022	Urea displaced by 1 unit DDGS
\$F\$186	TRIANGULAR	Minimum =	30%	Maximum =	100%	Likeliest =	%06	Fraction of CaCO3-CO2 lost in the field
\$G\$113	TRIANGULAR	Minimum =	-3381	Maximum =	-3381	Likeliest =	-3381	Avoided CH4 emissions by livestock
\$M\$176	BETA	Alpha =	7	Beta =	4	Scale =	3.15	Dry Mill Ethanol Production: Non-Combustion VOC
\$M\$179	BETA	Alpha =	2	Beta =	2	Scale =	1.71	Dry Mill Ethanol Production: Non-Combustion PM10
\$AA\$8	NORMAL	20th percentile =	0.89	80th percentile =	0.93			Crude naphtha refining effic.
\$AE\$256	NORMAL	20th percentile =	176080	80th percentile =	293460			Farmed Trees Farming Energy Use: Btu/dry ton
\$AE\$310	TRIANGULAR	10th percentile =	0.37	90th percentile =	0.42	Likeliest =	0.384	Biomass-Fired Power Plants efficiency (IGCC)
\$AI\$256	NORMAL	20th percentile =	532	80th percentile =	886			N Fertilizer Use for Farmed Trees Farming
\$AU\$256	NORMAL	20th percentile =	162920	80th percentile =	271540			H. Biomass Farming Energy Use
\$AY\$256	NORMAL	20th percentile =	7980	80th percentile =	13290			N Fertilizer Use for H. Biomass Farming
\$BO\$256	TRIANGULAR	Minimum =	0	Maximum =	390	Likeliest =	195	CO2 Emissions from Landuse Change: Corn Farm
\$BS\$256	TRIANGULAR	Minimum =	-225000	Maximum =	0	Likeliest =	-112500	CO2 Emissions from LUC: Farmed Trees Farm
\$BW\$256	TRIANGULAR	Minimum =	-97000	Maximum =	0	Likeliest =	-48500	CO2 Emissions from LUC: H.Biomass Farm
\$C\$256	WEIBULL	5th percentile =	19963	95th percentile =	34224	50th percentile =	23288	Corn Farming Energy Use: Btu/bushel of corn
	Cell \$B\$220 \$B\$220 \$S\$525 \$S\$545 \$F\$22 \$S\$545 \$S\$545 \$S\$545 \$S\$545 \$S\$545 \$S\$513 \$S\$514 \$S\$5144 \$S\$5144 \$S\$556 \$S\$131 \$S\$5144 \$S\$556 \$S\$131 \$S\$556 \$S\$131 \$S\$5113 \$S\$556 \$S\$556 \$S\$5566 \$S\$5556 \$S\$5556 \$S\$5556 \$S\$5556	Cell Distribution SBS20 TRIANGULAR SBS23 TRIANGULAR SBS23 TRIANGULAR SF523 TRIANGULAR SF523 TRIANGULAR SF5523 TRIANGULAR SF5523 TRIANGULAR SF553 TRIANGULAR S1566 TRIANGULAR S1551 BETA S1551 BETA S15516 TRIANGULAR S15516 TRIANGULAR S15516 TRIANGULAR S15511 TRIANGULAR S15513 BETA S15514 BETA S15515 TRIANGULAR S15516 TRIANGULAR S15516 TRIANGULAR S15516 TRIANGULAR S155	CellDistributionParameter1SBS20TRIANGULARMiniuum =SBS21TRIANGULARMiniuum =SBS23TRIANGULARMiniuum =SS455TRIANGULARMiniuum =S5545TRIANGULARMiniuum =S5547TRIANGULARMiniuum =S1546TRIANGULARMiniuum =S1546TRIANGULARMiniuum =S1546TRIANGULARMiniuum =S1541TRIANGULARMiniuum =S1545TRIANGULARMiniuum =S1546TRIANGULARMiniuum =S1541TRIANGULARMiniuum 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TRANGULAR Minimum = 2.246 Maximum = 0.375 SFS23 TRANGULAR Minimum = 1.48 Maximum = 1.4755 SFS23 TRANGULAR Minimum = 1.46 Maximum = 2.47% SFS25 TRANGULAR Minimum = 1.4755 Maximum = 2.47% SFS25 TRANGULAR Minimum = 1.4755 Maximum = 2.47% SFS25 TRANGULAR Minimum = 5.3.18 Maximum = 2.47% SFS65 TRANGULAR Minimum = 5.3.16 Maximum = 2.47% SFS5 TRANGULAR Minimum = 5.3.16 Maximum = 2.47% SFS65 TRANGULAR Minimum = 5.3.16 Maximum = 2.47% <t< td=""><td>CellDistributionParameter1AluetParameter2AluetsParameter358520TRANGULARMinum=0.136Maximum=0.375Ukeless=58521TRANGULARMinum=2.43Maximum=30.07Ukeless=58523TRANGULARMinum=2.72Maximum=30.07Ukeless=58524TRANGULARMinum=2.724Maximum=2.816Ukeless=57523TRANGULARMinum=5.734Maximum=2.734Ukeless=56461TRANGULARMinum=5.734Maximum=2.747Ukeless=57523TRANGULARMinum=5.734Maximum=2.747Ukeless=58546TRANGULARMinum=5.734Maximum=2.747Ukeless=58541TRANGULARMinum=1.476Ukeless=1.647Ukeless=58541TRANGULARMinum=1.716Maximum=2.747Ukeless=58541ETAAppa=2.19Maximum=6.76Ukeless=58541ETAAppa=2.1076Maximum=6.76Scale=58541ETAAppa=2.74Maximum=6.76Scale=58541ETAAppa=1.075Bets=4.766Scale=58541ETAAppa=2.96Maximum=6.76Scale=58541ETAAppa=2.96Maximum=6.766Ukeless=58541</td><td>Cell Detribution Parameter1 Value1 Parameter3 Value3 Parameter3 Value3 58520 FRANGULAR Minum= 0.136 Maximu= 0.375 Lueiset= 27.49 58520 FRANGULAR Minum= 2.24 Maximu= 0.375 Lueiset= 27.49 58520 FRANGULAR Minum= 2.24 Maximu= 17.73 Lueiset= 27.49 58520 FRANGULAR Minum= 2.74 Maximu= 27.79 Lueiset= 27.49 58521 FRANGULAR Minum= 1.74 Maximu= 27.79 Lueiset= 27.49 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47</td></t<>	CellDistributionParameter1AluetParameter2AluetsParameter358520TRANGULARMinum= 0.136 Maximum= 0.375 Ukeless=58521TRANGULARMinum= 2.43 Maximum= 30.07 Ukeless=58523TRANGULARMinum= 2.72 Maximum= 30.07 Ukeless=58524TRANGULARMinum= 2.724 Maximum= 2.816 Ukeless=57523TRANGULARMinum= 5.734 Maximum= 2.734 Ukeless=56461TRANGULARMinum= 5.734 Maximum= 2.747 Ukeless=57523TRANGULARMinum= 5.734 Maximum= 2.747 Ukeless=58546TRANGULARMinum= 5.734 Maximum= 2.747 Ukeless=58541TRANGULARMinum= 1.476 Ukeless= 1.647 Ukeless=58541TRANGULARMinum= 1.716 Maximum= 2.747 Ukeless=58541ETAAppa= 2.19 Maximum= 6.76 Ukeless=58541ETAAppa= 2.1076 Maximum= 6.76 Scale=58541ETAAppa= 2.74 Maximum= 6.76 Scale=58541ETAAppa= 1.075 Bets= 4.766 Scale=58541ETAAppa= 2.96 Maximum= 6.76 Scale=58541ETAAppa= 2.96 Maximum= 6.766 Ukeless=58541	Cell Detribution Parameter1 Value1 Parameter3 Value3 Parameter3 Value3 58520 FRANGULAR Minum= 0.136 Maximu= 0.375 Lueiset= 27.49 58520 FRANGULAR Minum= 2.24 Maximu= 0.375 Lueiset= 27.49 58520 FRANGULAR Minum= 2.24 Maximu= 17.73 Lueiset= 27.49 58520 FRANGULAR Minum= 2.74 Maximu= 27.79 Lueiset= 27.49 58521 FRANGULAR Minum= 1.74 Maximu= 27.79 Lueiset= 27.49 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47 5856 FRANGULAR Minum= 1.74 Maximu= 27.47 27.47

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Residual Oil-Fired Power Plants (Utility Boiler)	NA NG recover effic.	Crude recovery efficiency	N Fertilizer Use for Corn Farming: N grams/bushel	Natural Gas-Fired Power Plants (Utility Boiler)	NNA NG recovery effic.	CG refining effic.	P2O5 Fertilizer Use for Com Farming	Natural Gas-Fired Power Plants (Simple Cycle Gas Ti	NNA FG recovery effic.	FRFG Refining effic.	K2O Fertilizer Use for Com Farming	Natural Gas-Fired Power Plants (NGCC turbine)	NA NG processing effic.	CARFG refining effic.	g CaCO3 / bu com	Coal-Fired Power Plants efficiency (Utility Boiler)	NNA NG processing effic.	CD refining effic.	Coal-Fired Power Plants efficiency (IGCC)	NNA FG processing effic	LSD refining effic.	CH4 GWP	N20 GWP	Conv. Diesel LHV	Ethanol LHV	Conv. Gasoline LHV	Conv. Diesel HHV	Ethanol HHV	Coal HHV	Conv. Gasoline HHV	Conv. Diesel density	Ethanol density	NG density	Conv. Gasoline density	NG carbon ratio
		0.98	470				175	0.331			215	0.53			1419.4				0.47			0	0	128450	76330	116090	137380	84530	20608570	124340	3167	2988	22	2819	0.724
		Likeliest =	50th percentile =				50th percentile =	Likeliest =			50th percentile =	Likeliest =			Likeliest =				Likeliest =			Location =	Location =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =	Likeliest =
0.358	0.99	0.99	577	0.358	0.99	0.86	273	0.4	0.99	0.87	391	0.63	0.99	0.87	2129.1	0.366	0.99	0.9	0.53	0.99	0.89	4	52	140600	78650	123500	148000	86770	21010000	132600	3357	2998	53	2952	0.739
80th percentile =	80th percentile =	Maximum =	90th percentile =	80th percentile =	80th percentile =	80th percentile =	90th percentile =	Maximum =	80th percentile =	80th percentile =	95th percentile =	Maximum =	80th percentile =	80th percentile =	Maximum =	90th percentile =	80th percentile =	80th percentile =	Maximum =	80th percentile =	80th percentile =	Std Deviation =	Std Deviation =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =	Maximum =
0.337	0.96	0.96	305	0.337	0.96	0.85	88	0.3	0.96	0.84	18	0.45	0.96	0.84	710	0.315	0.96	0.88	0.4	0.96	0.85	25	298	120600	75770	108000	128640	83660	20230000	112800	2952	2971	21.2	2721	0.721
20th percentile =	20th percentile =	Minimum =	10th percentile =	20th percentile =	20th percentile =	20th percentile =	10th percentile =	Minimum =	20th percentile =	20th percentile =	5th percentile =	Minimum =	20th percentile =	20th percentile =	Minimum =	10th percentile =	20th percentile =	20th percentile =	Minimum =	20th percentile =	20th percentile =	Mean =	Mean =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =	Minimum =
NORMAL	NORMAL	TRIANGULAR	WEIBULL	NORMAL	NORMAL	NORMAL	WEIBULL	TRIANGULAR	NORMAL	NORMAL	WEIBULL	TRIANGULAR	NORMAL	NORMAL	TRIANGULAR	NORMAL	NORMAL	NORMAL	TRIANGULAR	NORMAL	NORMAL	LOGNORMAL	LOGNORMAL	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR	TRIANGULAR
\$C\$310	\$C\$34	\$C\$8	\$G\$256	\$G\$310	\$G\$34	\$6\$8	\$K\$256	\$K\$310	\$K\$34	\$K\$8	\$0\$256	\$0\$310	\$0\$34	\$0\$8	\$S\$256	\$S\$310	\$S\$34	\$S\$8	\$W\$310	\$W\$34	\$W\$8	\$B\$61	\$B\$62	\$C\$11	\$C\$20	\$C\$8	\$D\$11	\$D\$20	\$D\$49	\$D\$8	\$E\$11	\$E\$20	\$E\$44	\$E\$8	\$F\$44
Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Prod_TS	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs	Fuel_Specs

Coal carbon ratio	Conv. Gasoline carbon ratio	N2O emission rate for fertilizer	Type of electricity displaced by ethanol plant electricity	Percent moisture of farmed trees during transport	Percent moisture of herbaceous biomass during transport	
0.637	0.863	0.02%		25%	15%	
Likeliest =	Likeliest =	Location =		Likeliest =	Likeliest =	
0.66	0.88	1.65%	ю	25%	15%	
Maximum =	Maximum =	Mean =	Maximum =	Maximum =	Maximum =	
0.6	0.85	1.11%	-	25%	15%	
Minimum =	Minimum =	Std Deviation =	Minimum =	Minimum =	Minimum =	
TRIANGULAR	TRIANGULAR	LOGNORMAL	DISCRETE	TRIANGULAR	TRIANGULAR	
\$F\$49	\$F\$8	\$B\$210	\$B\$394	\$C\$314	\$C\$315	
Fuel_Specs	Fuel_Specs	Inputs	Inputs	Inputs	Inputs	