Evaluating Biomass Energy Policy in the Face of Emissions Reductions Uncertainty and Feedstock Supply Risk

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Abstract

Biofuels have received legislative support recently in California's Low-Carbon Fuel Standard and the Federal Energy Independence and Security Act. Both discuss new fuel types, but neither provides methodological guidelines for dealing with the inherent uncertainty in evaluating their potential life-cycle greenhouse gas emissions. Emissions reductions are based on point estimates only. This work develops a Monte Carlo simulation to estimate life-cycle emissions distributions from ethanol and butanol from corn or switchgrass. Life-cycle emissions distributions for each of the modelled feedstock and fuel pairings span an order of magnitude or more. Corn ethanol emissions range from 50 to 200 g CO2e/MJ, and each feedstock-fuel pathway studied shows some probability of greater emissions than a distribution for gasoline. Potential GHG emissions reductions from displacing fossil fuels with biofuels are difficult to forecast given this high degree of uncertainty in life-cycle emissions. Incorporating uncertainty in the decision making process can illuminate the risks of policy failure (e.g., increased emissions), and a calculated risk of failure due to uncertainty can be used to inform more appropriate reduction targets in future biofuel policies. The current practice of modelling cellulosic biomass yields based on point values that have been aggregated over space and over time conceal important energy supply risks related to depending on biomass for transportation energy, particularly those related to local drought conditions. Using switchgrass as a case study, this work quantifies the variability in expected yields over time and space with a switchgrass growth model and historical weather data. Even with stable, productive states, yields vary from 5 to 20 Mg/ha. Yields are likely to be reduced with increased temperatures and weather variability induced by climate change. Thus, variability needs to be a central part of biomass systems modelling so that risks to energy supplies are acknowledged and risk mitigation

strategies or contingency plans are considered. Irrigation, a potential risk mitigation strategy, can very often negate the impacts of drought, although system-wide irrigation is an expensive method to stabilize crops (costing \$0.10 to \$1.90/gallon). Unless many surplus acres of cellulosic crops are planted, there will be insufficient ethanol to meet the EISA targets 10 to 25% of the time under rain-fed conditions. Thinking in terms of yield ranges, not point estimates, is essential in planning a long-term energy system dependent on biomass.

Acknowledgements

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On a personal note, I would like to thank the EPP Mafia (you know who you are) for making these four years Pittsburgh pass so enjoyably and so memorably. I don't know of another such group of excellent people who would throw a surprise birthday party for someone they had known for less than two months. And a foreigner, at that.

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Chapter 1. Introduction

1.1 Research Motivation

The US energy portfolio is presently undergoing an interesting transition. In contrast to past energy shifts, there are three key motivating factors: reducing oil consumption, increasing the percentage of resources used that are domestic, and decreasing greenhouse gas (GHG) emissions. The need to reduce GHG emissions largely distinguishes the current push for new energy sources and technologies from previous efforts to find low cost, domestic energy options, and has certainly helped diversify the primary energy sources used for electricity and for transportation. The electricity sector has seen a ten-fold increase in installed wind capacity in the past decade because it is domestic (and therefore politically attractive), has lower GHG emissions than major incumbent fuels, and, perhaps most importantly, is comparatively inexpensive versus other renewable electricity generating technologies. The transportation sector has seen increased use of biofuels for similar reasons.

Biomass is only a small part of the energy mix, and is likely to remain so in the future. Projections by the US Energy Information Administration (EIA) suggest that biomass will be a persistent supporting character in the US energy portfolio, thanks to state and federal legislation supporting or mandating its use. By its nature as a biological resource rather than one more strongly dependent on technological development and industry, the biomass energy sector has interesting non-traditional features. There are no wind versus food debates, nor are there global agricultural shifts and carbon emissions directly precipitated by increased US battery production. Though there are implementation challenges related to other renewable energy technologies and types, recommendations regarding increasing the use of biomass energy need to be carefully scrutinized from several different, often unrelated directions so that unintended, known negative consequences are avoided wherever foresight allow.

By necessity, this dissertation covers only a small number of the myriad issues surrounding biomass energy used for ground transportation in the United States. The focus of this work is uncertainty and variability in estimates for life-cycle greenhouse gas emissions from biofuels, and variability in forecasts for future cellulosic biomass availability. Following a quantitative assessment of the uncertainty in life-cycle GHG emissions from several biofuel pathways, the discussion focuses on the degree to which uncertainty and variability can be addressed in biomass system models is discussed in the context of biofuel policy implementation. This is follow by suggestions regarding how policy might be improved given persistent uncertainty in emissions reductions or feedstock supplies. Though this work is motivated directly by US bioenergy policy, the findings and methods presented here should be relevant to other similarly complex models, and not restricted specifically to biomass systems.

1.2 Research Questions

The issues mentioned above are discussed in the following three chapters. In more detail, the following research questions are asked and answered:

Chapter 2: Uncertainty in Life-Cycle Greenhouse Gas Emissions from Biofuels

1. What is the quantitative uncertainty associated with life-cycle greenhouse gas emission estimates for current (corn ethanol) and proposed biofuels (switchgrass ethanol, butanol)?
2. Which model input parameters (e.g., indirect land use change) are the most important in determining this range in output values?
3. Are there emissions reductions expected when shifting from bio-ethanol to bio-butanol?

Chapter 3: Uncertainty and Biofuel Policy Designs

1. What is the probability that the revised Renewable Fuel Standard (based on deterministic life-cycle GHG emissions models) included in the Energy Independence and Security Act will succeed in reducing transportation emissions associated with the production of corn- and switchgrass-based biofuels?
2. What potential policy design incorporates uncertainty in emissions estimates (for the RFS and LCFS) so that the likelihood of emissions reductions occurring can be evaluated?

Chapter 4: Consequences of Uncertainty in Biofuel Feedstock Supply

1. What are the weather-related supply risks to switchgrass grown in the continental United States? How do these risks change with future climate change?
2. To what degree can these supply risks be mitigated with the use of irrigation? And at what cost?
3. How does this variability affect biofuel system recommendations and policy compliance based on point estimates?

The fifth and final chapter in this dissertation summarizes the results that answer these questions, and provides commentary on how some of the challenges related to biomass energy might be dealt with. The last chapter concludes with some suggestions for future work related to the analyses presented in this dissertation.

1.3 Background

1.3.1 Biomass Energy for Transportation in the US

In the US, the primary biofuel used in transportation is ethanol made from corn. In 2011, 13.9 billion gallons of corn ethanol were produced, as shown in Figure 1 [1]. This is substantial growth from the 1981 production level of 83 million gallons when ethanol was used as a fuel additive to improve engine performance [2]. The 1981 volume of ethanol used about 1% of US corn, whereas the volume in 2011 accounted for more than 25% of total US corn use [3]. The US now produces more ethanol than any other country, having overtaken Brazil (where ethanol is made out of sugarcane) in 2005. In 2011, about 5.5 billion gallons of ethanol were produced in Brazil. Biodiesel, made primarily out of soybeans, is the second category of biofuels used in the US. In 2011, 970 million gallons of biodiesel were produced. This is substantial growth from an initial production volume of 9 million gallons in 2001 [4]. Together, current ethanol and biodiesel volumes are small compared to liquid fossil fuels (less than 7% of fuel consumption), but biofuels are projected to be a growing part of the energy mix as petroleum use remains largely flat as shown in the Annual Energy Outlook (AEO) projections in Figure 2 [5].

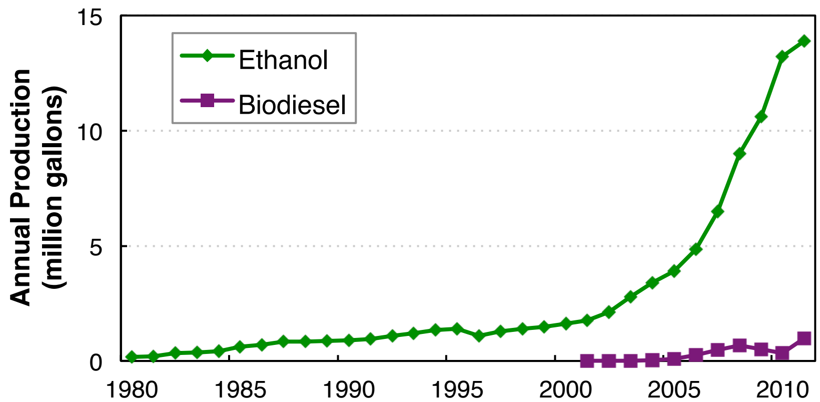

Figure 1. Ethanol and biodiesel production volumes over time.

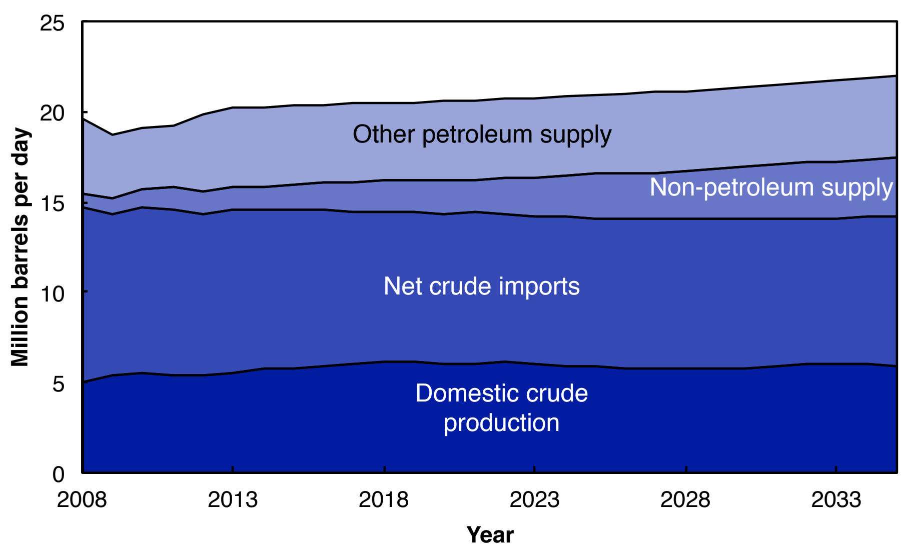

Figure 2. AEO projections for liquid fuel sources through 2035.

The capacity and expertise for these volumes evolved, in part, due to efforts by the US Departments of Energy (DOE) and of Agriculture (USDA) to make biofuels an economic alternative to imported oil [6]. The US DOE program started shortly after the oil embargo of the late 1970s, when alternative transportation fuels first became a national priority. A wide variety of non-food crop options, from woody biomass to agricultural residues to organic waste matter, were considered as candidate feedstocks from which to produce ethanol or biodiesel as part of the US DOE's Bioenergy Feedstock Development Program [7]. Field test results placed *Populus* genus trees (of which poplars are an example) as the top candidate for woody biomass, and *Panicum virgatum*, or switchgrass, as a good grass candidate. The aim of the program was to find crops that could produce high, stable yields with little input across much of the United States. For switchgrass, yields from test plots across the country (results reported in [8]) inform models predicting locations and yields for future cellulosic ethanol systems. DOE research by the Genomic Science Program is now focused on engineering biomass to be easily broken down into individual sugars during the fuel production process, and on improving the efficiency of the cellulosic ethanol production phase where those sugars are fermented to ethanol [9]. For an interesting case study on how breeding programs, as well as field-level knowledge and practice improvements, can affect yields and feasible growing locations, Olmstead and Rhode [10] present the shifting wheat frontier in North America over the past 70 years in the face of a changing climate.

The USDA program to support biofuels started in the 1990s, and is operated out of the USDA's Office of Energy Policy and New Uses. This group has funded studies into net energy balance, and techno-economic performance for corn and cellulosic ethanol production. These serve as the basis of many government and private studies on the merits of corn ethanol and soy biodiesel (see [11] for a list of publications).

1.3.2 Ethanol Production

All biomass feedstocks contain polymeric sugars, though types and quantities vary across species. These plant sugars are broken down into individual molecules (monomerized) and fermented into ethanol. Lignin, ash and other compounds are also present in most biomass feedstocks [12]. Lignin is a complex grouping of molecules that is not readily broken down, as it provides structure, rather than energy storage, for the plant. In lignocellulosic fuel production, lignin is an important source of process energy.

In the case of starchy feedstocks such as corn, the major sugar polymer (starch) is relatively easy to hydrolyze into individual glucose molecules and ferment. This is one key reason why US ethanol is currently produced from corn rather than cellulosic crops. In the case of lignocellulosic feedstocks such as switchgrass, there are two primary sugar polymers: cellulose and hemicellulose. Cellulose is difficult to monomerize due to its crystalline structure. Hemicellulose saccharification is more difficult than starch but easier than cellulose due to its lesser degree of organization at the molecular level [13]. When these cellulosic sugar polymers are monomerized, the fermentation process is similar to corn ethanol production, though different enzymes are required to process the new sugar types in addition to glucose.

1.3.3 Policy and Biofuel Use

The capacity for world-leading biofuel production was enabled through policies encouraging or mandating the use of biofuels, and the presence of biofuel production subsidies. At the federal level, ethanol blenders have received tax credits in the range of \$0.40 to \$0.60/gallon since the 1980s. At the end of 2011, corn ethanol was subsidized at \$0.45/gallon while cellulosic ethanol was subsidized at $1.01/gallon. At this point, the policy defining the corn ethanol credit was allowed to lapse. Currently, corn ethanol is not subsidized in the US, while cellulosic ethanol persists. The tariff on imported ethanol (previously set at $0.54/gallon) also lapsed at the end of 2011, so the corn ethanol industry finds itself in somewhat new circumstances. It will be interesting to see how the ratio between domestic and imported ethanol changes with time.

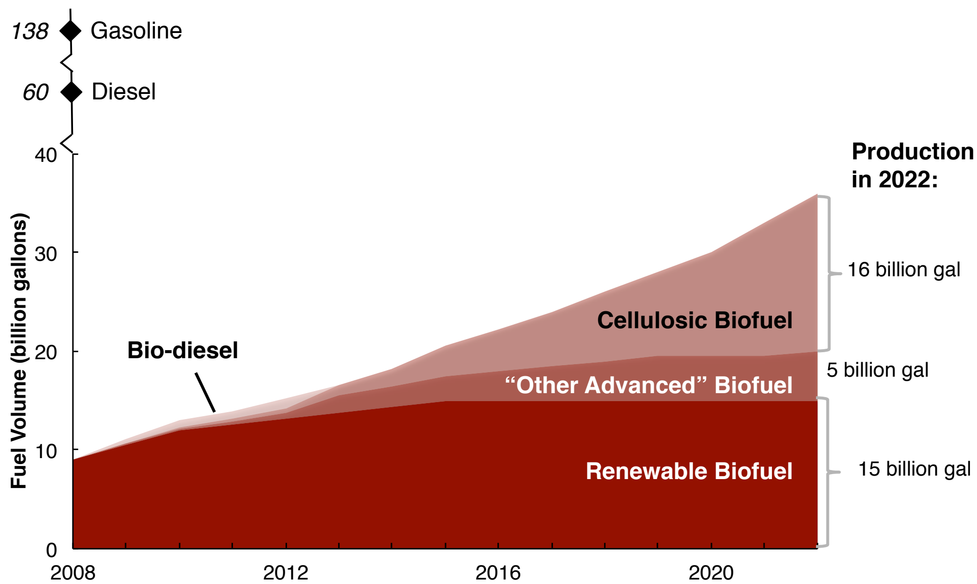

Figure 3. EISA volume mandates over time by fuel type.

In addition to federal subsidies, the federal Energy Independence and Security Act of 2007 (EISA) includes biofuel volume mandates though its Renewable Fuel Standard (RFS) [14]. Four fuel classifications are included in EISA: bio-diesel, renewable biofuel (which is essentially corn ethanol), cellulosic biofuel (which is essentially ethanol made out of any cellulosic source), and a catch-all category called other advanced biofuels. Volumes of most fuels are required to increase year-on-year, with the exception of corn ethanol, which hits a plateau of 15 billion gallons per year in 2015. Cellulosic ethanol surpasses corn ethanol at the end of the policy tenure at 16 billion gallons in 2022. These volumes are illustrated increasing over time in Figure

3. For biofuels to qualify in each category, they must meet life-cycle greenhouse gas emissions reduction targets defined in the RFS. These targets are 20% for corn ethanol, 50% for both cellulosic ethanol and bio-diesel, and 60% for the other advanced biofuel category (summarized in Table 1). The life-cycle emissions from each fuel type are calculated by the US Environmental Protection Agency (US EPA). They found that corn ethanol not using coal offers between 16 and 47% emissions reductions (depending on production assumptions), and switchgrass ethanol offers a 128% emissions reduction [15]. An important note, all corn ethanol production facilities that existed before 2007 when this act came into force are not required to produce ethanol that meets this 20% reduction target, but their output is counted towards the annual totals.

Table 1. GHG reduction requirements under EISA.

Fuel Classification	% Decrease in Emissions	Baseline Fuel Type
Bio-diesel	50	Diesel
Renewable biofuel	20	Gasoline
Cellulosic biofuel	60	Gasoline
Other Advanced biofuel	50	Diesel/Gasoline

In California, a Low-Carbon Fuel Standard (LCFS) was implemented in 2007 [16]. This policy requires state-wide life-cycle GHG emissions from transportation fuels to be 10% lower than a base case where only fossil fuels are used. The California Air Resources Board (CARB) calculates life-cycle emissions for all candidate alternative fuels (including biofuels, electricity, and hydrogen) as well as emissions for the incumbent gasoline and diesel. They report (to four significant figures) that the gasoline blend used in California emits 95.86 g CO_2e/MJ, diesel 94.71 g CO_2e/MJ, corn ethanol produced in California using natural gas for process heat and drying the distiller's dried grains ('California; Dry Mill; Dry DDGS, NG' in the CARB lookup table) emits 88.90 g CO_2e /MJ, and the otherwise equivalent corn ethanol produced in the Midwest emits 98.40 g CO_2e /MJ [17]. The fuels evaluated under this policy are more specifically defined than they are in the RFS; specific process characteristics and locations are used rather than nationally representative corn ethanol as defined in the RFS.

There are, of course, biofuel policies in other countries. The UK's Renewable Transport Fuels Obligation and the European Union's Renewable Energy Directive also depend on the results of life-cycle assessments of biofuels and incumbent fossil fuels to quantify greenhouse gas emissions reductions.

1.3.4 Life-Cycle Assessment

Life-cycle assessment (LCA) has become an important tool for environmental policy makers, playing a crucial role in the development of the California LCFS [18] and the RFS defined in EISA. Life-cycle assessment began as framework to assist in determining environmental impacts of a product by accounting for emissions to the environment from each stage in the supply chain, the use phases, and the end-of-life treatment of the product. The precise activities included in the analysis are defined as the system boundary. This approach, termed a process-based LCA, was initially used to assist in comparing and deciding between two similar products; Coca-Cola commissioned an early LCA study to compare and evaluate different product packaging types [19]. A functional unit is necessary to compare different products that fulfill the same general function for a fair comparison. In the Coca-Cola case, this could be something like amount of material needed to hold 12oz of beverage. The process-based LCA has since been developed into an ISO (International Organization for Standardization) standard, which guides the practice [20].

An economic input-output LCA (EIO-LCA) approach was developed to address shortcomings in process-based models, such as cut-off error related to setting too small a system boundary. Given an economic input-output table, which relates economic inputs and outputs between all tracked sectors of an economy, all of the upstream economic activities related so some amount of produced good or service (defined by monetary units) can be quantified. Economic activities of each sector in a region or country are assigned environmental impacts, so some portion of the total environmental impacts throughout the supply chain can be allocated to the economic activity caused by one particular product or service of interest [21]. The environmental impacts discussed in relationship to biofuels so far have been limited to climate change caused by greenhouse gas emissions, but these impacts can also include eutrophication, acidification, or human toxicological impacts.

1.3.4.1 Uncertainty in LCA Models

Assessing life-cycle greenhouse gas emissions from biofuels is more complex than comparing aluminum cans to glass bottles. Modelling such a complex system introduces new challenges to the LCA framework. During the course of any systems modelling, including LCA, modellers must make many decisions regarding what will or will not be included in the system, data sources most appropriate to characterize the system, and methods to estimate values for which no data are available. As a result, life-cycle analysts evaluating the same product or service may make different decisions in these areas and arrive at different and sometimes disparate conclusions. This is particularly troublesome because these different results may suggest different courses of actions for decision makers. Large, complex systems frequently require many modelling decisions to be made, which can make it difficult to arrive at the "true" value that quantifies the impact of product or service. Understanding and addressing the magnitude of the uncertainty in model output is essential for robust decision-making.

Uncertainty in the life-cycle assessment context can be broadly categorized as either parameter uncertainty or model uncertainty. Parameter uncertainty results from not precisely knowing a specific input value. This can result from: unavailable data for which proxy data must be used; measurement error on collected data; or, data that vary temporally or geographically for the system under analysis. Model uncertainty is broader in scope compared to parameter uncertainty. Model uncertainty results from not knowing how to construct (parts of) a mathematical model to represent a real-world process. Some examples of model uncertainty include emissions allocation from a process between multiple co-products; the evolution of economically-mediated production impacts over space and/or time; the choice of what global warming potentials to use in calculating climate change impacts; and, the choice of which processes to include or exclude from the analysis (i.e., defining the system boundary).

Quantitative methods to deal with uncertainty in LCA, as suggested by many previous studies and summarized by Lloyd and Ries [22] and Williams and colleagues [23], include probabilistic simulation, intervals, scenario modeling, fuzzy data sets and analytical uncertainty propagation. When dealing with parameter uncertainty, probability distributions are specified using data and/or expert judgments, then simulation methods and uncertainty importance analyses are used to establish uncertainty in output [24]. Quantifying the range or impact of model uncertainty is often more challenging than parameter uncertainty, as many difficulties of model uncertainty cannot be addressed by any amount of data collection, especially those projecting future system developments. Often the best that can be done is to perform a scenario analysis by constructing all reasonable and feasible models, and then using the least and greatest output values to establish bounds on quantitative model results. In the biofuels context, recognizing uncertainty complicates a decision maker's task of choosing among fuel types; however, neglecting uncertainty in favor of (relative) simplicity can lead to policy failure.

1.4 Challenges to Biomass Use for Energy

1.4.1 Food Versus Fuel Debate

The United Nations declared an emergency in late 2007 due to global food price spikes, after which time many studies were undertaken to investigate the causes. In a World Bank policy report, Mitchell found that 70 to 75% of the increase in the price of food commodities from 2002 to 2008 can be attributed to the increase in biofuel production from grains and oilseeds in both the United States and in Europe [25]. A Congressional Research Service report similarly forecast that EISA (and other global biofuel policies) would substantially impact food prices [26]. The price of corn in the US as reported by the USDA National Agricultural Statistics Service (NASS) shows an increasing trend from 2007 onward in Figure 4. The push to increase cellulosic ethanol rather than corn ethanol is partially motivated by this need to divert less food grain from nutrition to biofuels.

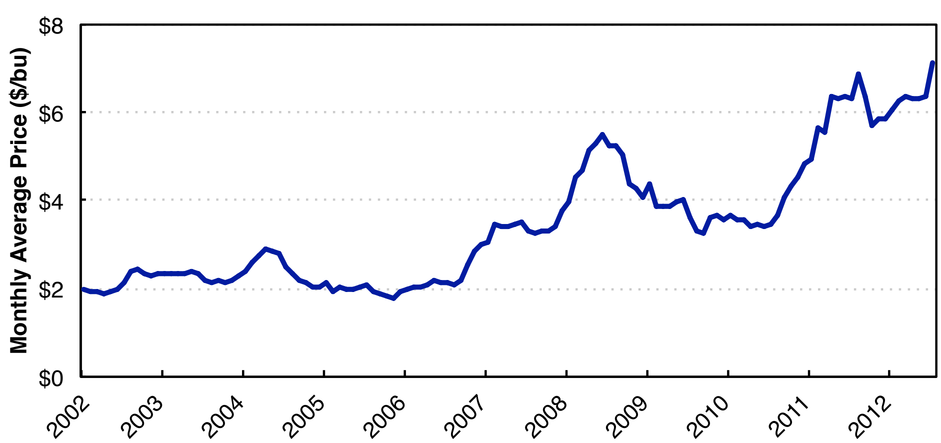

Figure 4. Average monthly corn prices from January 2002 to July 2012.

1.4.2 Unfavourable Land Use Changes

Prior to about 2007, most life-cycle assessment studies found both corn ethanol and soy biodiesel to have greenhouse gas emissions benefits when compared to gasoline or conventional diesel, so long as natural gas was used instead of coal to provide production process heat in a reasonably efficient plant [27], [28]. Two key studies were released in 2007 and 2008 that challenged this conclusion. The first study, by Fargione and colleagues, suggested that planting more corn (or other biomass feedstocks) to satisfy growing biofuel demand alters the landscape if it was not previously used for agricultural purposes. The change often resulted in a substantial release of carbon into the atmosphere [29]. They examined planting choices in South America and the United States, and defined and calculated a "biofuel carbon debt" to illustrate how long various biofuels must be produced and used until the initial loss of terrestrial carbon is offset by the GHG emissions reductions from the displacement of liquid fossil fuels. This process was called direct land use change (DLUC).

The second, by Searchinger and colleagues, investigated carbon release from indirect land use change (ILUC), or, land use change caused by changing economic conditions related to increased demand for biofuel crops [30]. For example, corn becomes more valuable as the US consumes more due to increasing corn ethanol production. As a globally traded commodity, this change induces increased corn production abroad. The increased corn production could be on agricultural land, or it could be on land that was previously grassland, or forest. As with domestic land use change, this too causes a transfer of carbon into the atmosphere, and takes decades, if not centuries, of biofuel use to repay this debt.

With strategies such as those highlighted by Tilman and colleagues [31] and discussed in greater detail by a National Academies report [32], biofuels can be produced in a way offers greenhouse gas reductions while sidestepping some of food price impacts. These publications highlight the need to use agricultural crop wastes or low-input grasses planted on unused agricultural lands in order to avoid land use change issues and competition with food crops. They also highlight using otherwise unexploited organic matter in municipal solid waste streams, which, if utilized, again sidesteps the crucial issues of food for fuel and agricultural land competition.

1.4.3 Crop Supply Risks from Drought

Biomass supplies are at risk due to natural variability in yields caused by changing local meteorological (or other) conditions. Biomass yield variability has not been dealt with extensively, or quantitatively, in the literature to date that discusses various futures for the biofuels industry. A review of insurance statistics provides some insight into the reasons for crop losses.

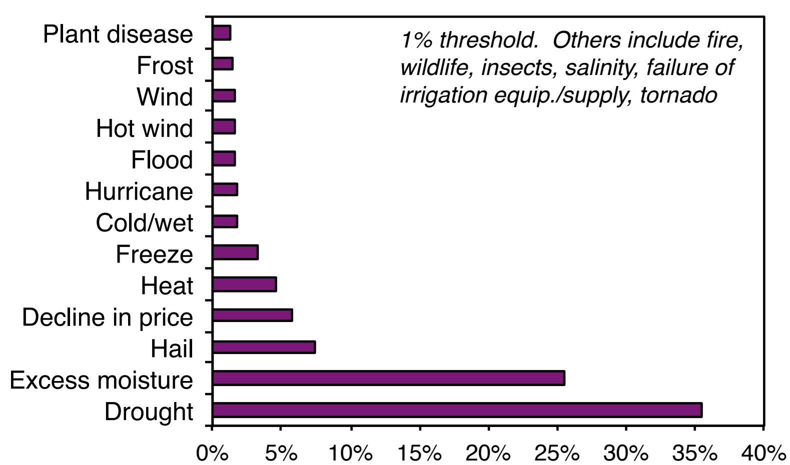

Figure 5. Distribution of total FCIC crop insurance indemnities from 2000 to 2011 across cause of loss description.

The Federal Crop Insurance Corporation (FCIC) covers the loss of many crop types for a wide variety of causes across the US. The FCIC has about 200 million acres insured across the US (about half of all planted acres). The data plotted in Figure 5 are gathered from a database of the

USDA's Risk Management Agency, which operates and manages the FCIC [33], and show percentages representing total indemnities by cause of loss from the period 2000 to 2011. Drought is the single most costly cause of crop loss in the US. Drought may be a particular challenge for new, cellulosic crops because they have not benefited from years of breeding programs to increase drought resistance (such as that which has benefited food crops like corn and wheat), and because cellulosic biomass systems planned and assessed by researchers are assumed to be rain-fed only.

1.4.3.1 Drought Indices

The term 'drought' means different things to different people, depending on what is affected by drought. If rainfall is the primary concern, then a lack of precipitation is enough to declare drought conditions. If other flows of water, such as surface and subsurface water, affect the outcome of concern, those flows would be considered in addition to direct precipitation when evaluating drought. If evapotranspiration on a field is the metric of concern, then temperature conditions also play into whether or not drought conditions have taken hold.

To resolve the potential ambiguity surrounding the term drought, standardized drought indices are used to indicate the severity and geographic extent of water deficiency (or excess). In the US, a commonly used drought index is the Palmer Drought Severity Index (PDSI). This is a hydrological drought index defined by Palmer in 1965 [34] in response to a recognized need for an index which could be compared between regions and drought events over time. Though initially identified as a meteorological index, it fulfills the current definition of a hydrological index. The PDSI considers precipitation, evapotranspiration (which is also dependent on temperature), and ground-level water flows, all of which affect soil moisture levels.

Alley provides a solid critique of the PDSI calculation methodology, highlighting some assumptions of convenience made in evapotranspiration modelling, difficulty in defining regional factors to normalize the index geographically and temporally, and the convoluted relationship between empirical data and the resulting index value [35].

A meteorological index called the Standardized Precipitation Index (SPI) was introduced by McKee in the mid 1990s to address some of the shortcomings of the PDSI [36]. The calculation steps (laid out nicely in [37]) are as follows:

1. Generate time series data for cumulative precipitation over a region of interest. Common timespans for which to calculate cumulative data are 1, 2, 3, 6, 9, 12, and 24 months (all timespans for which the National Climatic Data Center (NCDC) performs SPI calculations). For example, a January SPI-1 data set would include total rainfall for every January in the time period of interest, whereas an SPI-3 data set (three months) might include total rainfalls from June to August.
2. Fit a probability distribution function, usually a two- or three-parameter gamma function, to historical precipitation data for a region of interest.
3. Generate a cumulative distribution function from the parameters obtained in the fit. Input the CDF output (values between 0 and 1) to an inverse standard normal distribution to get standard precipitation index values.

By using a standard normal distribution for the index, familiar statistics are meaningful, such as 0 indicating median rainfall, or ± 0.68 for one standard deviation more or less precipitation than historically expected in the specific region of interest. The calculation methodology is also straightforward enough that the SPI can be calculated for a custom geographic area so long as sufficient time series data on precipitation are available. The relationship between SPI and precipitation is illustrated for three states, using historical monthly rainfall data from 1895 to 2011, in Figure 6. SPI and precipitation data are taken from the NCDC [38].

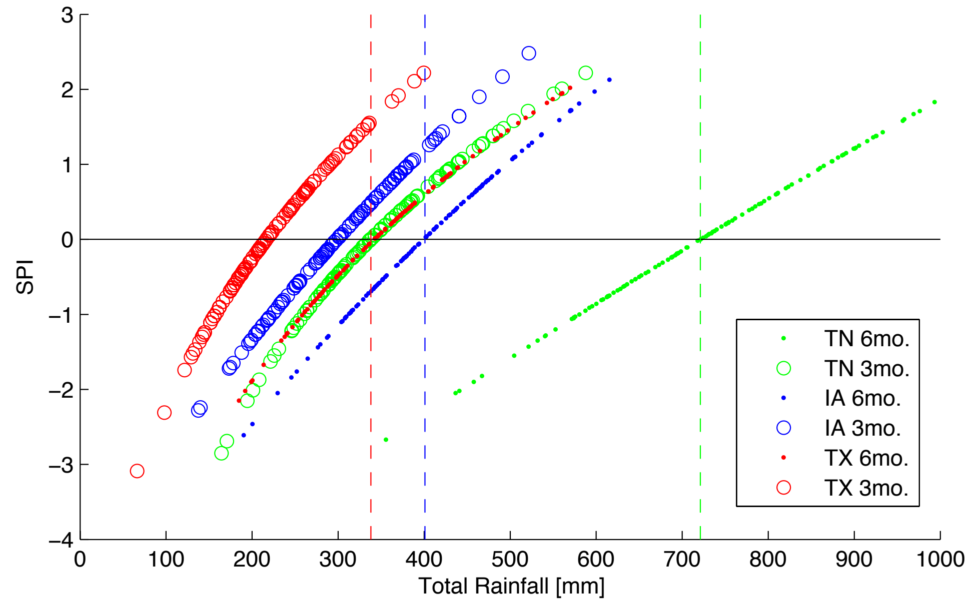

Figure 6. SPI-3 (April to June) and SPI-6 (January to June) plotted against rainfall for three states. Dashed vertical lines indicate median six-month rainfall.

Figure 6 illustrates, among other things, when precipitation is expected to occur in each state. In Iowa, more precipitation falls in the first three months of the year than in the second, as the median 3-month total increases from 280 to 400 mm. The opposite is true in Tennessee, where the 6-month median is more than twice the 3-month median. This sort of figure also illustrates the range of expected precipitation values based on the slopes of the lines. The 6-month Tennessee values cover a much wider range than the 6-month Texas values, for example. The three 3-month curves are close in slope.

1.4.3.2 Role of Irrigation in US Agriculture

Irrigation is a tool used to combat local water deficiency. Historically, irrigation was used as a national development tool in the West; western irrigation made agriculture possible, and agriculture supported industrial and commercial development. Interestingly, the U.S. Bureau of Reclamation is one of the biggest water providers in the western 17 states, and takes the name "reclamation" from an early federal policy goal to reclaim the land from its original, inhospitable state. As a result of this national approach to westward expansion, irrigation was given favourable treatment in policy. Water rights in the west follow prior appropriation doctrine, meaning the first to use a water resource for a productive application (i.e., agriculture) was given legal right to use that water going forward. Additionally, federally managed water made available for agriculture is very inexpensive to farmers and does not factor into the economic decision making of the individual farmer. Somewhat counter-intuitively, the value of that water to agricultural consumers is generally much lower than the value of water to industrial or residential consumers. If new agricultural consumers have no water appropriated to them (for example, in states or locations were there is not a lot of existing irrigation, such as the Southeast), and must compete with non-agricultural interests, water costs could be much greater than they are for western farmers. There is also interesting discussion surrounding the changing public opinion on the subject of national water priorities shifting away from agriculture. As a result of these complexities, no specific water prices or rights issues are dealt with quantitatively in this dissertation.

Again last night I had that strange dream,
Where everything was exactly how it seemed.
Concerns about the world getting warmer.
People thought that they were just being rewarded
For treating others as they'd like to be treated,
For obeying stop signs and curing diseases,
For mailing letters with the address of the sender.
Now we can swim any day in November.

"Sleeping In", The Postal Service

Chapter 2. Uncertainty in Life-Cycle Greenhouse Gas Emissions from Biofuels[1]

2.1 Abstract

Biofuels have received legislative support in California's Low-Carbon Fuel Standard and the Federal Energy Independence and Security Act. Both discuss new fuel types, but neither provides methodological guidelines for dealing with the inherent uncertainty in evaluating potential life-cycle greenhouse gas emissions from biofuels, as emissions reductions are based on point estimates only. This work demonstrates the use of Monte Carlo simulation to estimate life-cycle emissions distributions from ethanol and butanol from corn or switchgrass. Modelled distributions of life-cycle emissions for each feedstock and fuel pairing span an order of magnitude or more. Using a streamlined life-cycle assessment, corn ethanol emissions range from 50 to 200 g CO_2e/MJ, and each feedstock-fuel pathway studied shows some probability of greater emissions than a distribution for gasoline. Potential GHG emissions reductions from displacing fossil fuels with biofuels are difficult to forecast given this high degree of uncertainty in life-cycle emissions. This overall uncertainty is driven by the importance and uncertainty of emissions due to indirect land use change.

2.2 Introduction

Two pieces of legislation were recently passed in the US, the 2007 Energy Independence and Security Act (EISA) and the 2007 California Low-Carbon Fuel Standard (CA LCFS) [14], [16]. The renewable fuel standard (RFS) included in EISA addresses both national security

[1] This chapter is based on the following published paper: Mullins, K. A., Griffin, W. M., and Matthews, H. S. (2011) Policy implications of uncertainty in modeled life-cycle greenhouse gas emissions of biofuels, *Environ. Sci. Technol 45*, 132–138.

issues related to petroleum supply and the threats of anthropogenic climate change, specifying types of fuels, volumes required, and fuel life-cycle GHG reduction requirements. The life-cycle targets for expected corn and switchgrass ethanol emissions are 20% and 60% lower than gasoline, respectively. The CA LCFS requires the state fuel mix to have 10% lower emissions than would occur from fossil fuels alone by 2020 and promotes the use of life-cycle analysis to categorize acceptable fuel-process combinations. These acts require only the use of point estimates of emissions for each fuel classification. This reflects historic trends in the literature for biofuel life-cycle emissions calculations. Many studies aim to refine current models to produce increasingly precise emissions estimates, and mainly cover current- and near-term fuel types (primarily ethanol and biodiesel) and feedstocks (for example [39-41]). Encouragingly, several recently published studies have begun to address uncertainty in modeling biofuel systems [42], [43]. Both use Monte Carlo simulation as a tool to investigate the range of potential values for biofuel pathways and influential parameters in the model. Neither paper addresses indirect land use change (ILUC) or the policy implications of recent legislation given the uncertainty.

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

Based on trends in biofuel research, new fuel life cycles will need to be evaluated in the near future. This next generation research generally addresses two topics: new fuel types and non-fermentative production methods [44-49]. These papers reveal that longer-chain alcohols, particularly butanol and its isomers, are attractive alternatives to ethanol due to higher energy density (28 MJ/L LHV versus 21 MJ/L for ethanol) and greater compatibility with current fuel distribution infrastructure. The literature also describes how modifying microbial metabolism can produce these new fuel types. These novel production methods have little to no production-scale data (particularly at mandated fuel volumes), making life-cycle emissions difficult to predict and their contribution to compliance with renewable or low-carbon fuel standards even more difficult to forecast.

This chapter uses a streamlined life-cycle emissions model with Monte Carlo simulation to quantify the uncertainty in life-cycle GHG emissions associated with ethanol and butanol production from both corn and switchgrass feedstocks. The focus of this work is not to put forth a set of emissions values or ranges but to raise discussion concerning the implications of basing policy on life-cycle emissions data or methods that are uncertain.

2.3 Methods

Life-cycle assessment [20] allows for a holistic characterization of a process. This work utilizes a streamlined approach [50] focusing on the major life-cycle stages with respect to greenhouse gas emissions. This model considers six life-cycle stages: land use change; feedstock production; feedstock transportation; fuel production; fuel distribution; and, fuel combustion. These are illustrated in Figure 7. The functional unit of this study is 1 MJ fuel produced.

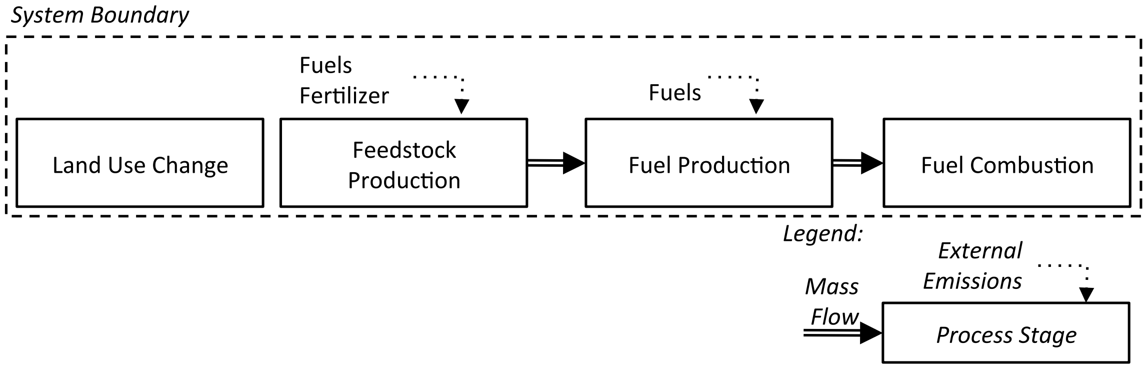

Figure 7. Ethanol life-cycle assessment system boundary.

The fuel production stage is central to this model, as the processes and resulting emissions depend on both feedstock and fuel. A thermodynamic model of maximum fuel yield from each feedstock provides a lower bound for feedstock quantity required per MJ fuel output. Contrasting these bounds with realistic fuel yields used in current models demonstrates the impact of technology and/or efficiency improvements on life-cycle emissions. To overcome the lack of production data for new fuels and production methods, production processes are based on currently modeled processes from the literature. Production energy demands are assumed to scale with fuel energy output. The upstream stages (land use change, feedstock production and transportation) depend only on feedstock type, with feedstock quantity depending on the thermodynamic model. Downstream stages (fuel distribution and combustion) depend on fuel type. Emission factors for upstream and downstream emissions are taken from the literature, and summarized in the following sections and in Appendix A. Life-cycle fossil fuel emissions factors are taken from Argonne's GREET model [51] and are common across all feedstock-fuel pairs to facilitate inter-fuel comparisons.

Five model runs are discussed in this paper. The first case is a set of point estimates used to obtain life-cycle emissions for the purposes of model calibration. The second uses parameter distributions for select input assumptions for use in Monte Carlo simulation (Table 6). The third is a modification of the Monte Carlo simulation (second scenario) that differs only in assuming maximum theoretical fuel yield values. The fourth is a modification of the second scenario that differs only in assuming a lower modal value in the switchgrass yield parameter distribution. The fifth scenario differs from the second only in excluding indirect land use change emissions (i.e., assuming zero ILUC emissions), while keeping the DLUC and carbon sequestration distributions.

2.3.1 Determining Fuel Yields

Biochemically converting feedstock to fuel can be broken into two steps: conversion of feedstock to sugar(s) (hydrolysis), and conversion of sugar to fuel (fermentation). Details, including sugar types and non-sugar components, are included in Appendix A.

In corn, starch can be hydrolyzed, or 'cooked', using steam and amylase. In switchgrass, hemicellulose is separated from cellulose and hydrolyzed using some combination of steam and dilute acid or base. An enzyme such as cellulase or a high-concentration acid solution catalyzes cellulose hydrolysis [13]. This model assumes 90% yield (base case) of hydrolysate for both feedstocks. Once hydrolyzed, monomeric sugars can be converted to an alcohol (i.e., fuel) with an assumed 95% glucose conversion efficiency, and 85% efficiency for all other sugar types [52].

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

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

Assuming average yields of 17 Mg dry matter (dm)/ha switchgrass [8] and 9.8 Mg dm/ha corn [53] and non-idealized hydrolysate and fuel yields, land requirements are approximately 0.01 m^2 corn/MJ fuel and 0.007 m^2 switchgrass/MJ fuel.

2.3.2 Land Use Change

Land use change resulting from biofuel life-cycle activities can be divided into two categories: direct land use change (DLUC) and, indirect land use change (ILUC). For EISA, the EPA performed an LCA for both corn and switchgrass ethanol, among other feedstock-fuel pairs [54]. Base case emissions factors for DLUC and ILUC for corn and ILUC for switchgrass are taken from this study, scaled based on increased fuel yield per hectare (89% for corn, 73% for switchgrass) to account for decreased land demand under higher feedstock yield and fuel conversion yields based on the assumptions made in this model. DLUC and ILUC emissions are 0.30 and 5.5 Mg CO_2e/ha/year respectively. Note that corn growth provides no soil carbon sequestration. This model takes switchgrass DLUC emissions to be a combination of direct conversion emissions from the California LCFS study [18], totaling 2 Mg CO_2e/ha/year, and a soil carbon sequestration value of 2 Mg CO_2e/ha/year from [8]. These assumed land use conversion and soil carbon sequestration emissions balance, which approximately matches the slight negative total calculated by the EPA study [54].

These land use emission factors are 30-year totals, undiscounted and amortized evenly over the time period (following Searchinger [30] and one EPA scenario). Time period and discount rate both impact land use emissions factors, but are not examined here (see [54] or [55] for an analysis of these variables). That said, work done by Schwietzke et al. suggests that emissions timings are not of critical importance given uncertainty in other parameters [56].

2.3.3 Feedstock Production

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

Fertilizer production is fossil fuel intensive, generating 3 kg CO_2e/kg N [51]. Corn requires more fertilizer than switchgrass, averaging about 150 kg N/ha [57] versus 74 kg N/ha [58].

Fertilizer application produces N_2O emissions via direct and indirect mechanisms. Direct emissions result from the nitrification-denitrification cycle on the field. Nitrogen is applied in the form of ammonium (NH_4^+), which is oxidized to nitrate (NO_3^-) by soil microbes. N_2O is a leaked intermediary of this oxidization and a by-product of the subsequent reduction of nitrate to N_2. Decomposition of uncollected crop residues also produces N_2O, which is included in feedstock production emissions. Indirect emissions are also a result of this nitrification-denitrification process, but the reaction takes place off the field. Nitrogen is volatized to ammonia and NO_x and deposited elsewhere, or transported by leaching and runoff. Estimates of switchgrass nitrogen requirements have increased over time as the relationship between nitrogen and deep root formation becomes better understood, so recent N_2O emissions estimates tend to be higher than previous. These emissions are modeled based on IPCC definitions (see [59]) and calculation methods. Emissions are 100 g CO_2e/kg corn and 68 g CO_2e/kg switchgrass, from IPCC Equations 11.6 and 11.7, using listed values for corn and field grasses (IPCC report Table 11.2), and assumed nitrogen application rates and feedstock yields.

2.3.4 Fuel Production

The production process varies by feedstock input and fuel output. As a result, modeling this life-cycle stage requires four semi-distinct models for each of corn or switchgrass butanol or ethanol. Figure 8 shows process steps for fuel production for corn and switchgrass as feedstocks. Process steps unique to each fuel include fermentation and fuel concentration/purification. Differing enzyme activity for fermentation and differing degrees of fuel solubility in water necessitate unique concentration/purification activities and process energy.

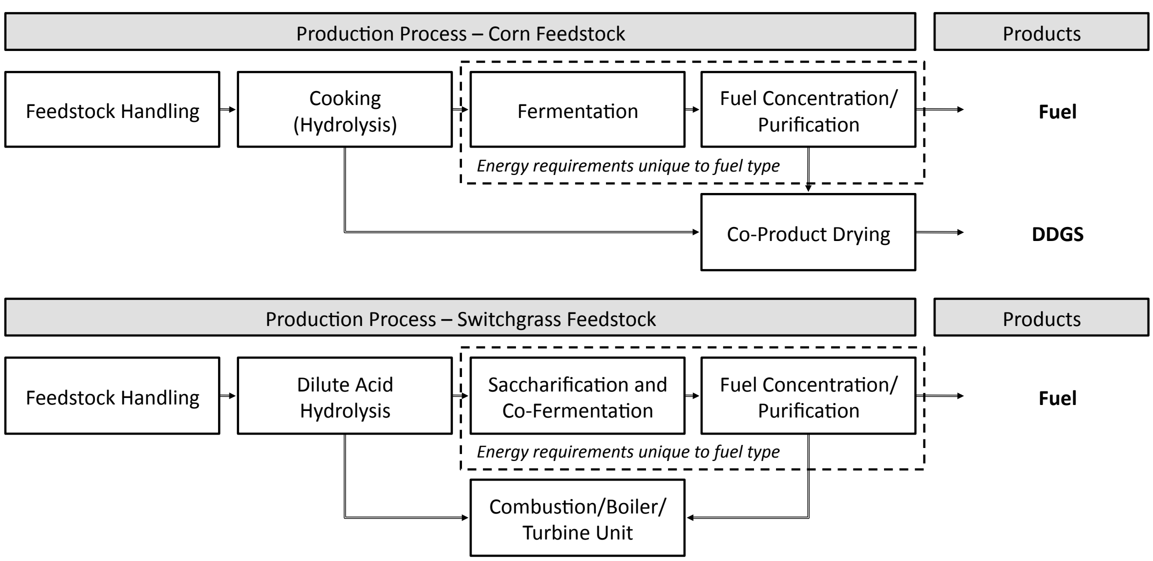

Figure 8. Fuel production processes.
Arrows indicate mass flow, and dashed boxes indicate stages where energy requirements are unique to the fuel type even with the same feedstock.

The corn ethanol process is assumed to be the USDA's corn dry-grind model [60]. Process electricity is from the grid and process heat is generated by natural gas combustion. To keep production systems between fuels as consistent as possible, the model maintains common process steps from the USDA model for butanol, replacing only the fermentation and fuel concentration/purification steps with those modeled by Wu [61]. This model assumes butanol is the sole fuel produced (allowing a closer comparison with corn) whereas Wu's process yields acetone, butanol and ethanol (ABE). ABE production process energy is used to approximate energy to produce maximum yield butanol. Energy use by stage is listed in Table 2, and total energy requirements are 0.46 MJ/MJ corn ethanol and 0.70 MJ/MJ corn butanol.

Table 2. Energy requirements for corn ethanol production.

	Electricity (MJ/MJ fuel)		**Heat** (MJ/MJ fuel)	
	Ethanol	*Butanol*	*Ethanol*	*Butanol*
Feedstock Handling	0.0051	0.0051	0	0
Hydrolysis	0.0019	0.0019	0.071	0.071
Fermentation	0.0034	0.013	0	0.46
Fuel Distillation	0.0005	0	0.17	0
Co-Product Handling	0.027	0.021	0.18	0.13
Total	*0.038*	*0.041*	*0.42*	*0.66*

Production of fuel from corn yields distiller's dried grains with solubles (DDGS), a co-product marketable as animal feed. Consistent with EISA and CA LCFS, system expansion is used to model emissions credits for DDGS displacement of soy meal. This value is 15 g CO_2e/MJ fuel, taken as an average value from GREET and BESS (summarized by [41]).

The switchgrass ethanol process is that of Aden et al. [52]. Non-fermentable portions of the feedstock and un-fermented sugars are supply process energy; they are combusted to generate steam for process heat and to drive a turbine. This model uses a 68% efficient boiler to provide steam, with surplus heat going to drive an 85% efficient turbine. In the case of insufficient energy available from these switchgrass components (e.g., the scenario where fuel production efficiency is maximized), the model considers two sources of supplemental process energy: additional switchgrass fed directly into the boiler, or natural gas and grid electricity (as is the case for corn fuels). Emissions for switchgrass as an energy source are based on upstream emissions from this model, 0.3 kg CO_2e/kg switchgrass from base-case assumptions. In the case of excess electricity, surplus electricity is sold to the grid for credit (0.2 kg CO_2e/MJ). Switchgrass energy content is based on expected composition [12] and energy density of each compositional element as listed in [52].

Cellulosic butanol is possible (see [62-64]), but no large-scale production models currently exist. Butanol production energy requirements are estimated by taking Wu's fermentation and distillation energies and replacing those steps in Aden's model, adjusted to account for the saccharification of cellulose within the fermentation step. Energy use by stage is listed in Table 3, and total energy requirements for switchgrass ethanol are 0.58 MJ/MJ and 0.82 MJ/MJ for butanol.

Table 3. Energy requirements for switchgrass ethanol production.

	Electricity (MJ/MJ fuel)		**Heat** (MJ/MJ fuel)	
	Ethanol	*Butanol*	*Ethanol*	*Butanol*
Feedstock Handling and Hydrolysis	0.015	0.015	0.15	0.15
Fermentation and Distillation	0.043	0.043	0.37	0.61
Total	*0.058*	*0.058*	*0.52*	*0.76*

2.3.5 Fuel Distribution

Post-production emissions depend only on fuel type, not on feedstock. Point estimate GREET model values for modal distribution (e.g., train, truck) and fuel type consumed by mode were assumed, listed below in Table 4 and Table 5. Ethanol emissions are 1.2 g CO_2e/MJ, 20% greater than those of butanol per functional unit due to the higher volumetric energy density of butanol.

Table 4. Modal distributions assumed for butanol and ethanol.

Mode	%	Distance (mi)	There (Btu/ton-mi)	Back (Btu/ton-mi)
Barge	40%	520	431	328
Pipe	0	600	253	0
Rail	40%	800	270	0
Truck	20%	80	1099	1099
Truck	100%	30	1099	1099

Table 5. Distribution of energy sources for each fuel transportation mode.

	Barge	Pipeline	Rail	Truck
Diesel	0%	20%	100%	100%
Residual Oil	100%	50%	0%	0%
Natural Gas	0%	24%	0%	0%
Electricity	0%	6%	0%	0%

2.3.6 Fuel Combustion

Following prior work (such as [39-41]), the only source of carbon in the fuel is assumed to be from the source feedstock, which in turn was provided by environmental carbon, so the CO_2 released is assumed to replace exactly that which was used to produce the feedstock. Thus, net combustion emissions are zero.

2.3.7 Monte Carlo Simulation

The simulation methodology is guided by a well-known reference on uncertainty [65]. Distributions are fitted where sufficient data are available (e.g., crop yields) or assigned based on min/max and modal values to model parameters. Monte Carlo simulations enable an investigation into how input uncertainty propagates through the life-cycle emissions model. The model code for Matlab is included in Appendix B. These distributions and underlying data sources are summarized in Table 6. The greatest uncertainty is associated with the land use change emissions, the N_2O emissions factors, and production emissions, where greater uncertainty is associated with the switchgrass and the butanol pathways, as fuels from switchgrass and butanol from any feedstock are currently unproven processes at any sort of large scale.

Table 6. Parameters for Monte Carlo simulation.

Parameter	Distribution	Unit	Data Source(s) and Notes
Parameters Common to Both Feedstocks			
Emissions Factor, Direct N_2O	Triangular (0.003, 0.01, 0.03)		Factor in direct N_2O calculations using IPCC 2006 methodology [59]
Emissions Factor, Indirect N_2O	Triangular (0.002, 0.01, 0.05)		Factor in indirect N_2O calculations using IPCC 2006 methodology [59]
Hydrolysis yield	Uniform (0.85, 0.95)		[66]
Glucose yield	Uniform (0.85, 1.0)		Yield of both fuels assumed the same. Ethanol yield of this magnitude is near-term realistic, butanol yield longer-term. Yield data from [66]
Other sugar yield	Uniform (0.75, 0.9)		Includes: Arabinose, Xylose, Mannose, Galactose. Yield of both fuels assumed the same. Ethanol yield of this magnitude is near-term realistic, butanol yield longer-term. Yield data from [66]
Parameters for Corn as Feedstock			
Corn yield	Beta (α=21.62, β=5.86, [0,14.3])	Mg dm/ha	Fit to USDA corn-for-grain 2007 county-level data for Midwestern states (IL, IN, IO, KA, MI, MN, MO, NE, ND, OH, SD, WI)
Corn starch content	Triangular (62.6,67.3,72)	%w	[60], [67]
Indirect Land Use Change emissions	Triangular (0, 5.5, 11.7)	Mg CO_2e /ha/year	Mode: [54]. Lower bound 0 and upper bound from [30]
Direct Land Use Change emissions	Triangular (0, 0.3, 4.5)	Mg CO_2e /ha/year	Mode: [54].Lower bound 0 and upper bound from [29]
Nitrogen Application	Triangular (141,150,160)	kg N/ha	[57]
Production electricity, ethanol	Triangular (0.023, 0.038, 0.049)	MJ/MJ etOH	Mode: [60] model. Literature survey [68] provides lower bound from his work, upper bound from [69]
Production heat, ethanol	Triangular (0.32, 0.42, 0.51)	MJ/MJ etOH	Mode from [60] model. Literature survey from [68] provides lower bound from his work, upper bound from [69]
Production electricity, butanol	Uniform (0.031, 0.051)	MJ/MJ buOH	Base case from [61] model. Upper and lower points taken as % higher and lower than likely value from ethanol model.
Production heat, butanol	Uniform (0.50, 0.83)	MJ/MJ buOH	Base case from [61] model. Upper and lower points taken as % higher and lower than likely value from ethanol model.
Parameters for Switchgrass as Feedstock			
Switchgrass yield	Beta (α=21.62, β=5.86, [0,21.6])	Mg dm/ha	Yield data for sample plots from [8] used to calculate appropriate distribution mean. Distribution shape parameters assumed the same as from USDA 2007 corn data.
Switchgrass yield (Scenario 4 only)	Triangular (5.2, 12.9, 21.6)	Mg dm/ha	Lower bound from [58], mode from [70], upper bound as above [8]
Glucan content	Triangular (31.0, 34.4, 37.2)	%w	[12]
Xylan content	Triangular (20.6, 22.9, 26)	%w	[12]

Parameter	Distribution	Unit	Data Source(s) and Notes
Mannan content	Triangular (0.29, 0.32, 0.36)	%w	[12]
Galactan content	Triangular (0.67, 1.0, 1.2)	%w	[12]
Arabinan content	Uniform (2.6, 3.4)	%w	[12]
Lignin content	Triangular (17.3, 19.2, 21.1)	%w	[12]
Indirect Land Use Change emissions	Triangular (0, 1.7, 15)	Mg CO_2e /ha/year	Mode: [54]. Lower bound 0 and upper bound from [30]
Direct Land Use Change emissions	Triangular (0, 2, 4.5)	Mg CO_2e /ha/year	Mode: [54]. Lower bound 0 and upper bound from[29].
Carbon sequestration	Triangular (0.73, 1.95, 4)	Mg CO_2e /ha/year	[71], [72]
Nitrogen Application	Triangular (55, 74, 100)	kg N/ha	[72] for upper and lower bounds, [58] for mode
Production energy, ethanol	Uniform (0.44, 0.72)	MJ/MJ etOH	[52] for expected value, [73] for lower bound and range (from presented literature review). Assume constant split between heat and elec as total varies.
Production energy, butanol	Uniform (0.63 1.20)	MJ/MJ buOH	[52], [61]. Percentage below and above likely value taken from etOH distribution to provide lower value, doubled to provide upper production value. Assume constant split between heat and electricity as total varies.

2.4 Results and Discussion

2.4.1 Model Calibration

Total point estimate emissions of 45 g CO_2e/MJ for corn ethanol, which excludes the land use stage, from this model are comparable to other studies with similar system boundaries ([41], [51], [74] find 41, 58 and 60 g CO_2e/MJ respectively). Corn butanol emissions are about 20% higher than those of corn ethanol, which is consistent (though greater) than the difference in one other corn butanol LCA [61]. Higher butanol life-cycle emissions are mainly due to higher fuel production emissions and a lower DDGS emissions credit compared to corn ethanol. The upstream stages for corn ethanol and butanol are common. Complete point estimate life-cycle emissions for each feedstock-fuel pathway are broken down by stage in Appendix A, with net emissions summarized in Table 7.

2.4.2 Simulation Results

Figure 9 shows PDFs for six combinations of feedstock, fuel type and production energy source. Mean values are summarized in Table 7, and complete distribution statistics are included in Appendix A.

Four cases for switchgrass (SW) as feedstock are investigated in this model: two using fossil fuels in the form of grid electricity and natural gas for heat (noted with [FF]) for production process energy, and two using the direct combustion of switchgrass for heat and electricity (noted with [SWf]). Switchgrass ethanol production sees an electricity surplus because the energy in the lignin and unfermented sugars is greater than the heat and electric energy required in the production process. As a result, the pathway has negative production emissions due to a grid electricity displacement credit. The SW EtOH [FF] and [SWf] cases are very similar because a supplementary source of energy is required only under a small set of simulated input values. Butanol production energy demand exceeds the amount available in lignin and unfermented sugars; therefore, external energy is required. Fossil fuel emissions factors are greater than that of switchgrass (0.02 kg CO_2e/MJ), accounting for the large production emissions difference between the two butanol cases.

Table 7. Summary of total emissions from point estimate and Monte Carlo simulations.

Model (Shorthand)	**Point Estimate Scenario Emissions** *(g CO_2e/MJ)*	**Mean Emissions from Monte Carlo (MC) Simulations** Base MC Scenario *(g CO_2e/MJ)*	MC, max fuel yield *(g CO_2e/MJ (%))*	MC, lower SW yield *(g CO_2e/MJ (%))*	MC, no ILUC *(g CO_2e/MJ (%))*
Corn ethanol (Corn etOH)	101	112	97 (-13%)[1]	n/a	63 (-44%)
Corn butanol (Corn buOH)	119	131	115 (-12%)	n/a	81 (-38%)
Switchgrass ethanol, fossil fuel production energy (SW etOH [FF])	18	50	68 (+36%)	71 (+42%)	6 (-88%)
Switchgrass ethanol, switchgrass production energy (SW etOH [SWf])	18	48	59 (+23%)	69 (+44%)	4 (-92%)
Switchgrass butanol, fossil fuel production energy (SW buOH [FF])	48	90	98 (+9%)	112 (+24%)	46 (-49%)
Switchgrass butanol, switchgrass production energy (SW buOH [SWf])	31	76	77 (+1%)	99 (+30%)	32 (-58%)

1- the percentages in MC with max fuel yield, MW with lower SW yield, and MC with no ILUC are changes from the Base MC Scenario.

Maximizing fuel yield presents diverging impacts for corn- and switchgrass-based fuels. As shown in Table 7 Column 3, mean GHG emissions decrease for corn by more than 10%. Upstream emissions decrease due to decreased land demands resulting from lower feedstock requirements. In contrast, GHG emissions for switchgrass-based fuels increase with increasing fuel yields. While upstream emissions decrease with decreased land demands, the unfermented sugars that provide process energy (and potentially an electricity displacement credit) vanish with maximum fuel yields. The result is that all feedstock-fuel pathways require supplementary process energy, thereby producing GHG emissions rather than receiving a GHG credit. The increased process emissions outweigh the decreased upstream emissions, resulting in increased total emissions for the switchgrass pathways.

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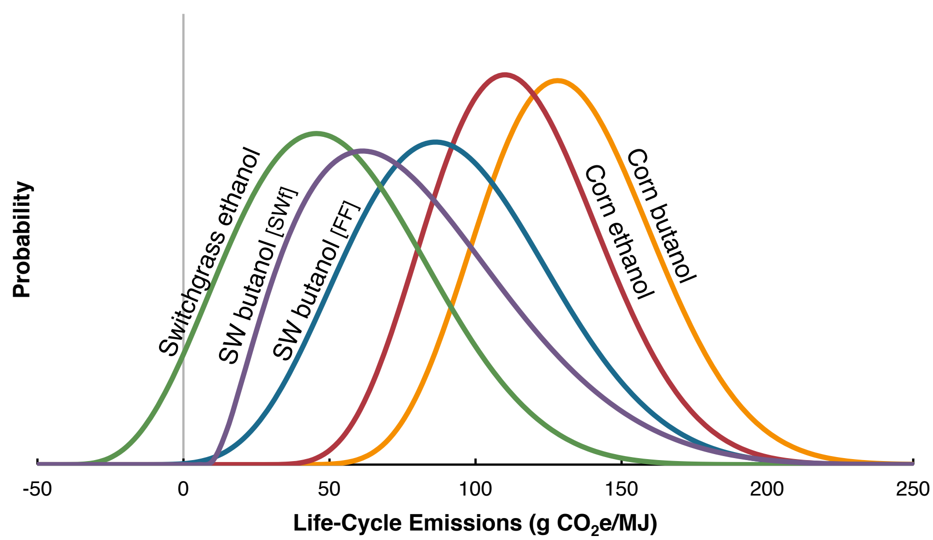

Figure 9. Probability distributions for total GHG emissions.
Curve identifications list shorthand for feedstock type, fuel type and production energy source (if necessary) as listed in Table 7.

The switchgrass emissions distributions are wider than those of corn due to greater uncertainty associated with this less proven cellulosic production pathway. This model assumes that the switchgrass distribution has the same negatively skewed shape as corn. When this distribution is adjusted to reflect lower yields found in the literature than assumed in the base case (assigning a new yield distribution with lower bound 5.2 Mg/ha from Schmer et al. [58], mode 12.9 Mg/ha from Wullschleger et al. [70] and keeping the upper bound constant), both the mean values of the swichgrass-based fuels and the uncertainty associated with the output distributions are greater. Figure 10 shows the impact of these yield change on the switchgrass ethanol PDF.

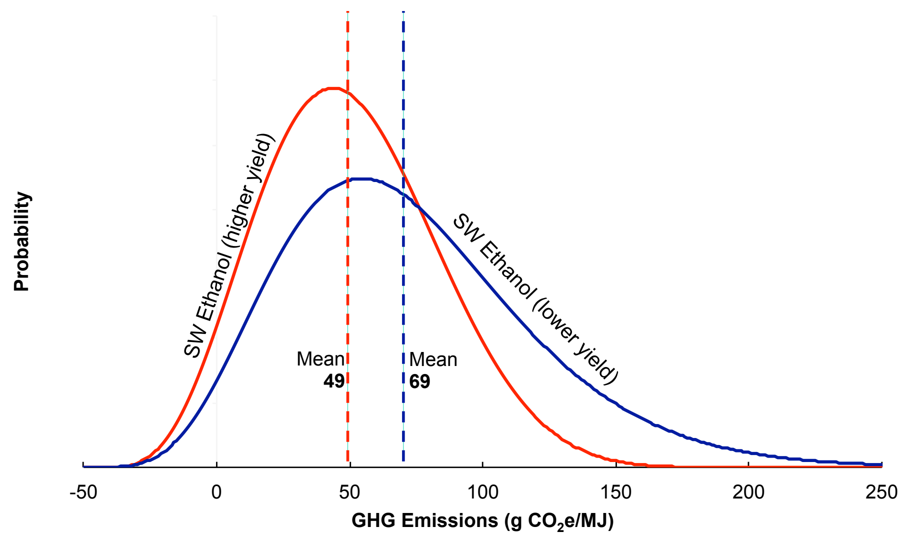

Figure 10. Impact of shifting the mean switchgrass yield on final emissions probability distribution.

Feedstock yield determines upstream emissions, which include the highly uncertain ILUC emissions (distribution mode adjusted to 2.3 Mg CO_2e/ha/year to account for the lowered yield), so changes here have substantial impacts on the expected life-cycle emissions, as shown in the mean value changes in Table 7 Column 4. For switchgrass to provide convincingly low carbon fuels, yields must be carefully tracked because of their large impact on emissions calculations.

As mentioned previously, there is no correlation assumed between the parameters input into the Monte Carlo simulation. Generally, when correlation is introduced into these simulations, the standard deviation of the distributions decrease while the mean remains about the same. This outcome is illustrated nicely in a paper by Bojacá and Schrevens discussing stochastic sampling under correlation when modelling parameter uncertainty in these sorts of models [75]. The impact of correlation on the interpretation of the model results presented here is that the mean values for the various fuels would remain in the same rank order, and in the same category regarding whether or not the fuel has greater or less emissions than gasoline. With less variance in output distributions for life-cycle greenhouse gas emissions for each fuel, there is less overlap between distributions, so the likelihood that corn will have greater emissions than gasoline will increase, and the likelihood that switchgrass ethanol has lower emissions than gasoline will increase, because of their relative positions compared to the gasoline distribution.

2.4.3 Model Sensitivity to Input Parameters

The sensitivity of the total life-cycle greenhouse gas emissions to each of the input parameter distributions (listed in Table 6) is calculated using Spearman's rank-order correlation. Table 8 shows this correlation coefficient as well as the percent contribution to variance for the uncertain input parameters for the ethanol fuel pathways presented above, with a cut-off value at a 1% threshold. Butanol data are similar, and are included in Appendix A. If better characterized, it is this ordered list of parameters most influential in driving emissions that offers the greatest opportunity to decrease the overall uncertainty associated with life-cycle biofuel emissions.

The ILUC emissions factor is overwhelmingly the key parameter for each scenario, due to both the high contribution to total emissions from ILUC and the high degree of ILUC uncertainty (i.e., wide distribution of possible values). Improving the economic models that forecast indirect land use change and associated emissions presents an opportunity to greatly increase the confidence with which biofuels emissions can be predicted. This, of course, assumes ILUC uncertainty can be substantially reduced with better knowledge; some argue much of this uncertainty is irreducible, at least in the near future [76], so an emissions range that spans an order of magnitude may be the best one can anticipate.

Table 8. Percent contribution to variance and rank order correlation values for three ethanol pathways.

Parameter	Corn ethanol		SW etOH FF		SW etOH SWf	
	ConV (%)/ ROVC					
ILUC emissions factor	85.1%	0.91	66.2%	0.79	70.5%	0.81
DLUC emissions factor			4.6%	0.21	5.0%	0.22
Soil C sequestration factor			2.8%	-0.16	3.0%	-0.17
Direct N_2O emissions factor	4.1%	0.20	2.7%	0.16	2.9%	0.17
Feedstock yield	6.7%	-0.25	1.8%	-0.13	1.9%	-0.13
Production energy			17.0%	0.40	13.4%	0.36
Glucose conversion efficiency	2.2%	-0.15				
Hydrolysis efficiency			3.0%	0.17	2.0%	0.14

The direct N_2O emissions factor plays a significant role in total emissions for all feedstock-fuel pathways. IPCC [59] is not the only source admitting uncertainty in N_2O emissions from nitrogen fertilizer. In a widely cited paper, Crutzen et al. [77] suggest total N_2O emissions are 5 to 8% of applied N (by mass), which is greater than the total using the IPCC 1% factor in each of the direct and indirect N_2O calculations. Using the ranges, rather than point estimates, listed in the IPCC report, this 5 to 8% range falls within the possible emissions in this model. So, it is really the mode that is controversial.

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

The shape of each life-cycle emissions distribution (Figure 9) reflects the influence of these key parameters. For example, the ILUC emissions factors for corn are more symmetric than for switchgrass, which are positively skewed. There is corresponding symmetry and skew in distributions for corn fuels and switchgrass (SWf) fuels, respectively.

To further explore the impacts of the identified key variables, each was fixed, in turn, and the resulting overall life-cycle emissions for the corn ethanol case are presented in Figure 11. The variables are all fixed at an extreme value, the 95th percentile, with the base case presented as the first distribution plotted. Three variables which are in some way an efficiency (hydrolysis efficiency, feedstock yield, and starch content in feedstock composition) will shift the distribution towards lower emissions values when pegged at a high value because their output is negatively correlated with the final distribution; when the system runs more efficiently in some regard, emissions decrease. The other four variables are positively correlated with the final output, so when they are pegged at a high value, the output distribution is shifted towards higher emissions values. Fixing the ILUC parameter has the greatest impact by one measure: it shifts the median value the most, and completely relocates the inter-quartile range. Fixing the feedstock yield at a high value reduces the variance to the greatest degree. This is because so many impacts through the upstream stages of the life cycle depend on the area of land per unit feedstock produced. DLUC and N_2O volatization are second and third to ILUC in terms of how substantial the inter-quartile shift is.

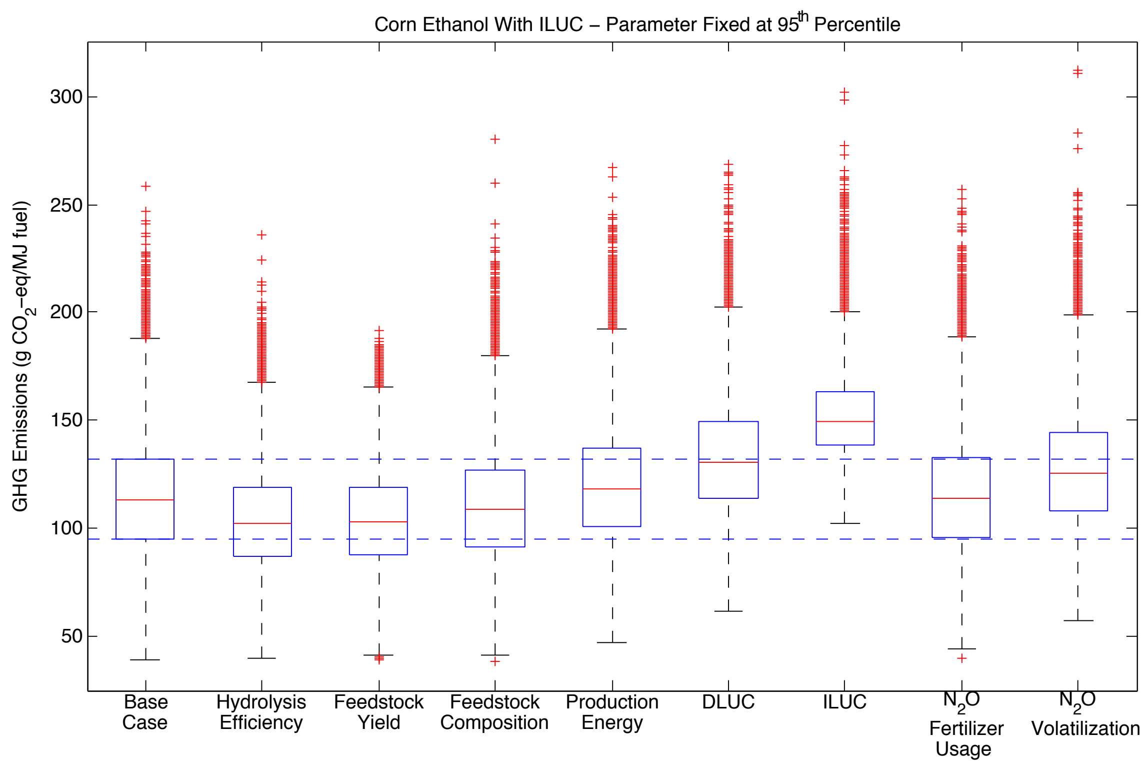

Figure 11. Impact on the distribution for corn ethanol of fixing each of the listed key parameters at their 95th percentile value.[2]

2.4.4 Butanol Compared with Ethanol

This chapter considers butanol from the greenhouse gas reduction perspective rather than from an economic perspective. In light of the Monte Carlo simulation results (see Figure 9), it seems butanol will have higher greenhouse gas emissions than ethanol produced from the same feedstock. The upstream emissions will be essentially the same for both fuel types, as they depend on are feedstock, and both fuel types require about the same mass of feedstock per unit of energy output (105 g switchgrass/MJ or 115 g corn/MJ). Though ethanol has a higher theoretical conversion efficiency than butanol (51% versus 41% by weight as a theoretical maximum), butanol has a higher energy density, so the input mass per unit energy output is very close [78].

[2] For this, and future, boxplots, the ranges are calculated as follows: The box, from bottom to top, indicates the 25th (Q1), 50th and 75th (Q3) percentile values from the data plotted. The interquartile range (IQT) is Q3 – Q1. The whisker below is defined as Q1 – 1.5IQT and the whisker above is defined as Q3 + 1.5IQT. Outliers fall outside of this whisker range.

The production emissions for butanol are higher than those of ethanol because butanol is more difficult to separate from water than ethanol, so, with currently available separation techniques, butanol will always require greater energy input than ethanol. In the downstream (distribution) phase of the life cycle, butanol does have an advantage over ethanol in greenhouse gas emissions. Due to its increased volumetric energy density, it costs less energy to transport butanol than ethanol; however, the distribution is such a small portion of total life-cycle emissions that this does not shift the balance in butanol's favour.

Note that this overall conclusion concerning buthanol is similar to that found by Wu et al. [61], though more favourable yields for butanol are assumed in this study. However, the US EPA found opposite results in the most recent RFS analysis document [15]. The EPA study suggests that corn ethanol offers 7-32% emissions reductions from gasoline, where corn butanol offers 20-40% reductions. Though several model assumptions differ between this work and that done by the EPA, the difference is largely due to assumptions of lower natural gas use in the fuel production stage; 0.66 MJ natural gas/MJ butanol (this study) versus 0.27 MJ natural gas energy/MJ butanol (EPA). This difference suggests that there is further research needed into the production requirements of butanol, as different assumptions arise from an as-of-yet unproven fuel type and lead to completely different comparative conclusions.

This isn't your song. This isn't your music.
How can they be wrong when
by committee they choose it all?
They choose it all.

"Plasticities", Andrew Bird

Chapter 3. Uncertainty and Biofuel Policy Designs[3]

3.1 Abstract

Previous research has established substantial uncertainty in life-cycle greenhouse gas emissions from biofuels and fossil fuels, though biofuel uncertainty is much greater. Given this uncertainty, some method by which to evaluate energy policies based on point estimate life-cycle assessment (LCA) data is necessary. This chapter establishes a 'risk of policy failure' framework to quantitatively assess the likelihood of a policy achieving its goals given uncertainty in regulated emissions. This framework is applied to the Energy Independence and Security Act of 2007 (EISA), and concludes that there is a meager 10% probability that corn ethanol (including indirect land use change, ILUC, emissions) will meet the 20% reduction target, and a 40% probability that switchgrass ethanol will meet its 60% reduction target. If ILUC is excluded from the system boundary, the likelihood these fuels will meet their target emissions reductions is 70 and 95%, respectively. In considering California's Low-Carbon Fuel Standard, data collected is insufficient to reduce emissions uncertainty to a degree where point estimates are an appropriate regulatory yardstick. The policy failure framework could be modified and applied to this type of policy as well, provided emissions distributions are calculated for each regulated fuel type.

3.2 Introduction

Building upon the results from the previous chapter, this chapter discusses how biofuel policies interact with the uncertainty in biofuel emissions. Two policies are discussed, the

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[3] This chapter is based in part on the following published papers:
Mullins, K. A., Griffin, W. M., and Matthews, H. S. (2011) Policy implications of uncertainty in modeled life-cycle greenhouse gas emissions of biofuels, *Environ. Sci. Technol 45*, 132–138.
Kocoloski, M., Mullins, K. A., Venkatesh, A., and Griffin, W. M. (2012) Addressing Uncertainty in Life-Cycle Carbon Intensity in a National Low-Carbon Fuel Standard, *Energy Policy*.

renewable fuel standard (RFS) included in the Energy Independence and Security Act of 2007 (EISA), and the low-carbon fuel standard (LCFS) as implemented in California. Their structures differ, so each policy as affected by emissions uncertainty in different ways. The LCFS includes more narrowly defined fuel types than does the RFS, so before discussing how uncertainty could be built into the policy, this work examines whether or not the increased amount of data necessary (or possible to acquire) to define these specific fuel pathways obviates the need to even include uncertainty in the policy design. The chapter concludes with a discussion of the current legal battle over the implementation of the LCFS in California and some reflections on what this might mean for LCA in policy going forward.

3.2.1 Two Policies, Both Alike in Dignity[4]

There are two policy designs used in the US that specifically address the use of biofuels for transportation: an RFS such as included in EISA [14] and an LCFS as is legislated in California [16]. Broad carbon taxes or cap-and-trade programs are other approaches to address carbon emissions from the transportation sector; however, these policy designs are most often discussed in a much broader context than a single sector, so they will not be specifically discussed in this dissertation. Both the RFS and LCFS aim to increased biofuel usage with the expectation that greenhouse gas emissions will be reduced when compared to a fossil fuel-based business as usual case, but each takes a different approach to achieve this end.

The RFS increases biofuel usage in the transportation sector with specific volume mandates. The volumes increase over time, with goals in 2022 of 15 billion gallons of advanced biofuel (i.e., corn ethanol) and 22 billion gallons of other advanced biofuels (mostly cellulosic ethanol with some biodiesel) [14] which have life-cycle greenhouse has emissions lower than the

[4] In fair America where we set our scene

incumbent fuel they replace (gasoline or diesel) as determined by the EPA (summarized previously in Section 1.3.3 and Figure 3). The reasoning is that if billions of gallons of lower-emissions biofuels are used, the relative gasoline and diesel shares of fuel consumption will decrease and greenhouse gas emissions will be avoided by this policy intervention.

The LCFS encourages, rather than requires, increased biofuels usage by mandating a state-wide fuel mix GHG emissions intensity reduction target. Instead of fixing a volume, the weighted average GHG emissions intensity of the fuel mix is fixed. The reasoning here is that some set of lower-carbon fuels will be used to reduce the GHG emissions from the average MJ of fuel used in a region by the target percentage. The target in California is 10% less than GHG emissions under a fossil fuel only scenario. Most biofuel types identified by the California Air Resources Board (CARB) have lower GHG emissions per unit fuel energy ("carbon intensity") than gasoline, so they are one category available to lower that carbon intensity value. Other alternative fuel types included are electricity, liquefied or compressed natural gas, or hydrogen [79]. The regulated entity here is the fuel blender, who choses the types and composition of the fuels sold to the market. In this system, blenders have the capability to sell or buy allowances. For example, if one blender has used a set of fuels that offers only an 8% reduction, they can buy allocations of carbon intensity from a blender who has achieved a reduction in carbon intensity greater than 10%. This policy style has been described in literature as an improvement over a strictly command-and-control style biofuel policy like the RFS, primarily due to increased flexibility in possible low-carbon fuel choices and a resulting decrease in cost per ton CO_2 avoided [80], [81].

Both policies both have their shortcomings. Emissions reductions from both designs are vulnerable to general increases in the fuel usage. In the RFS case, if gasoline and diesel use outpace the increase in low-carbon biofuel usage, meaning an increase in percentage composition of biofuels in the national fuel mix is not achieved, carbon emissions will increase. Thompson and colleagues [82] find that the decrease in price of gasoline due to reduced demand caused by an increase in biofuel use from the EISA RFS actually induces increased global gasoline consumption and increased global GHG emissions. This type of indirect emissions impact is not considered in either the RFS or the LCFS. Holland et al. [81] present an economic analysis, comparing different flavours of LCFS-designed policy alongside other policy interventions that aim to decrease transportation CO_2 emissions, and arrive at similar conclusions; emissions reductions are not obtained because the overall amount of fuel consumed can increase, even though the fuel mix is changed to include more low-carbon fuels.

One challenge faced by policy designers is how uncertainty in life-cycle emissions estimates affects the usefulness of policies based on specific numerical emissions reductions targets, and the robustness of emissions reductions claims.

3.3 Risk of Policy Failure Framework

Consider a case where the mean value for a fuel just meets some legislated percentage decrease (target) requirement from a life-cycle fossil fuel emissions value. This fuel would be accepted under legislation. However, with a high degree of uncertainty there is a possibility that the alternative fuel's emissions would be higher than the required target. Also, depending on the aggressiveness of the RFS or LCFS reduction target and the level of uncertainty surrounding the biofuel, there may be some non-zero probability that biofuel emissions are actually greater than those of the fossil fuel it intends to replace; its use could actually increase emissions. This probability is illustrated in Figure 12 for two representative biofuels with differing distribution widths (the distribution width of Fuel 2 being greater than that of Fuel 1). A failure of policy occurs if emissions are greater with a biofuel than with the displaced fossil fuel. The policy could also fail if the reductions do not meet the required target.

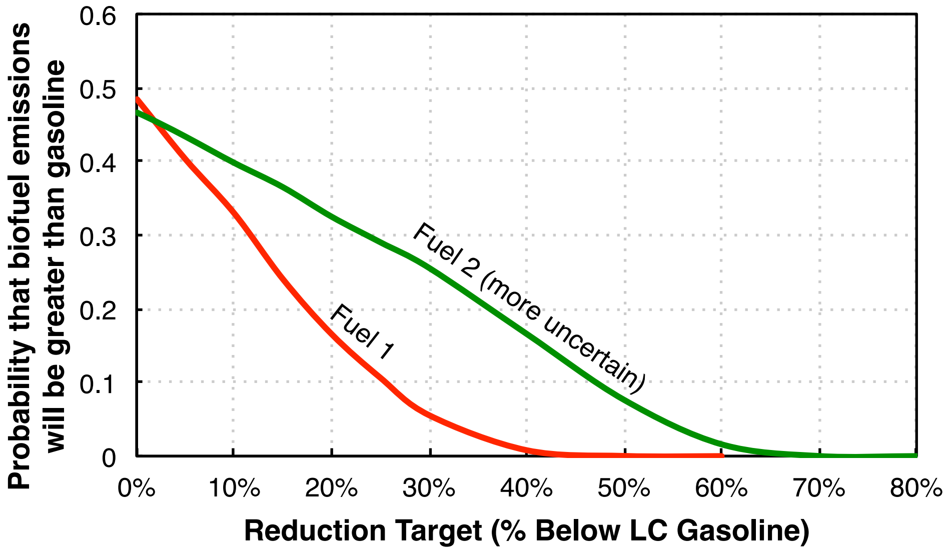


Figure 12. Probabilities of "policy failure" given policy emissions target exactly met for two different biofuels.

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

Considering this issue in a probabilistic way allows one to ask more nuanced questions about which fuel is preferable. Given the complexity and uncertainty in modelling environmental impacts of biofuels, a sophisticated decision making approach seems more appropriate than simply deciding that a whole category of fuels is acceptable based on a single value estimates of its impacts through the life cycle.

Perhaps a more responsible policy design approach is to perform an uncertainty analysis (such as the Monte Carlo analysis demonstrated here) on the feedstock-fuel pathways of interest, choose an “acceptable” degree of confidence in reductions occurring (on the x-axis), and then legislate a corresponding percentage target (on the y-axis).

3.4 Incorporating ‘Risk of Policy Failure’ in Current Policy Designs

3.4.1 Renewable Fuel Standard

The renewable fuel standard design simply compares two fuels (a biofuel to an incumbent such as gasoline or diesel), so the impact of including uncertainty can be assessed by replacing a point estimate with a probability distribution in the comparison. This in effect replaces the question - “Is the new fuel better or worse than the target?” with a more nuanced one - “What is the likelihood that the new fuel of better or worse than the target?”

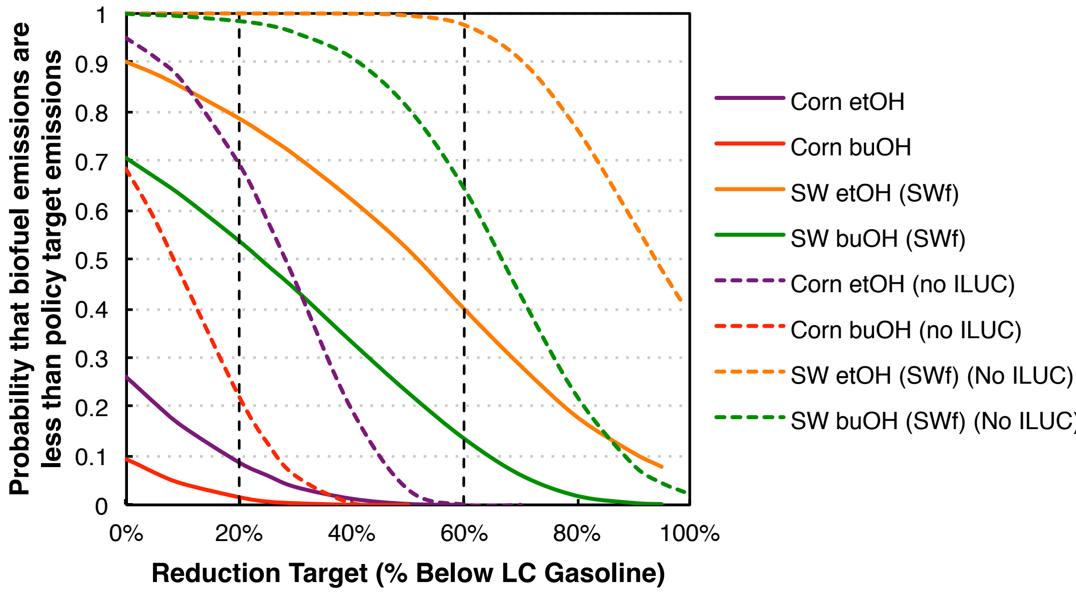


Figure 13. Probabilities that each fuel type will meet a specified reduction target. EISA targets for corn (20%) and switchgrass (60%) ethanol are specifically indicated.

Figure 13 presents the likelihood that biofuel emissions will be less than or equal to the RFS target emissions levels (i.e., meet the target), defined as a percentage decrease from gasoline, as the policy target becomes more aggressive (i.e., as the percentage increases). In this comparison, illustrated in Figure 14, distributions for the biofuels are taken from the previous chapter, and the distribution for gasoline is taken from Venkatesh et al. [83], acknowledging that this is a comparison between two uncertain quantities. From Figure 13, corn ethanol has a probability of lower emissions than gasoline of 0.25 (which is at the y-intercept, or the 0% point), and an even lower chance of meeting the 20% EISA target. The fuel with the lowest GHG emissions, switchgrass ethanol (SWf), is very likely to have lower emissions than gasoline (p = 0.9) but it does not meet EISA target of a 60% decrease; the likelihood of lower emissions than the target is about 0.4.

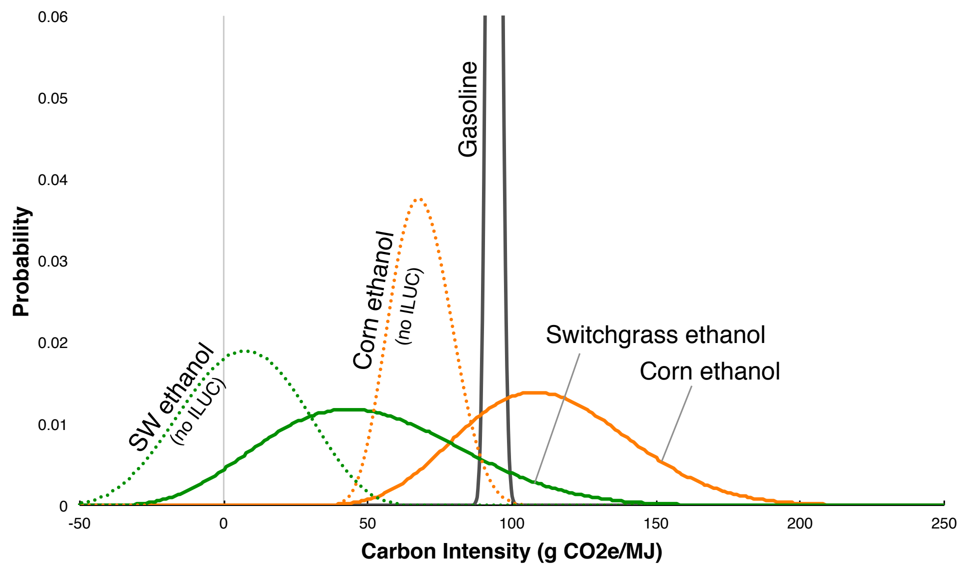


Figure 14. Comparison between emissions distributions for corn and switchgrass ethanols and gasoline.

Including indirect land use change emissions is somewhat controversial (see [84] for some discussion). If ILUC emissions are simply not included as part of the life cycle, biofuels show greater promise to reduce GHG emissions. Taking the distributions into account (Figure 13, dashed curves), a randomly selected gallon of corn ethanol has a probability of almost 0.7 of meeting the 20% reduction target. Switchgrass butanol shows almost the same probability of meeting its 60% reduction target, while switchgrass ethanol looks very likely to surpass the target. ILUC emissions are of particular importance as they have the greatest influence on life-cycle emissions (as discussed in Chapter 2) and will tip the decision for or against each of the ethanol types modeled here. ILUC, then, requires particular attention in order to reduce the possibility of making the wrong policy recommendation.

3.4.2 Low-Carbon Fuel Standard

The LCFS designed for California offers an opportunity to reduce the uncertainty associated with biofuels because it disaggregates biofuels into more precisely defined fuel types, such as Midwestern corn ethanol with process heat from coal. Additionally, some data from fuel produces and blenders are reported to the government, in an opt-in program, so that they can prove which fuel types they used and get the appropriate carbon intensity (less than the default) assigned to their fuel blend. The potential for increased data means there is potential to reduce the uncertainty in GHG emissions.

As discussed previously in Chapter 2, there are a handful of key parameters that determine the magnitude and variance of fuel GHG emissions. These conclusions inform the parameters for which more and better data are desirable. Unfortunately, not all parameters are uncertain for the same reason. Three categories can be helpful in defining the parameters, and will influence how uncertainty might be addressed:

Spatial or temporal variability: A category particularly relevant to agricultural systems, this source of uncertainty in an input parameter results from not knowing a precise 'where' or 'when' with which to define the data required in a model. From Chapter 2, feedstock yield and composition varies by time and place. Hydrolysis efficiency and production energy vary by ethanol plant, and vary in time as plant conditions improve due to technology advancements, or degrade due to plant age. These can be measured and verified.

Data limitations: This represents uncertainty that can theoretically be reduced with sufficient time and effort, but where parameters cannot be easily measured due to limitations in data quality or aggregation along the supply chain. For biofuels, feedstock production characteristics such as feedstock yield and nitrogen fertilizer application rate have a significant impact on carbon intensity estimates, but it may be difficult to determine appropriate values for the feedstock used at a particular biorefinery. Some ethanol refineries may establish contracts with specific farms to meet their feedstock requirements, but obtaining data on feedstock yields or fertilizer application rates at the farm level may be problematic if farmers are hesitant to provide precise operational data. Additionally, feedstock of unknown provenance presents an insurmountable obstacle.

Scientific uncertainty: An input parameter is uncertain because the underlying physical process, or the system which determines the parameter value, is not known or not well understood. Until these issues are resolved with improved understanding or models, the parameter uncertainty cannot be resolved. Land use change emissions and the nitrogen volatization rate would fall into this category. Due to the complexity of the systems being modeled, validating land use change estimates may be virtually impossible. Nitrogen volatization could be better understood with better field level tests; however, obtaining sufficient data to characterize each field providing biofuel feedstock will be a challenge even when the volatization models are sound. The nitrogen volatization parameter would then suffer from data limitations. Perhaps the only way to deal with scientific uncertainty in policy design is to commit to updating regulatory targets regularly in order incorporate the best science to date.

The degree to which increased data availability can reduce the uncertainty in emissions can be tested by fixing "knowable" parameters at some fixed value (e.g., median, lower or upper bound) and measuring the change in the resulting life-cycle emissions distribution. At best, this list includes the parameters influenced by spatial or temporal variability and data limitations:

- Feedstock sugar composition
- Hydrolysis efficiency
- Production energy requirements
- Field-level nitrogen application rate
- Crop yield

As shown in Figure 15, if the distributions for ethanol from corn and from switchgrass for which data could be reported are fixed at their mean values, there is not a substantial reduction in distribution width, nor does the median value shift very far. This suggests that the design of the LCFS offers limited potential to reduce uncertainty in emissions for the biofuels considered.

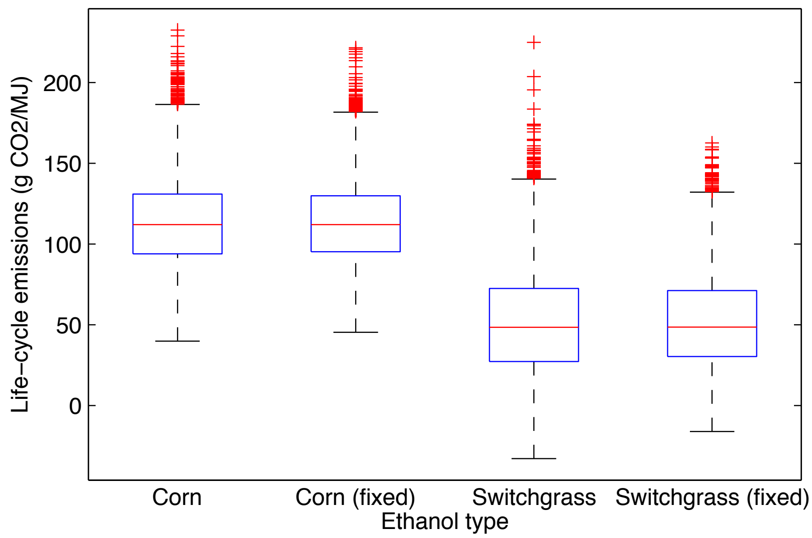


Figure 15. Distributions including the base case simulation and a simulation where "knowable" values are fixed at the parameter distribution mean.

The question, then, of how an LCFS-type policy can be improved to better account for uncertainty arises as intensive data reporting/collection is insufficient. Similar to the RFS analysis, the LCFS policy can be examined by replacing point estimates with probability distributions. That said, it is not possible to calculate a simple probability of policy failure *a priori* – a percentage reduction target for the whole transportation system can be achieved in many different ways; fuel types used and the quantity of each type are both sets of data necessary to evaluate the probability of failure. One way to estimate a probability of policy failure is to generate a year-end (or other reporting period length) distribution representing the regional fuel mix. This is done by sampling distributions for each fuel used in the region based on how often it is used (or perhaps weighted by energy, or volume, depending on the functional unit of the study). Statistics of interest, including mean emissions, standard deviation, etc., can be considered alongside the expected reduction target. Using the reduction target and this PDF will produce a probability of failure statistic. This approach is illustrated in Figure 16.

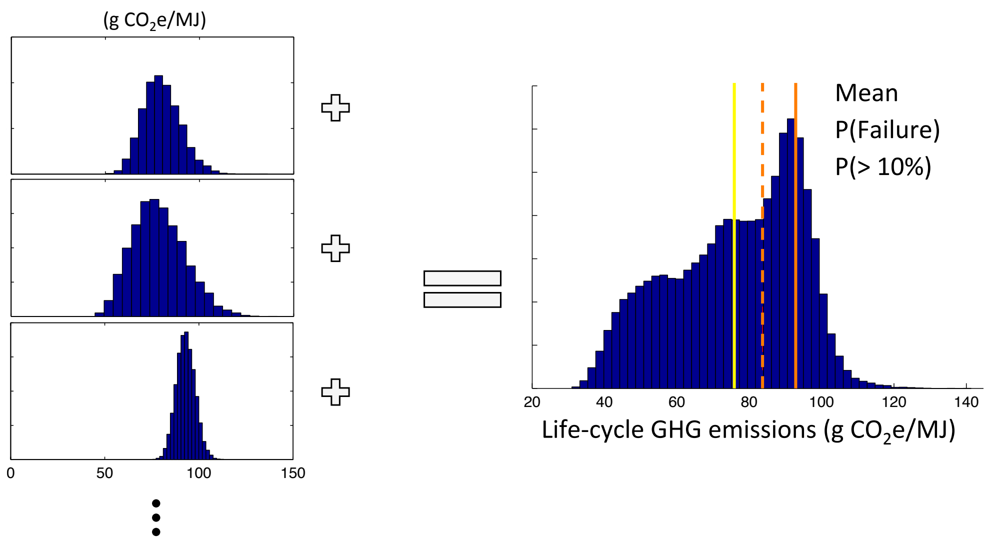


Figure 16. Methodological illustration of how to calculate the probability of policy failure for an LCFS.
Individual fuel types are on the left, with the weighted, total PDF of all fuels on the right. Vertical lines indicate (from right to left): business-as-usual emissions, 10% reduction target, and new distribution mean.

The methodology illustrated in Figure 16 requires a distribution of life-cycle greenhouse gas emissions to be calculated for each fuel type considered in the policy. This thesis and work published by Venkatesh et al. ([83], [85]) can be an example method to follow to generate such distributions, and the important parameters identified therein can be helpful to future modellers identify key variables before constructing complex Monte Carlo simulation models.

3.5 Legal Action and the LCFS Policy Framework

In 2009, two suits by two different groups of plaintiffs were filed in a U. S. District Court in California against the California Air Resources Board's (CARB) Low-Carbon Fuel Standard.

The first was put forth by the National Petrochemical and Refiners Association, the American Trucking Association, the Center for North American Energy Security, and the Consumer Energy Alliance. The second was filed by the Rocky Mountain Farmers Union, Redwood County Minnesota Corn and Soybean Growers, Penny Newman Grain Inc., Growth Energy, the Renewable Fuels Association, Rex Nederend, the Fresno County Farm Bureau, the Nisei Farmers League and the California Dairy Campaign. In general, the first group represents fossil fuel interests, while the second represents ethanol interests.

The suits were similar, and are addressed by the same summary ruling delivered in December 2011 by Judge Lawrence O'Neill. The Rocky Mountain Farmers Union suit has three arguments, namely that LCFS implementation is unconstitutional because it violates the Supremacy Clause and the dormant Commerce Clause, and it violates provisions in the Clean Air Act. Each of these three arguments, as presented by the plaintiffs, and the response from CARB are discussed briefly in the following paragraphs. All information is taken from motions submitted by the Renewable Fuel Association plaintiffs and responses from Judge O'Neill [86], [86], [87].

One important feature of EISA is that bio-refineries that were operating or were under construction in 2007 (the year of legislation) are not obligated to prove emissions reductions versus gasoline. CARB's LCFS does not grandfather the older ethanol plants in, thereby "penalizing" them in a way that Congress did not. The plaintiffs argue that this is in violation of the Supremacy Clause (Article VI, Clause 2 of the Constitution), which states that federal law must be followed when conflicts between federal and state or local laws arise; federal law trumps state law. The issue the plaintiffs allude to here is that corn ethanol that is treated favourably under federal laws is treated unfavourable under state laws.

To implement the LCFS, CARB assigns carbon intensities to a list of different fuel pathways. Midwestern corn ethanol, in most pathways, has a higher carbon intensity than California corn ethanol, which in turn has a higher carbon intensity than Brazilian sugarcane ethanol [17]. The plaintiffs argue that the higher Midwest values are due to factors outside of the producer's control, such as transportation distances and electricity grid mix – this amounts to California trying to influence through internal regulation the decisions that are made in other states. Furthermore, to receive this carbon intensity rating, or to change a carbon intensity rating, regulated entities must get approval from CARB. Essentially, this means California is an "arbiter of interstate transportation of fuel and feedstocks", which it has no grounds to do under the Commerce Clause. This clause means that the federal government can regulate interstate commerce, but no specific state can do so unless specific conditions are met.

The Clean Air Act gives the Environmental Protection Agency (EPA) the authority to ensure that biofuels regulation does not end up with any geographic restrictions on where biofuels can be sold. The LCFS does just this in restricting what types of fuels will be sold in California.

The plaintiffs argue that the material harm they suffer because of this legislation is not offset by any benefits. Higher carbon fuels will simply be sold in markets outside of California (the issue of emissions shuffling), so GHG emissions will not be substantially changed by the LCFS. Additionally, any emissions reductions expected to be achieved by this legislation will be negligible on a global scale, so there will not even be indirect benefits to anyone.

The defendants (CARB) argue that the *framework* they use to evaluate the carbon intensity of fuels is indiscriminately applied; it is identical regardless of where the fuel comes from. The data used, of course, depend on location. With respect to regulating the activities of out-of-state, they argue that the LCFS simply creates a market for biofuels, so it does not directly regulate any decisions made by farmers, ethanol producers, etc. out of state. Beyond this, Congress gave California the authority to regulate fuels and fuel additives for emissions controls purposes when they wanted to enact stricter emissions limits than exist federally. They argue that this means Congress has already authorized California to affect interstate commerce.

Judge O'Neill ruled that the LCFS does directly discriminate against out-of-state ethanol, and therefore agrees that the LCFS violates the Commerce Clause. This conclusion was reached because the availability of lower-carbon electricity in California favours Californian ethanol and puts other ethanol at a price disadvantage, and penalizing transportation distances necessitated by interstate commerce hinders interstate commerce. Judge O'Neill found that that CARB did not make a compelling case that GHG emissions reductions could only be achieved through LCFS, a discriminatory policy. He suggests that alternatives discussed by experts, such as a carbon tax on fossil fuels or increased vehicle efficiency, should have been discussed and considered.

The fact that Midwest ethanol and California ethanol are chemically/physically identical, and that they have identical tailpipe emissions is mentioned many times throughout the documents to weaken the case for discriminating between in- and out-of-state ethanol. However, when CARB tried to use the fact that it has Congressional permission to regulate fuels and fuel additives (which affect emissions) to support their claim that they are already not subject to the Commerce Clause in this area, the Plaintiffs rebut by saying that the LCFS does not quantify chemical properties in the same way that previous legislation did, so that Congressional permissions does not apply to greenhouse gas emissions. In my non-expert legal opinion, this seems to stem from the fact that GHGs are global pollutants, and LCA metrics are not the traditional environmental metrics used in environmental regulations. So, there seems to be space for precedent setting here since regulators and lawmakers don't seem to know precisely how to deal with them.

Evidence of imperfect understanding of the purpose of life cycle assessment, the science of climate change (and therefore motivation) behind the LCFS. The Judge's Ruling to Plaintiffs contained the following (emphasis mine):

> "The Rocky Mountain Plaintiffs contend that instead of focusing on local GHG emissions, *like smog in the Central Valley*, the LCFS has a purpose and aim that is broader than its territory."

The plaintiffs and the Judge discuss how greater transportation distances penalize Midwest ethanol; this is confusing, as emissions from transportation make up a very small percentage of total life-cycle emissions. The only exhibit provided by the ethanol plaintiffs is a copy of the LCFS, including the carbon intensity look-up tables, so there are no citations to understand what specific data motivate their points. It seems reasonable to conclude that the case made by CARB did not sufficiently address this error.

This turn of events is unfortunate, but not because the California LCFS was going to be a shining example of effective and efficient climate change legislation; the research presented and cited in this thesis raises a number of issues surrounding the deficiencies. Some of those deficiencies could be addressed through some policy redesign suggested here and elsewhere. In my view, the unfortunate turn of events was the apparently poor explanation and defence of life cycle thinking as the way of quantifying carbon emissions in legislation, and how improved future policies based in life cycle analyses, or any sort of systems analysis which casts a wide net, may be subject to prejudice by those who are not well versed in the methods simply because of this precedent.

Come on little plants, we're groovin' in the sunlight
Spread your leaves and dance, reach up for the blue sky
Soak up all the water, I won't leave your roots dry
Drink it up now baby, let your cells multiply

Photosynthesis is my favorite chemical reaction
When the plants are growing it gives me so much satisfaction
Chlorophyll's the green stuff, I just can't get enough
Building up your cell walls, so you grow up big and tall

"Photosynthesis", The Hot Toddies

Chapter 4. Consequences of Uncertainty in Biofuel Feedstock Supply

4.1 Abstract

The current practice of modelling cellulosic biomass yields based on point values that have been aggregated over space and over time obscures important risks related to depending on biomass for transportation energy, particularly those related to local drought conditions. Using switchgrass as a case study, this work quantifies the variability in expected yields over time and space with a switchgrass growth model and historical weather data. Even with stable, productive states, yields vary from 5 to 20 Mg/ha. Yields are likely to be reduced with increased temperatures and weather variability induced by climate change. Variability needs to be a central part of biomass systems modelling so that risks to energy supplies are acknowledged and risk mitigation strategies or contingency plans can be considered. Irrigation, one risk mitigation strategy, can very often negate the impacts of drought, although system-wide irrigation is an expensive method to stabilize crop yields (costing \$0.10 to \$1.90/gallon). Unless many surplus acres of cellulosic crops are planted, there will be insufficient ethanol to meet the EISA targets 10 to 25% of the time under rain-fed conditions.

4.2 Introduction

The Energy Independence and Security Act of 2007 (EISA), in addition to implementing a renewable fuel standard, addresses the issue of the United States' undesired dependence on foreign sources of oil [14]. In addition to reducing greenhouse gas emissions from the transportation sector, as discussed extensively in the previous two chapters, EISA requires increased biofuel usage to address this energy security issue. The concept of energy security is not new, and has motivated US energy policy for some time, so it is surprising that the term is often used without being precisely defined. Those approaching the energy security topic from an economic perspective investigate topics like fossil energy supply diversity, demand resiliency, or the impact of oil supply fluctuations on US GDP [88-90]. Economists working in this area actively debate the feasibility of energy security. Many argue that moving away from imported oil is going to be a major challenge in the near- to mid-term [91], [92]. Researchers and policy makers who advocate biofuels as a way to reduce oil consumption and reduce the US dependence on unstable foreign oil sources take as given that a shift towards biofuels will reduce the risks in fuel availability, or simply have chosen not to specifically define the term 'energy security' in their context (for example, [80], [93], [94]). Energy security in relation to biomass is defined in this chapter as having a stable enough feedstock supply to adequately provide ethanol in quantities required to satisfy legislated volume targets.

Discussions in literature do not sufficiently acknowledge that a change in the domestic energy portfolio to include biomass does not *necessarily* translate to a reduction in risk. A change in the energy supply portfolio brings different supply risks, which may or may not be preferable to the previous set of risks (e.g., fossil fuel supply disruptions due to infrastructure damage). The three dominant alternative energy sources, wind, sun and biomass, are each subject to natural temporal variation. This variability results in chronic resource shortages. Intermittency in biomass can result from periods of water or temperature stress on the crop. Of the two, a lack of water is the most important [8]. This issue has received less attention than either wind or solar, in part because the possible interventions in wind and solar electricity are similar (commonly addressed with fossil backup energy during times of deficiency [95] or some sort of energy storage technology [96]) and because of the shorter time the system could conceivably be “down” due to the forces of nature. Biomass shortages are likely to occur on the annual time scale rather than hours or days.

Biomass intermittency has received some attention in literature, but this has been in the context of chemical and industrial process design. To maintain a financially viable bio-processing facility, Kou and Zhao [97], [98] and Mu et al. [99] recommend facilities be designed to accommodate variability in feedstock input quantity and/or composition. Otherwise, they cannot maintain a stable output of ethanol (potentially in addition to other products).

Crop availability issues are likely to be exacerbated over time, as a number of studies report that drought severity and frequency is predicted to increase under many future climate scenarios (see [100], [101] for two examples). Tied into this are expectations of increasing temperatures, and increasingly variable temperatures [102]. Water stresses will increase both due to meteorological changes, and due to a general increase in water demand from growth in most major demand sectors, as discussed by Roy and colleagues [103]. This could lead to chronic, multi-year biomass shortages. These could be very costly, given that annual crop insurance payments for drought alone are on the order of billions of dollars (see Figure 5) [33]. If the number of planted acres to consider or insure increases with a move towards more energy crops, these social costs are likely to increase. They will be borne increasingly to support an emerging bio-energy sector rather than food or fibre as was previously the primary, if not exclusive, reason for social support. Crop subsidies, then, need to be compared with energy subsidies in addition to USDA food/fibre subsidies.

This chapter takes switchgrass as a case study crop to examine the supply risks related to dryland energy crop farming by using observed, historical weather data to model crop yields. The calculated crop yields provide insight into how significant an issue this variability might be locally, and in terms of national biofuel availability. In light of the changing climate issues, simulated weather data are used to explore how yields may change under different expected climate conditions. Finally, crop loss risk mitigation through irrigation is explored in terms of technical potential and cost effectiveness, and alternative mitigation strategies such as researching increasingly drought-resistant cultivars or ethanol storage are discussed qualitatively.

4.2.1 Regions of Interest

Energy security is generally considered at the national level. Drought is usually regional, and yet can have national significance. As such, it is necessary to approach the analysis of crop availability knowing the areas most likely to produce bioenergy feedstocks, and how weather-related risks, which vary across the country, affect these production areas. In this yield analysis, the US is disaggregated at the state level, with weather data from one city from each continental state assumed to represent the overall trends in that state.

Projections of spatial biomass supply by Agricultural Statistical District (ASD) are available from the Policy Analysis System (POLYSYS) model [104]. This model is commonly used to as a source for projected crop locations and prices (for some examples, see [6], [105-108]). POLYSYS is an economic-based modelling framework developed at the University of Tennessee, the USDA, and Oklahoma State University for use in assessing US agricultural and energy policies. It simulates the U.S. agricultural sector's response to various bioenergy-planning decisions influenced by policy, economics, etc. in the form of regional crop planting decisions. There are 305 ASDs in the continental United States, and they are defined as groups of counties that share similar agricultural practices and climate conditions. The model uses a comprehensive set of input parameters that include crop demand and costs, agricultural income and livestock characteristics to predict crop supply by ASD. Supply changes over time use estimates for base yields for seven regions, to which annual yield gains are applied (summarized in Table 9).

Table 9. Assumed yield percentage gains and actual yields over time for the POLYSYS model.

Region	Annual yield gains	Yields (Mg/ha)				
		Base	*2015*	*2022*	*2025*	*2030*
Northeast	1.50%	10.9	12.5	13.7	14.2	14.2
Appalachia	5%	13.1	19.6	24.2	26.2	26.2
Corn Belt	3%	13.4	17.4	20.2	21.4	21.4
Lakes States	1.50%	10.7	12.4	13.5	14.0	14.0
Southeast	5%	12.3	18.4	22.7	24.6	24.6
South Plains	5%	9.6	14.4	17.8	19.3	19.3
Northern Plains	1.50%	7.8	8.9	9.8	10.1	10.1

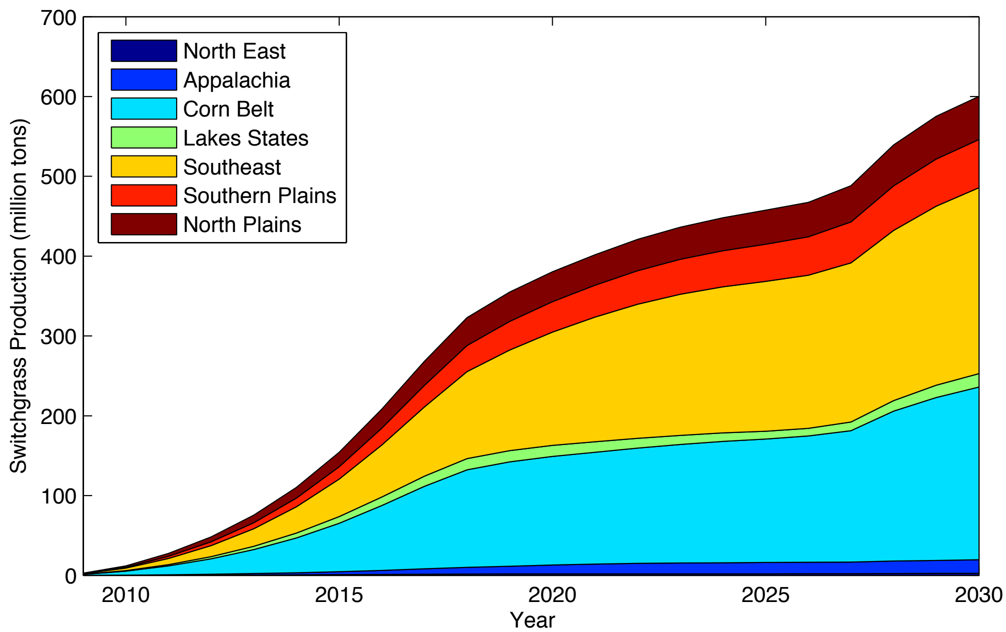


Figure 17. Increasing switchgrass production over time ($95/ton, high ethanol demand scenario in POLYSYS).

Figure 17 shows projected switchgrass production quantities for these seven regions. The Corn Belt and the Southeast are expected to produce the majority of switchgrass, with the Southeast overtaking the Corn Belt as the single largest producing region by 2020. Note that not all of these regions contain the same number of states or counties. The region in which each state falls is listed in Appendix A. States are categorized into one of the seven regions by having the same expected base yields and annual yield gains (due to crop breeding and research). The Corn Belt has the highest base yield in 2006 at 5.98 ton/acre (13.4 Mg/ha), but by 2020 (year when yield gains are assumed to plateau), Appalachia and the Southeast have the highest expected yields at 11.7 and 11 ton/acre (26.2 and 24.6 Mg/ha) respectively (summarized for all regions in Table 9 above). These yields are quite optimistic based on reported and modelled yields (see Section 4.4.1 below). Figure 18 illustrates ASD-level yields for the year 2022 plotted in Figure 17 above, included to demonstrate the general areas in which switchgrass is expected to be grown. This picture does not change substantially through time. The top five states by estimated switchgrass production in 2030 are, in descending order, Missouri, Kentucky, Arkansas, Illinois, and Oklahoma. No switchgrass is expected to be grown in the West under rain-fed conditions.

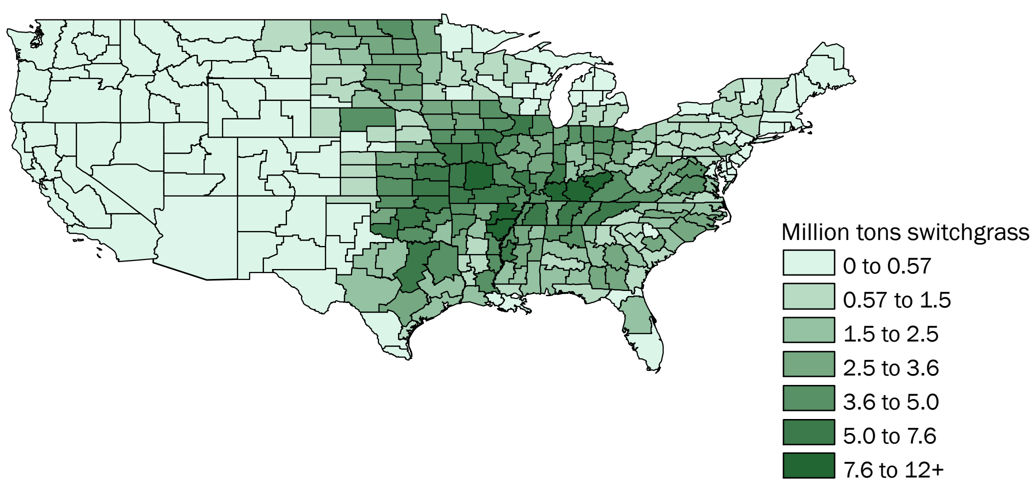


Figure 18. Distribution of switchgrass growth across POLYSYS regions ($95/ton, 2022 high ethanol demand scenario).

4.3 Methodology

An overview of how each distinct model (identified in a green box) built or implemented in this chapter relates to each other, and the values that flow between them, is presented in Figure 19. Section numbers below each model correspond to the chapter section in which they are presented. The white boxes represent input data and output results.

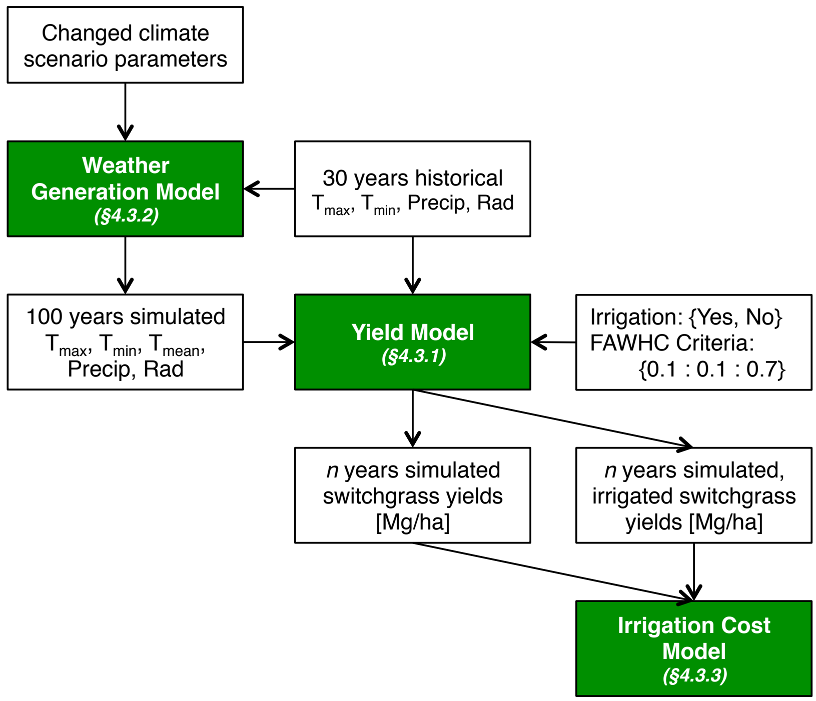


Figure 19. Overall data flow diagram. Section numbers indicate where the models are explained in this chapter.

Unless otherwise noted, all yield values presented in this chapter are simulated using a switchgrass growth model. The yields are either generated using historical, observed meteorological data for one location in each state, or generated using simulated weather data that was, in turn, generated based on the observed meteorological data. Within the yield model, the yields over time can be calculated assuming that some irrigation system is present, or not. Finally, the irrigated yields and the non-irrigated yields are passed to an irrigation cost model to determine cash flow differences between the irrigation and non-irrigation to evaluate that decision.

4.3.1 Switchgrass Yield Model

The switchgrass growth model built here, as defined by Grassini et al. [109], was published with the intention of generating annual crop yield values that could be used to inform energy policy models and discussions. Nair and colleagues present a review of many different crop models [110], highlighting that model results are improving, but there is still a need for better input data and better model calibration. So, the overall yield trends observed in this chapter are reliable, but specific yield values should not be taken as precise predictions. It is important to keep in mind that the annual yield time series output by this model vary due to changes in precipitation and temperature (which drive drought conditions), and not to other factors such as an overabundance of local water or acute weather phenomena (such as hail) noted in Figure 5 because the model is not equipped to deal with these situations (i.e., there is no 'hail' module). Variability over time would be greater if these other causes for crop loss were included, and could be a fruitful line of investigation for future work.

The switchgrass growth model is composed of five interacting modules (described in detail below), and operates at a daily time step, calculating daily biomass production. Inputs include daily rainfall, mean, high, and low temperatures, and solar insolation, as well as information about soil characteristics and crop growth performance. Thirty years of daily data are used as the historical meteorological data set. Data from one city in a relatively agricultural area from each state are taken, so one location is assumed to be representative of the whole state (as often there are records for only one to a handful of cities available for each state). A closer examination of variability within states would provide important information regarding how uniform yields are across the state and how reasonable the single city assumption is. The city selected from each state is listed in Appendix A. The historical data are taken from the database assembled by the USDA for use in their weather generating software, GEM [111]. These data include daily observations for maximum and minimum temperature, precipitation, and solar radiation. Mean daily temperatures are calculated as the average between high and low values.

A complete list of input parameters to the switchgrass yield model is included in Appendix A. When daily biomass accumulation values (output in g/m^2) are summed over an entire growing season, the result is an annual crop yield value. When many years are modelled, variability in yield over time can be assessed. The Grassini model is not publically available as a stand-alone program or as code, so a model was built in Matlab. The code is available in Appendix C for others to use if they wish. The five interacting modules mentioned previously are defined as follows:

Module 1 - Crop development index: The development of the switchgrass is modelled as a sigmoidal (s-shape) function (bounded by 0, not yet developing and 1, meaning fully mature). It is affected only by daily mean temperature in relation to cultivar-specific temperature parameters, including optimal temperature, and temperatures above or below which no development occurs. Daily, incremental development is tracked and is taken as input to various other modules.

Module 2 - Leaf area index (LAI) expansion: The LAI is a dimensionless index that describes the fullness of the canopy. It affects rainfall partitioning in the soil and water balance function, and the rate of conversion of solar radiation to biomass (i.e., crop growth). The LAI value depends on the crop development stage index and a water stress factor.

Module 3 - Soil water balance: The soil water balance model is the most complex of the five. There are five sub-modules within this function. Rainfall can be intercepted by the canopy (a function of the leaf area index) and not be available to the soil layer. Heavy rainfall can result in water lost to surface runoff - the top layer can hold 110% of capacity right after rainfall, and the excess will runoff. Water evaporates from the upper layer of soil, in a quantity that depends on temperature, solar radiation intensity, LAI, and previous water concentration in the upper soil layer. Water transpires through the plant during growth, in a quantity determined by existing biomass/development stage and temperature. Water for transpiration can come from either the top or bottom soil layer. Finally, excess water that may be in the top soil layer at the end of a day filters down to the bottom layer so that it is not oversaturated. These four water flows are tracked through each day, and are graphed for a sample year (1971) in Iowa in Figure 20 and Figure 21, illustrating all of the possible water behaviours.

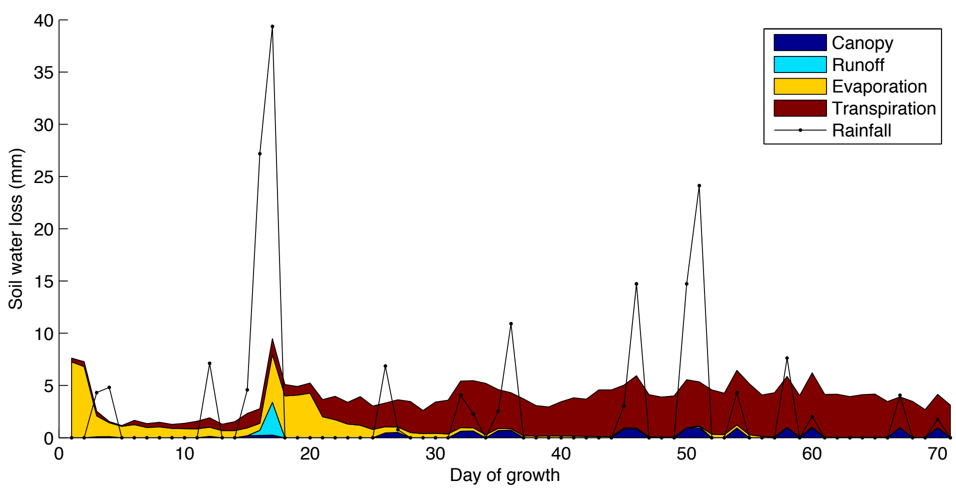


Figure 20. Soil water depth changes over time for Iowa data, 1971.

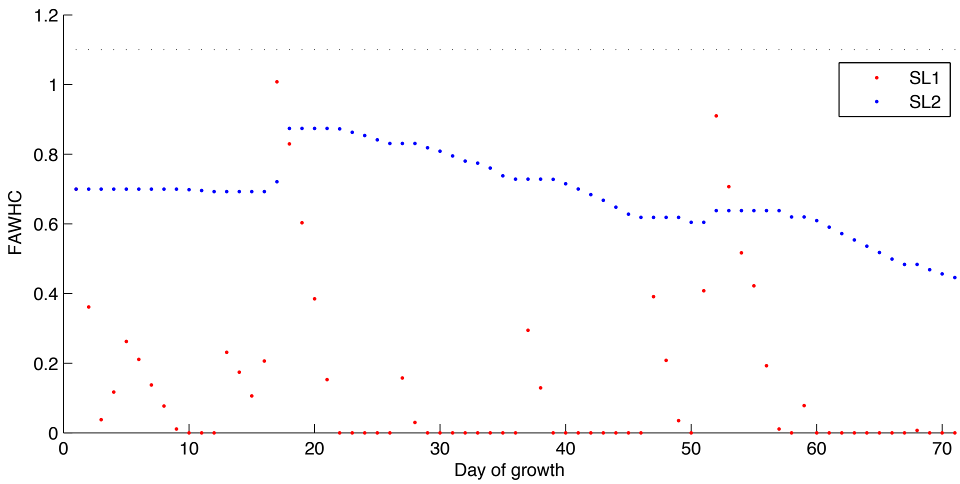


Figure 21. Fraction of available water holding capacity (FAWHC) filled over time for Iowa, 1971 data.
'SL1' indicates the thinner, top layer of soil, and 'SL2' indicates the lower, deeper level of soil.

Module 4 - Crop growth and biomass production: The mass of new biomass produced each day is a function of the amount of photosynthetically active radiation intercepted by the canopy (which is a function of the LAI), the rate at which the plant can convert radiation energy into biomass, and water and temperature stress factors.

Module 5 - Water and temperature stress factors: Crop growth is retarded by insufficient water, or temperatures that are too low. Specific water stress factors are applied to the LAI function and the biomass growth function, and a specific temperature stress factor is applied to the biomass growth function.

Supplemental calculation details necessary to complete the model but which are not documented in the Grassini manuscript or its references are taken from publication on crop evapotranspiration published by the Food and Agriculture Organization of the United Nations (FAO) [112].

A key parameter assumed at the beginning of the model run is the fraction of available water holding capacity filled at the date of growth initiation ($FAWHC_{AGI}$), as an abundance of soil water can make up for some lack of rain during the growing season, and a deficit of soil water can make that situation worse. This fraction varies from 0 to 1. The fraction of available water holding capacity (FAWHC) filled at the date of AGI is assumed to decreases as the SPI decreases. An FAWHC of 0.6 corresponds to the median precipitation scenario (SPI median value is 0, from Section 1.4.3.1), as this is taken as the default value for the model runs in Grassini et al. [109]. It seems unlikely that even in a severe drought scenario the top two meters of soil would be completely dry, so the model was run assuming no precipitation at all, over various FAWHC at growth initiation ($FAWHC_{AGI}$) values. For a range of $FAWHC_{AGI}$ values, the FAWHC of the lower soil layer at the time of growth completion asymptotically approaches a value of 0.1, while top layer is constantly exhausted of moisture. As a result of this information, $FAWHC_{AGI}$ is assumed to decrease linearly from 0.6 to 0.1 with a decrease in precipitation scenario likelihood, and increase from 0.6 to 1 with an increase in precipitation scenario likelihood.

Irrigation is modelled in one of two ways, depending on the irrigation technology used. Irrigation can be introduced in this model by increasing rainfall (it falls from above the canopy and can therefore be intercepted at that state), or the irrigation water can be introduced below the canopy level so that the first interaction in the model is at the soil surface water saturation check. Using central pivot irrigation (discussed below in Section 4.3.3), the former approach is used. At each time step (each day), the model checks to see if the soil moisture (FAWHC) is below a specified threshold. If it is, 25 mm of water is added to the model value (at one of the two places explained previously). This corresponds to about 1in of water, a value assumed based on irrigation information from the USDA Irrigation Guide [113] and soil layer assumptions. Using this irrigation decision criterion, the amount of water used and the yield increase that results from irrigation does not vary significantly if less or more water is applied per irrigation event. The only change of significance is the number of irrigation events; if less water is applied, it has to be applied more often. This would affect only the operations costs of the system.

4.3.2 Weather Generation Model

To assess the impacts of a changing climate on switchgrass yields, which also begins to address the assumption that past yields will be equal to future yields made in many models, this chapter includes a simulation of weather data based on historical data, but in which certain parameters have been modified so that the output weather data are representative of a changed, future climate. As stated previously, this exercise is intended to show changing trends in yields, not to suggest exact magnitudes for the changes in variability or expected values for yields in any region.

Weather simulation programs have been tools for modellers for the past 30 years. They output data such as the maximum and minimum temperatures, precipitation, wind speed, dew point and solar radiation. Many used for applications that requite daily data, such as this crop yield model, are built upon a stochastic simulation method for temperature, precipitation and solar radiation suggested by C. W. Richardson, as described in [114] and [115], and more fully defined as the WGEN model by Richardson in [116]. The simulated weather data are based upon historical data from a particular region and time period, and time series are often generated when empirical data are not available over a sufficiently long time period for the modeller's purposes.

In most daily weather generation models, temperature and solar radiation data are conditioned on precipitation. Precipitation is modelled in two parts: whether or not there is any precipitation (dry or wet conditions; a binary random variable), and when there is precipitation, how much falls. In the commonly used Richardson model, the wet or dry state is simulated as a Markov process; the status of the current day depends on the status of the previous day(s). In its simplest form, it uses a first-order Markov model, meaning the status is conditioned only on the previous day; if it was dry yesterday, the likelihood that it will be dry today is P_1, and the likelihood it is wet is ($1-P_1$), where P_1 is based on this historical data. Higher order models have been used by more recent studies, though to more accurately reproduce long wet or dry spells (see excellent discussion in [117]). The quantity of precipitation on wet days is generally modelled using either an exponential function or a two-parameter gamma function, as both heavily weigh small amounts of precipitation but skew positively to allow for the low probability of much higher precipitation quantities. With the precipitation time series generated, temperature and solar radiation data are then modelled using a first-order linear auto-regressive model. Means and standard deviations for each temperature time series, conditioned on precipitation, are calculated over some relevant time period (daily, weekly, monthly) across all years of historical data (i.e., two means for each two-week period are calculated, $\{\mu_{dry}\ \sigma_{dry}\}_i$ and $\{\mu_{wet}\ \sigma_{wet}\}_i$). Time series of residuals are generated for each of maximum temperature, minimum temperature and solar radiation using the standard deviations calculated. This residual value is modified by a lagged correlation matrix (modified based on what temperatures and solar radiation happened the previous day) and to which a simultaneous correlation matrix (modified based on what the other meteorological values of the same day) of normally distributed errors is added. Finally, the means and standard deviations calculated from the initial, historical data are added to these modified temperature and radiation residuals. Basically, these correlations ensure that if it was hot and sunny yesterday, today is more likely (relative to average that time of year) to be hot and sunny than not, and if it is very sunny, it is more likely to be hot (relative to average that time of year) than not. The means ensure that the larger trends over time are preserved.

The simulated data for this analysis are generated using methods for precipitation and temperature from Chen and colleagues [118], who implement the Richardson model as described above (using a second-order Markov chain), but additionally implement a /smoothing algorithm to reduce jaggedness in the mean temperature profiles. The jaggedness arises because the temperature means are calculated for two-week time periods, so each year is characterized by a set of 26 max/min temperatures. Without any modifications, there tends to be a jump between the temperature on the last day of one period and the first day of the next period. The smoothing algorithm simply reduces this jump. This particular implementation of the Richardson model was used because Chen and colleagues have graciously made the Matlab code available online. To simplify the model and hasten calculation time, a less sophisticated model for solar radiation is used. Means and standard deviations for solar radiation data are calculated using dry days, and a scaling factor is used to simulate radiation for wet days, following methods described by Zhang et al. [119]. In summary, simulated weather data used as input to the switchgrass yield model (results in Section 4.4.3) use:

- Second-ordered Markov chain to generate precipitation occurrence patterns;
- Two-parameter gamma distribution to generate precipitation magnitude data, smoothed to reduce gaps between successive two-week periods;
- Conditional relationship between the maximum and minimum temperatures; and,
- Scaling factor of 0.5 to scale mean daily solar radiation on dry days for wet days.

Given this weather simulation program from Chen et al., certain parameters in the model are modified in order to produce a climate that is changed from the historical climate. The following scenarios are examined, with data presented in the form of box plots to illustrate key statistics:

1. Base case weather, simulated using historical data (sources and locations described previously) and unmodified parameters (so that yields from simulated, modified climate data are not compared to historical data)
2. A higher temperature case, based on a scenario used in a future US drought study [103]. In the weather generation model, mean values for Tmin and Tmax time series. [μ_{temp}+2] are modified as suggested in the Roy study.
3. A higher variability in temperature case, based on results shown in a study on temperature anomalies by Hansen [102]. This is implemented though modified standard deviation values for Tmin and Tmax [1.2 σ_{temp} and 1.3 σ_{temp}] as shown in the Hansen study.
4. A higher dry- and wet-spell length scenario. Rather than modify precipitation amounts, which vary regionally (see [101]), the impacts of increased dry or wet spell length are examined. This is accomplished by modifying the transition probabilities for precipitation occurrence in the Markov matrices, making it 10% (relative, not percentage points) more likely that there will be longer dry spells, or wet spells. This is done not specifically following a procedure undertaken in another study, or using empirical data found elsewhere, but as a way to compare the yield sensitivity to spell length alongside temperature modifications.

By using the three modifications in some combination with each other, six scenarios (in addition to the base case simulation results) are compared in the following section. The results are only compared among themselves in order to get a sense of the sensitivity of crop yields to different changes in climate conditions and see if there are general trends to anticipate. These simulated weather data are not used in the yield model with the irrigation option enabled, so there is no cost comparison between current yields and future, climate changed yields. Cash flow values from those yield time series seem too speculative to be of much use quantitatively, but this analysis could be done in the future with a more comprehensive assessment of specific, local climate change in each state or region.

4.3.3 Irrigation Cost Model

Irrigation costs are modelled from the perspective of an individual, private farmer who has two options: install irrigation and mitigate the risks of low yields (thereby increasing relative revenue) or do not install irrigation. Yields under irrigated conditions are modelled for each state using the same 30 years of historical weather data from a city in each state as were input to the yield model to assess yield variability (presented without irrigation in Figure 23). The irrigated farm will expect higher yields than the non-irrigated farm, but will have to bear increased farming costs due to capital investment in irrigation infrastructure and associated operating costs. Annual net after tax cash flow values are compared between the irrigation and the non-irrigation scenarios to assess how often irrigation provides (undiscounted) financial benefits, and provide insight into how the farmer might make a decision into whether or not to invest irrigation (or some other technology to increase yields, not discussed quantitatively here).

Irrigating can be separated into two stages: drawing water from a source (either ground or surface), and distributing that water on the fields to irrigate (three options). Ground water requires the installation and operation of well and water pump. Surface water requires a smaller pump than well water, as there is usually not much vertical distance for the water to travel. The three different irrigation systems considered here are as follows:

- *Flood irrigation*. Water is pumped through pipes with spaced gates that can be slid open to allow water to flow in channels between row crops, perpendicular to the length of the pipe. This is the least expensive to install, and the least water efficient. Maximum area is about 160 acres (65 ha) per system.

- *Central pivot irrigation (CPI)*. This is a sprinkler type of irrigation, where water is sprayed on the crops from above. The water pipe pivots around a central tower. Maximum area is about 125 acres (51 ha).
- *Subsurface drip irrigation (SDI)*. Water is slowly released to the root zone of the crop by perforated pipes buried below the surface of the field. This is the most expensive system to install, and the most water efficient. Maximum area is about 125 acres.

For all types of irrigation used in this model, well-drawn water is the option used, based on the predominance of well water use for irrigated agriculture in the states of interest (for example, 66% in Texas, 95% in Kansas, 82% in both Oklahoma and Arkansas [120]). In these states, the percent of acreage irrigated in 2007 was 15, 10, 4, and 54% respectively[121]. Nationally, 56 of the 400 million acres of cropland are irrigated [122].

The system design and costs are the same across all states, and are based on a review of irrigation cost planning literature published by Agricultural Extension Services in several states of interest (Texas, Kansas, Arkansas, Tennessee), as well as an irrigation guide put out by the USDA and an excellent (though somewhat old – published 1996) report that the NRC put together on the current state of irrigation in the US and anticipated challenges for the future [120], [123-126].

All specific values assumed are presented in Appendix A. The model assumed well water pumps are powered by natural gas, because the energy cost is less than electric motors. A central pivot irrigation system is the case carried through the results and discussion section, with values for flood irrigation and sub-surface drip irrigation included in Appendix A for completeness. SDI is much more expensive that CPI ($200,000 system cost versus $76,000), so the economics are much less favourable with that option. Flood irrigation infrastructure is less expensive at $5,000, but do not include the potentially necessary land leveling (so that water flows to all parts of the field). Additionally, this method requires furrows between the rows of crops, but switchgrass is not likely to be planted in neat rows (one of the reasons it offers better erosion resistance than something like corn [72]). Both are reasons why flood irrigation is not emphasized in detail in this chapter.

In this study, the capital expenses are paid for through a loan with a payback period that coincides with the lifetime of the infrastructure (15 years for irrigation infrastructure, 25 years for the well). Items that vary yearly are the revenue from crop sales, and operating expenses related to labour, energy, and water use. System maintenance and insurance are yearly expenses, but are assumed to be a fixed percent of initial capital costs. Other items do not vary year upon year.

Note that the price assumed for switchgrass ($102/Mg) is quite high, but is the estimate for the lowest value farmers would be willing to accept to grow switchgrass, according to an NAS report assessing the Renewable Fuel Standard [107]. High crop prices will, in general, tend to encourage more farmers to choose to grow switchgrass, and will push the individual farmer towards irrigating once the decision to plant switchgrass has been made. As expected revenue increases (with increasing crop production), the value of crops lost to drought will increase, so irrigation will make better financial sense. Note also that the assumed national cost of water, at $20/acre-foot, is low compared to the cost to non-agricultural consumers and to the value of water conservation activities, which can be in the hundreds of dollars per acre-foot range [127]. Both of these values are explored in a sensitivity analysis in the following section.

Also note that in this model the price of switchgrass does not vary with supply, even though supply can vary substantially from year to year. Drought years, which cause low yields, would certainly shift the supply curve and apply upward pressure on market prices. This is challenging to model because there are no large bioenergy crop markets upon which to base economic relationships of supply and demand. In general, prices would increase in low supply years, and decrease in high supply years. Comparing this to a flat price assumption, revenue losses would be less in low supply years, and revenue gains would also be less in high supply years, resulting in an overall blunting of revenue spikes in either direction. However, acreage may not be as easily switched to switchgrass as something like corn because the crop stand takes about 3 years to reach expected productivity levels [8], which supports the assumption that farmers are making planting decisions based on expected prices years ahead. Additionally, the issues assessed here regarding irrigation require a planning horizon of several decades, so it seems reasonable that the farmer would make decisions using an expected long-run price.

In the cost results discussions below, no net present values (NPV) are calculated. Unless the discount rate is very low, the proximity of cash flows to the present is important to the outcome; this is why capital investments are depreciated quickly, so that tax breaks arrive earlier than later. In this case, cash flows are weather dependent, and cannot be predicted. If drought occurs right after irrigation is installed, and yield benefits are realized quickly, the NPV might strongly suggest irrigation be installed. If that same drought occurs towards the end of the project lifetime, the same yield benefits would barely register in the NPV calculation so the decision could be a resounding no to an irrigation decision. In the discussion, an average annual undiscounted cash flow (the expected next-year cash flow to a farmer) is used to inform decision making. Given possible future weather conditions and yields, the farmer makes a decision to irrigate based on whether or not the next year is expected to be more or less profitable under irrigation.

4.4 Results and Discussion

4.4.1 Model Validation

McLaughlin and Kszos [8] report a summary of the yields found across the US from the DOE's switchgrass evaluation test plots. At each of test plot site, between two and 12 different switchgrass cultivars were planted and harvested yearly (or twice yearly) to establish expected yields and to determine which cultivars performed better in which areas. Their paper presents average annual yield by location, and maximum and minimum annual harvests for the two top performing cultivars in each location. Anywhere from two to nine years of yield data inform the reported mean, maximum, and minimum values. In Figure 22, yield results for select states from the switchgrass yield model (described in Section 4.3.1) using the historical data (plotted in the figure with grey bars) are compared with field test yields in the same states (coloured bars) from this McLaughlin and Kszos paper in order to establish some context for modelled values.

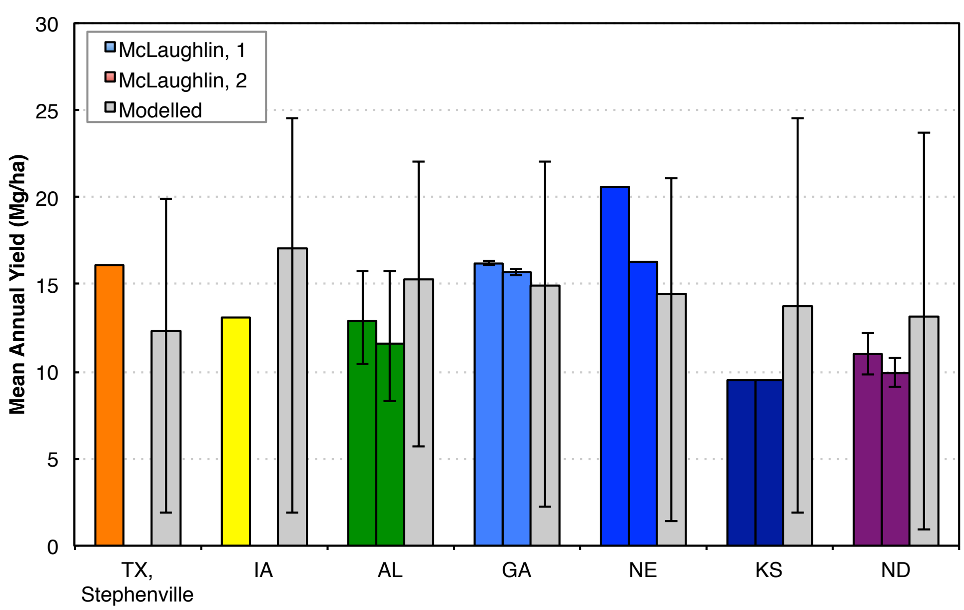


Figure 22. Switchgrass yield model output (grey) compared to reported yields by McLaughling and Kszos.

In all but two 'McLaughlin' locations, mean annual yields from the two highest yielding cultivars are presented in the journal article, and plotted in Figure 22. In Texas ('TX, Stephenville') and Iowa ('IA'), results for only one cultivar are available (hence the missing bar in the chart for these locations). The error bars on the McLaughlin data are the range in average yield values for the two cultivars for the span of the trials. The 'Modelled' series of data are the mean values from 30-years' modelled yields in each state. The error bars represent the minimum and maximum annual average yields in that state over those 30 years. As such, the grey error bars encompass more yields than the McLaughlin error bars because they cover more years of data.

The empirical data all fall within the range of values from the modelled data, though the mean modelled values tend to be higher than the mean empirical values (four of seven states). This may be because, as discussed earlier, the model does not capture many of the reasons why crop yields vary and are lower than expected under ideal conditions. The mean modelled values also tend to be more consistent from state to state than the empirical values; this is likely because of relatively few region-specific characteristics in the model are not able to fully capture the non-climatic changes from site to site.

4.4.2 Yield Variability

In the following sections, results from the switchgrass yield model (defined in Section 4.3.1) are presented and discussed. Boxplots showing yield variability over the 30 years of meteorological data are presented in Figure 23. The data are taken from 1961 to 1990 for one location from each state in the continental US (listed in Appendix A). These data show there are a wide range of median values across these states. There is also substantial variability at each location modelled; almost all of the interquartile ranges (the 25th to 75th percentile range) cover at least 5 Mg/ha, and some cover upwards of 10 Mg/ha. For mean values around 15 Mg/ha, this translates to a variability of 30 to 60% in many locations. States in the Southwest and the Northwest are generally well below states in all other regions. Additionally, all but one outliers falls at the low end of the yield values (South Carolina is the exception), not the high end.

To further investigate the relationship between mean value and variability, in Figure 24 mean yield values for each state of the 30 years of data (plotted in Figure 23) are plotted against their standard deviations. States with extreme values (highest or lowest means or standard deviations) are noted in the figure; New York has the highest variability, Arkansas has the lowest, West Virginia has the highest yields and Connecticut the lowest. Given a goal of reliably high yields, states towards the upper left corner of the graph (low variability, high mean yield) would be preferred over states in the lower right (high variability, low mean yield). The front of points (states) between increasing mean and increasing standard deviation are also included in Figure 24, and include Arkansas, Mississippi, Minnesota, and West Virginia. There are no strong geographic trends upon which to make recommendations based on this comparison.

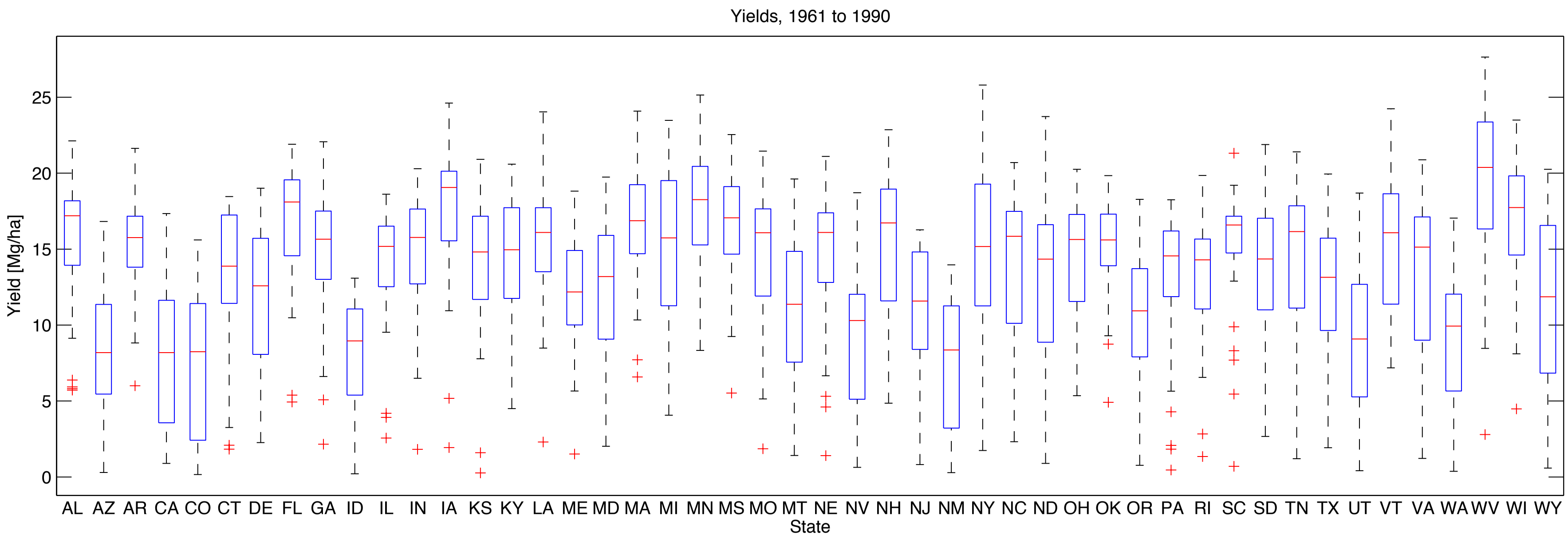


Figure 23. Yield distributions over the 48 continental states for weather conditions from 1961 to 1990.

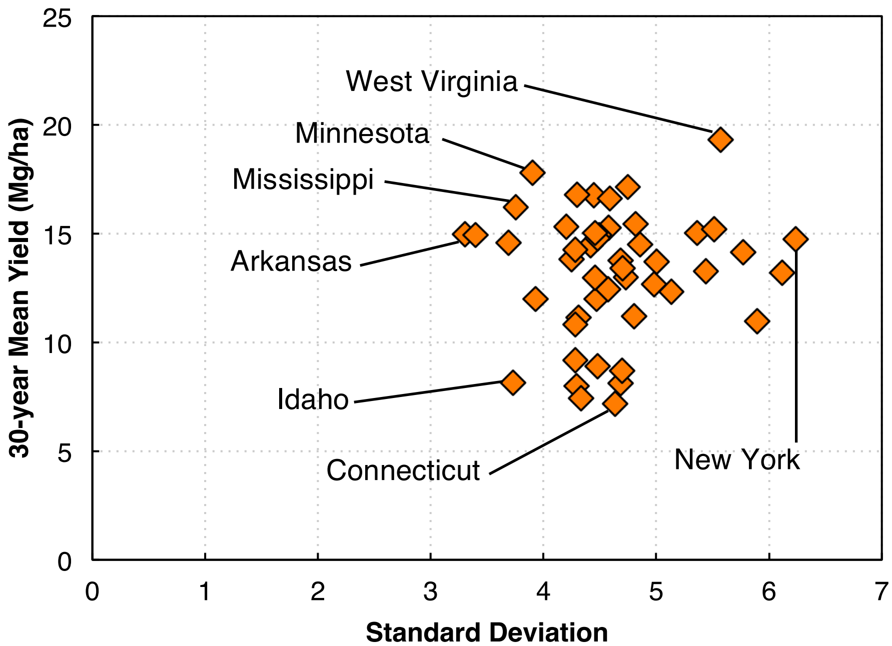


Figure 24. Plot of mean yield versus standard deviation for yields using 30 years of historical weather.

	1 AL	3 AR	9 GA	13 IA	14 KS	15 KY	16 LA	21 MN	22 MS	23 MO	25 NE	32 ND	34 OK	39 SD	40 TN	41 TX
1 AL		0.20	**0.66**	-0.17	**0.37**	-0.13	**0.43**	**-0.40**	**0.62**	0.10	0.17	-0.11	0.28	-0.10	0.23	0.16
3 AR			0.16	-0.09	0.11	0.11	0.31	0.09	0.18	**0.57**	0.07	-0.31	**0.82**	-0.13	0.30	**0.61**
9 GA				-0.24	0.22	0.22	0.35	-0.29	**0.61**	0.06	-0.07	-0.03	0.16	-0.09	**0.49**	0.11
13 IA					0.05	0.28	-0.28	**0.48**	-0.22	0.17	**0.50**	0.06	-0.12	0.23	0.18	-0.13
14 KS						0.09	0.10	-0.09	0.20	**0.46**	0.04	-0.11	0.20	0.21	**0.46**	0.05
15 KY							-0.13	0.06	0.01	**0.42**	-0.06	-0.07	-0.06	-0.08	**0.69**	-0.22
16 LA								-0.04	**0.70**	0.14	-0.15	0.02	0.33	-0.10	0.05	**0.56**
21 MN									-0.29	0.01	-0.08	-0.11	0.00	0.07	-0.07	0.07
22 MS										0.11	-0.06	-0.01	0.15	-0.05	0.35	0.36
23 MO											0.07	-0.06	**0.56**	0.06	**0.53**	0.26
25 NE												0.24	0.01	0.29	-0.02	0.06
32 ND													-0.19	**0.42**	-0.19	0.00
34 OK														-0.09	0.11	**0.62**
39 SD															-0.08	0.18
40 TN																0.01
41 TX																

Figure 25. Correlation of historical model yield between some relevant states, listed by state abbreviation and FIPS code.
Bold values are statistically significant. Green indicates a positive correlation, red indicates a negative correlation.

One important aspect of the historical time series comparisons that is not maintained in the simulated weather data presented in the following section is regional correlation.

Meteorological variables generated in the weather simulation are not modelled with any correlation, simultaneous or past, between locations, even though correlations do exist. Correlations in yields based on historical data are presented for select, relevant states in Figure 25. In this figure, green cells indicate a positive correlation, and red cells indicate a negative correlation, and the colour gradient indicates the strength of the correlation. The statistically significant correlation values are bolded. Some neighbouring states demonstrate significant correlation, though not all do. All but one of the statistically significant correlations are positive; the lone negative value is between Minnesota and Alabama. That most correlations of note are positive and are between about 0.4 and 0.8 suggest that there are not a lot of obvious opportunities to diversify planting locations so as to reduce the likelihood that everywhere switchgrass is grown will have low yields at the same time. This highlights the potential for widespread, simultaneous yield decreases.

The POLYSYS dataset breaks yield values and projected yield increases (as a percent of the initial yield assumption) across the US into seven regions, discussed in Section 4.2.1. The region to which each state belongs is summarized in Appendix A. Disregarding yield variability within each state over time, the variability of the statistics of central tendency (median or mean) over all of the locations within one POLYSYS region suggests that a regional aggregation across 3 to 11 states misses some key data. For example, in the plains regions, separated into North Plains and Southern Plains, mean yields in each state that makes up these regions vary from about 8 (lowest mean yield out of the mean yields from the 8 states in the SP region) to 18 (highest mean yield of the same 8 states) and from about 7 to 15 Mg/ha, respectively, as shown in the 'lowest' and 'highest' columns of data in Table 10. Taking the mean of means suggests the SP region should be modelled with a 9.4 Mg/ha yield and the NP region with an 11.8 Mg/ha yield. Using these mean regional values completely neglects the different productivity levels of the constituent states. Considering yield variability over time in one location also illustrates a shortcoming of neglecting temporal variability. The mean yield across states in the Southeast (SE) region for this 30-year period is 14.9 Mg/ha (assuming equal contribution from each state). If, for example, the very dry meteorological conditions of 1987 arise, the Southeast yield would instead be only 8.1 Mg/ha, a decrease of about 45% from that mean value.

Table 10. Modelled yields as aggregated to POLYSYS regional definitions.

POLYSYS Region	States Within	30-yr Mean Yield Values (Mg/ha)		
		Mean	*Lowest*	*Highest*
Southeast (SE)	11	14.9	13.3	16.8
Southern Plains (SP)	8	9.4	7.2	14.9
Northeast (NE)	8	13.6	11.1	16.8
Corn Belt (CB)	7	14.7	13.8	17.1
Great Lakes (Lake)	3	15.5	14.7	16.6
Appalachia (App)	3	14.8	12.4	19.3
North Plains (NP)	8	11.8	8.1	17.8

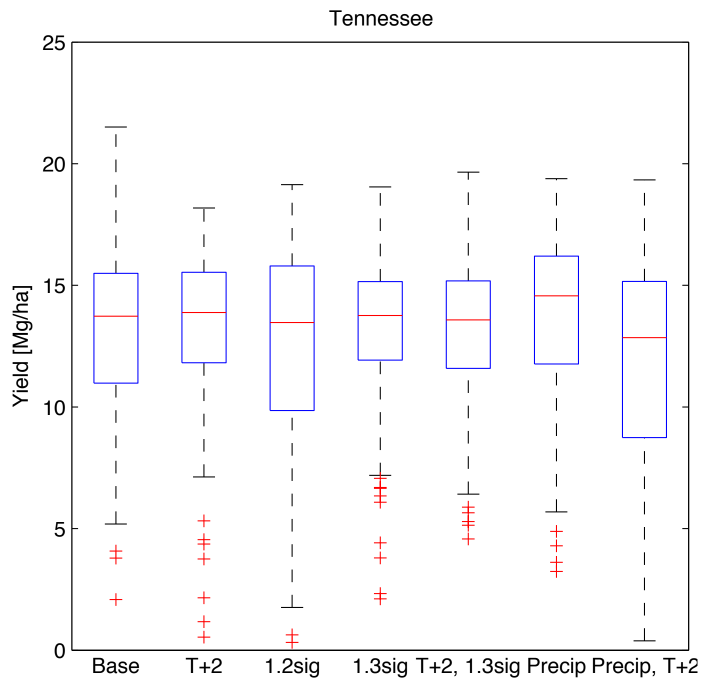
In general, models are built and plans are made based on temporally and spatially aggregated yields. Modellers' recommendations do not include how to deal with a 1987 (exceptional) sort of year, or how the developing biomass industry in Tennessee might deal with its outlier 1.2 Mg/ha yield in a year with very little precipitation (the lowest outlier in Figure 23). Yield variability needs to be a central part of models predicting biomass yields so that these issues spur consideration of the consequences of variability on model recommendations, and so that the biomass community begins to consider mitigation options, and contingency plans.

4.4.3 Modified Climate Scenarios

The previous results and discussions are all based on switchgrass yields generated using historical data. This section explores and challenges the assumption that past data can be used as a proxy for future data based on changing climatic conditions. Other factors that could and probably will affect future energy crop yields include better varieties (with improved drought tolerance, pest resistance, etc.) through research and better field-level operational knowledge. Those are not dealt with quantitatively in this dissertation, but would help to offset trends of lower yields and higher variability.

Figure 26 presents yield distributions for three states (Tennessee, Texas and Iowa) generated with the seven different cases of simulated weather data per state defined in Section 4.3.2. The first case is the base case, and presents yields calculated from simulated weather data (based on historical data for that state). The other six use weather data generated from a modified simulator. Cases two through five show modified temperature data: the second with increased mean temperature, the third and fourth with increasing temperature variability, and the fifth, with temperature both increased and more variable. The final two distributions relate to changed precipitation patters (but not precipitations quantities per precipitation event). In the sixth distribution, the probability of the precipitation status continuing is increased (i.e., if it rained for the past day or two, the likelihood that it will continue to rain is increased, with the same modification for two or three days of dry conditions). In the seventh, the increased wet- or dry-spell likelihood is combined with warmer temperatures. Though overarching conclusions cannot be made from just these three states, it is apparent that these states are affected in different ways by the six changed climate scenarios.

Tennessee is perhaps the least affected of the three locations shown here; the median value across the scenarios is remarkably constant, shifting only by about 1 or 2 Mg/ha. The lower yields, and what qualifies as an outlier changes the most for this state. Based on the results, the combination precipitation spell-length and temperature scenario increase has the greatest effect here. In Texas, none of the temperature modifications have a pronounced effect, but modifying precipitation patterns does. In Iowa, scenarios with temperature increases show the greatest change in median yields, rather than temperature variance or precipitation pattern modification.



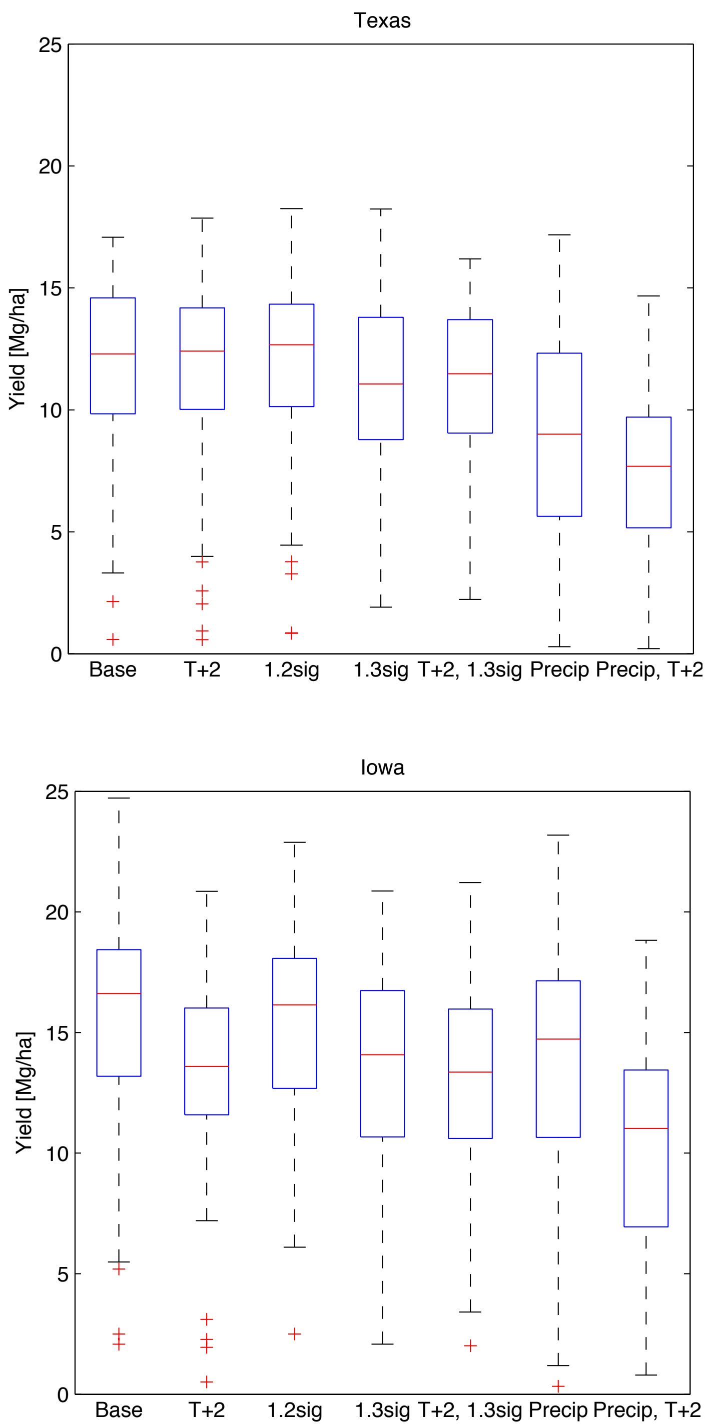


Figure 26. Yield distributions for 100 years of simulated weather data under various climate assumptions for Iowa, Tennessee, and Texas.
***T+2*: Mean temperature increase by 2C**
***1.2sig*: Standard deviation (st. dev.) for temperature increased by 20%**
***1.3sig*: St. dev. for temperature increased by 30%**
***Precip*: Transition between wet-wet and dry-dry more 10% more likely**

Data for all 48 states modelled are aggregated into plots of mean yield versus standard deviation (as done previously in Figure 24) for each of the seven climate scenarios modelled, presented in Figure 27. The yield values for each state are average values from the 100 simulated years of meteorological data. Standard deviation values are calculated using the 100 single-year yields for each state. The base case data are plotted on the top set of axes, with the modified climate scenarios on the six sets of axes below. The centre of mass on each plot is included, relative to the centre of mass for the base case, to indicate trends. Increasing the temperature standard deviation by 20% ('1.2sigma') results in the smallest change in the data. Increasing the temperature standard deviation by 30% ('1.3sigma') has a greater impact, suppressing some of the highest mean yield values. Modifying the precipitation patterns tends to decrease the mean yields as well, though it also produces the highest single state average yield value, and it tends to increase standard deviation. Increasing mean temperature by 2°C ('T+2') also tents to lower yield values. When the temperature is lower and more variable ('1.3sigma, T+2'), the points show slightly reduced range of mean values and slightly wider range of standard deviation values, though the centroid is not much changed from either of those scenarios run individually. Finally, modifying precipitation patterns and increasing expected temperatures has the greatest effect on the mean and standard deviation statistics; the overall mean yield (centroid y value) is about 20% lower than the base case, and the points are increasingly concentrated around the mean standard deviation (centroid x value).

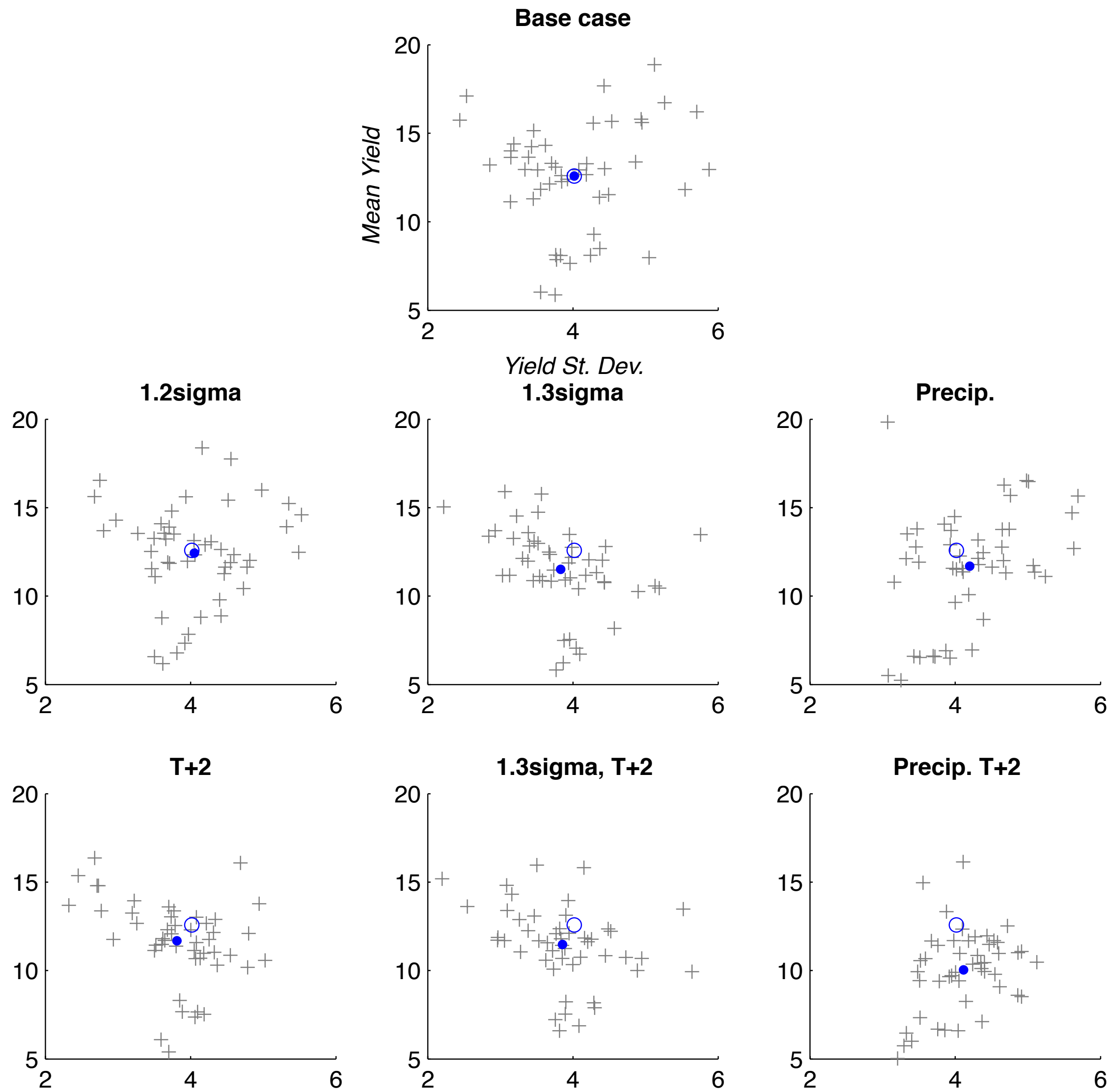


Figure 27. Comparison of mean and standard deviations for yields for all states, for each of the seven simulated weather scenarios.
Y-axis values are yields (Mg/ha) and x-axis values are standard deviations. Solid blue dots are the centroids of the data. The hollow blue dot is the centroid of the base case, plotted on the other scenarios for comparison. Each grey point represents one state.

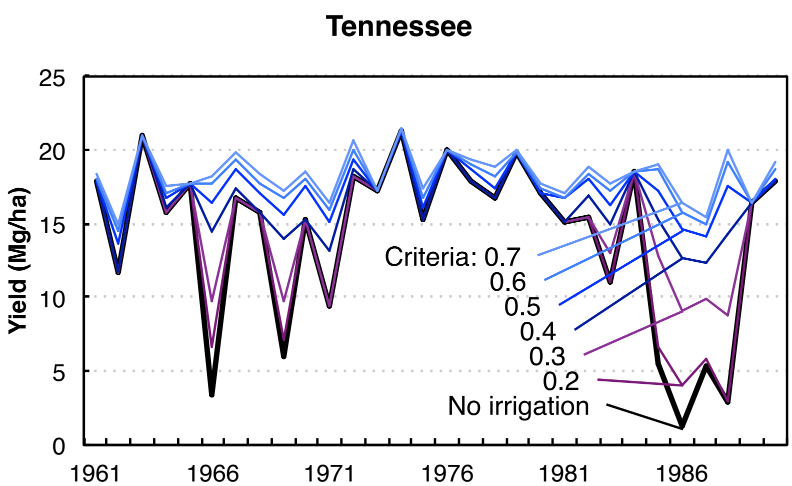
From the results plotted, it seems that as the climate warms and becomes increasingly variable, yields will tend to decrease in many states. Using historical yield data in projections without adjusting for these climate changes will lead to yield over-predictions. To compensate for ongoing over-predictions, increased acreage will have to be dedicated to switchgrass in subsequent years to maintain the same expected mass output (for example, to satisfy mandated volume targets). The impact on yield variability is much less consistent between the different climate cases, so no general conclusions or trends can really be drawn from the results presented here.

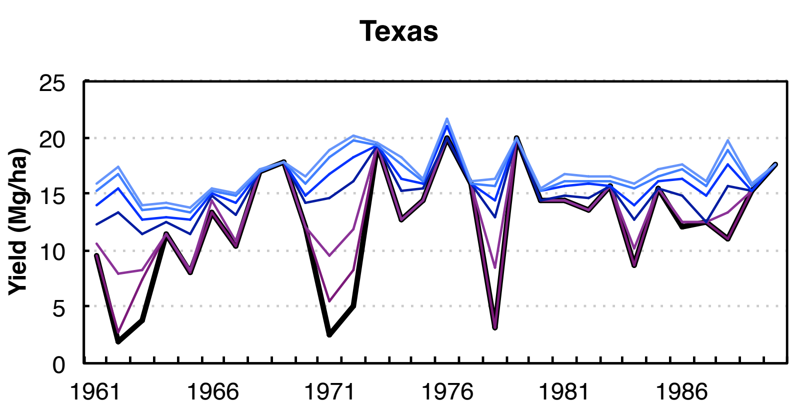
One factor related to climate change that can have a positive effect on agricultural yields is the CO_2 fertilization effect. As discussed by Lobell and colleagues [128], some plants, like wheat or rice, will have higher yields because more CO_2 is available to convert to biomass. Wheat and rice have C3 photosynthetic pathways, meaning that carbon conversion is directly related to CO_2 concentration (and to temperature). In contrast, C4 plants, like switchgrass or corn, tightly control the CO_2 concentration at the uptake site, so changing atmospheric conditions are not expected to affect maximum yields [129]. Ongoing research into the indirect impacts of increased CO_2 concentrations on yield, particularly in conjunction with drought conditions, suggests that water use efficiency is increased under drought conditions and higher CO_2 concentrations, so drought impacts on yields may be blunted somewhat [130]. The precise relationship between water stress, CO_2 and cellulosic crop yields is as of yet undetermined, but will certainly factor into this sort of model in the future.

4.4.4 Risk Mitigation through Irrigation

4.4.4.1 Reduction in Yield Variability

Irrigation was chosen as the technological option to mitigate the expected yield variability due to drought. The impact will depend on several parameters, most importantly how much water is applied and which of temperature or water stress is the primary cause of yield reductions. The impact of adding the option of irrigation is illustrated for three sample states in Figure 28. Here, yield time series data generated using the same historic meteorological data as was used previously (to generate Figure 23, for example), but different FAWHC criteria are applied over the 30-year period to yield different data series. As the criterion increases, irrigation water (at 25 mm per irrigation event) is applied more frequently during the growing season during dry years, so yields increase. One could read these graphs as showing that the top lines, with highest FAWHC values, express yield estimates in the presence of sufficient water, while the bottom lines estimate yields (often) with a deficit of water. By applying irrigation, the deficit can be erased and converge back to the higher levels. These series can be thought of as the technical potential to increase yield; water is applied when the criteria is met regardless of actual water availability.





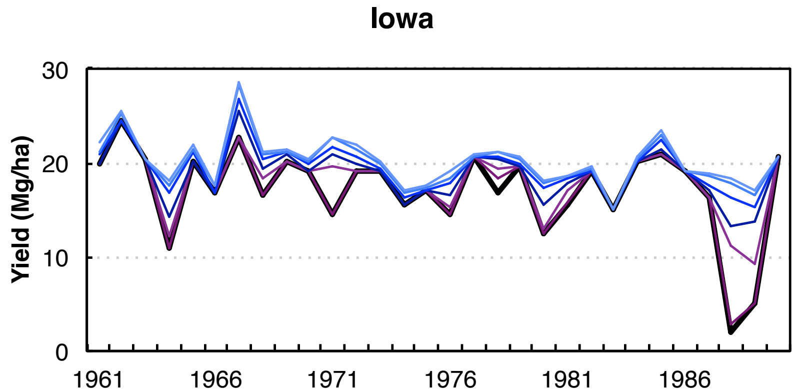


Figure 28. Impact of irrigation on historic model yields from Tennessee, Texas, and Iowa.

Several lessons can be learned from these time series graphs. First, not all variability is due to local water deficits; yields are far from constant even with near-constant water availability because of factors such as temperature. Texas, more often than the other two states shown here, has low yields and shows substantial variability; in a no-irrigation situation, the total uncertainty (defined as maximum minus minimum yield over the 30 years) is 146% of the 30-year mean value, while this value decreases to 57% at the 0.4 FAWHC criteria level of water availability. In Iowa, the uncertainty values as a percent of mean are similar to those in Texas (130% reduced to 65%), even though a visual comparison of the graphs suggests Iowa is a more reliable state. The values are similarly high in Iowa because the maximum yield (see year 1967 from the figure) increases substantially due to irrigation along with the increases from the very low yields in the late 1980s, which causes the range from the minimum to maximum value to remain fairly large.

The second point is there is a clear diminishing of returns from irrigation water on yields as the criterion increases. The diminishing returns from increased water application are more apparent in Figure 29 and Figure 30. As the FAWHC required increases from 0.2 through about 0.4 there are noticeable gains made in dry years. As the criteria moves beyond to 0.5 and above, the incremental gains are less and less. Figure 29 plots the absolute mean yield gain over 30 years (relative to the no irrigation, historical meteorological data scenario) against standard deviation for each state, to provide information about how absolute mean and variability statistics change relative to one another. Figure 30 plots the total uncertainty (defined as the maximum yield value minus the minimum) as a percent of the mean yield value over the 30 years for each state in which switchgrass is expected to be grown, and is therefore a relative measure of mean to variability in each location. In Figure 29, for criterion 0.1, the dispersion of data points is basically identical to the no irrigation case, as the centroids overlap. As the criterion increases, the cloud of points slowly shifts towards lower standard deviations and higher mean values, with the decrease in standard deviation much more pronounced than the increase in mean. Beyond the 0.5 criteria, the distribution of the data points does not change substantially, indicating that the crops have sufficient water and are not advantaged by more. This is supported by the results plotted in Figure 30. Given that most of the yield gains to be had are had by the time the 0.4 FAWHC irrigation criteria is applied, this time series (out of the six possible irrigation time series per state) is used as the 'irrigation' case in each location for the irrigation cost and risk mitigation discussions that follow in Sections 4.4.5 and 4.4.6.

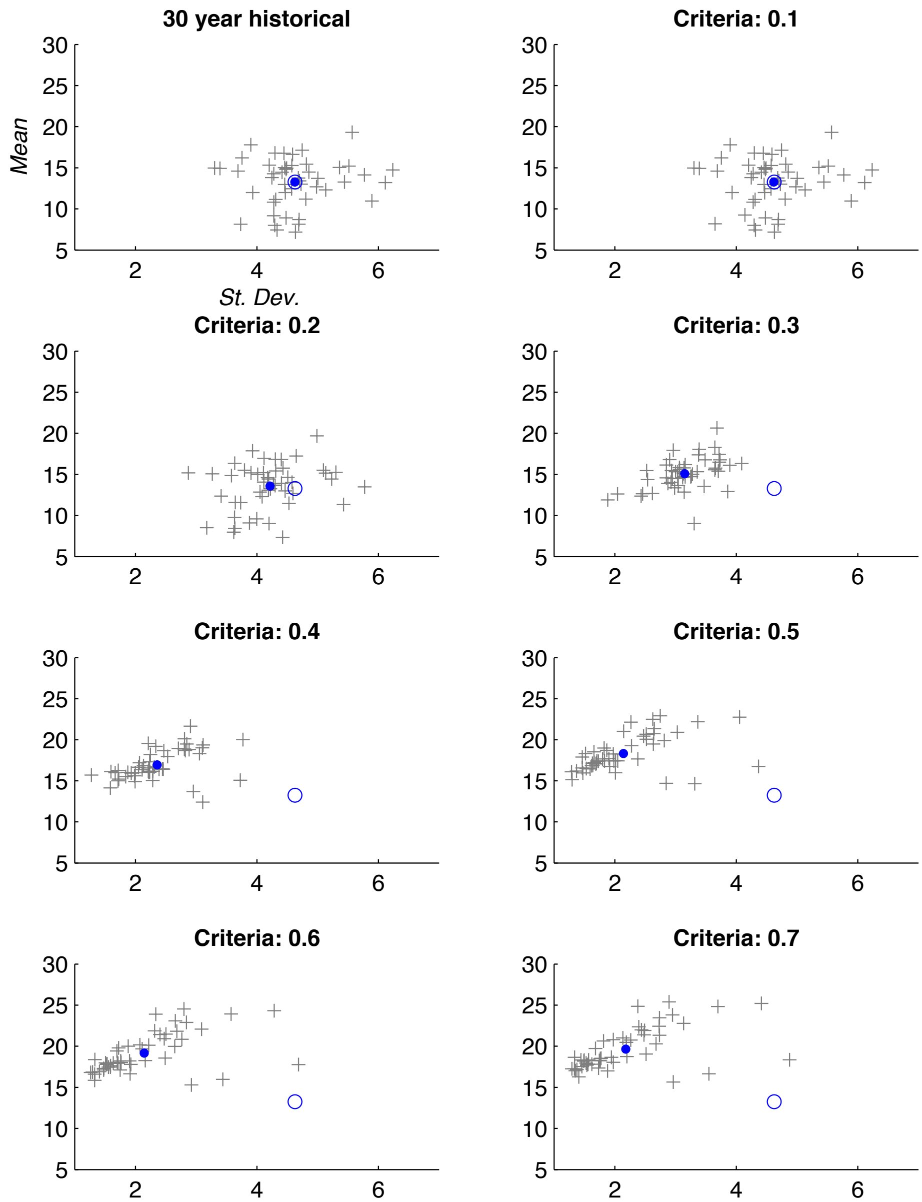


Figure 29. Comparison of mean and standard deviation statistics for 48 US states under increasing soil water availability (FAWHC criteria).
Y-axis values are yields (Mg/ha) and x-axis values are standard deviations. Solid blue dots are the centroids of the data. The hollow blue dot is the centroid of the '30 Year Historical' data, plotted on the other scenarios for comparison. Each grey point represents one state.

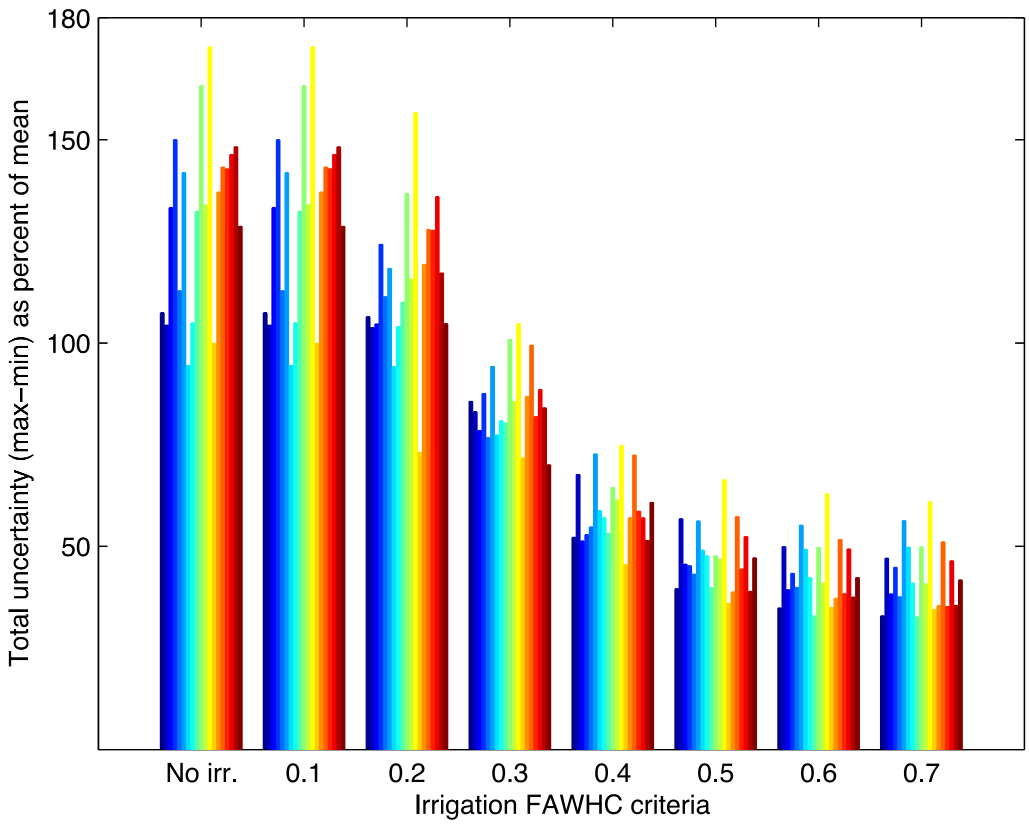


Figure 30. Total uncertainty (maximum – minimum yield) per state as a fraction of the mean yield over 30 years. Plotted are the no irrigation case and the seven different FAWHC criteria values use for irrigation decisions.

Figure 31 plots all annual yield data modelled from historical data for all states against the corresponding June PDSI value for un-irrigated and irrigated (criteria 0.4) yield values. The 'curve fit' line is not meant to suggest a linear model, but rather to illustrate the changing correlation between yield and increasing PDSI values (i.e., decreasing drought severity) with and without irrigation. Irrigation as a risk mitigation measure is quite effective at shifting the very low yield values upwards. The relationship between yield and PDSI is much less strong under irrigation, but there is still a spread in yield values (now 5 to 30 Mg/ha instead of about 0 to 30 Mg/ha). These values are now dependent on things other than severe water deficiency (such as temperature).

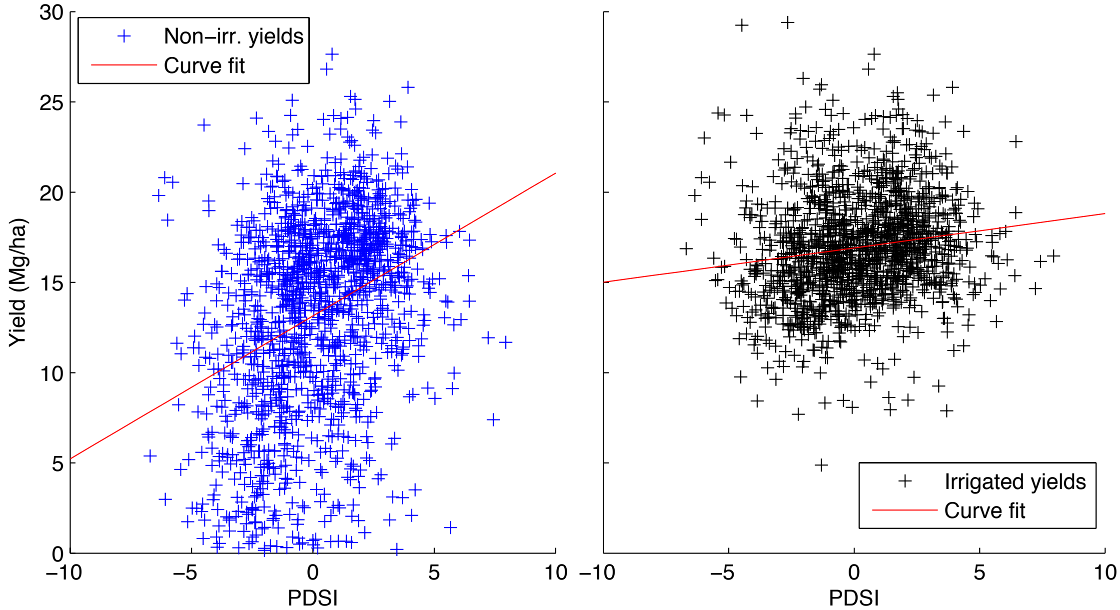


Figure 31. Yearly yield data for 1961 to 1990 for all continental states plotted against corresponding June PDSI values.

4.4.4.2 Water Consumption

Another important way to evaluate the irrigation scenarios is to directly compare the amount of water applied with the mean increase in yields, so switchgrass can be considered in some context with water applied to other US crops. This comparison is facilitated by the plot in Figure 32, which has the percentage change in mean yield for each state plotted against the average annual irrigation water applied. Looking at the 0.4 criteria series of data, average annual water application by state ranges from about 50 to 400 mm. The highest application rate is under the 0.7 criteria, which runs from about 150 to 650 mm, with only minimal yield increases. This plot also illustrates two distinct clouds of points; one which shows yield increases in the 10 to 30% range with modest water application, which include states with modest expected yields under rain-fed conditions, and one that shows much higher yield gains with greater irrigation water, which includes states with very low expected yields under rain-fed conditions. Note that in the states which see the greatest yield gains from water made available by irrigation (e.g., South Plains states), some amount of water is applied every year. In the other states, where irrigation water is applied to less benefit, it is not used every year because of sufficient rainfall, so a 100 mm annual average results from many years of 0 mm applied, and a few years with hundreds of mm water applied.

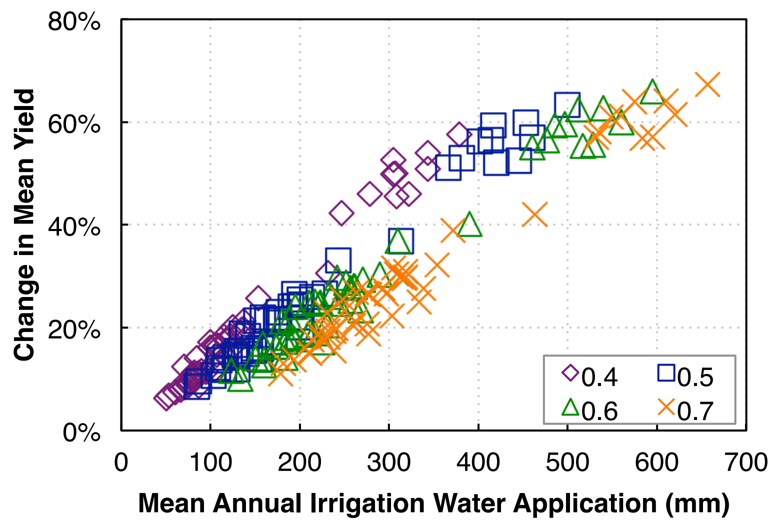


Figure 32. Comparison between percent change in annual mean yield and mean annual applied irrigation water (both means over 30 years).

To better understand states included in the high water application, high yield cloud of points, the data from Figure 32 criteria series 0.4 are plotted in Figure 33, but the series are now defined by which POLYSYS region contains the state (POLYSYS regions defined above in Table 10, Appendix A). These data are plotted on a logarithmic x-axis (linear y-axis) so that the points are more easily distinguishable. The two most water deficient regions are the Northern Plains (NP) and the South Plains (SP), as such, in those regions the greatest yield increases can be obtained, but at the greatest investment of water, because the yields were so low to begin with. At the other end of the plot fall states with a low potential for applied water to result in a substantial increase in the mean yield. Here, the opposite situation occurs; yields are comparatively high and stable under rain-fed conditions in the Southeast (SE) and in the Corn

Belt (CB), so there is not often substantial water deficiency and opportunities for added water to greatly increase yields.

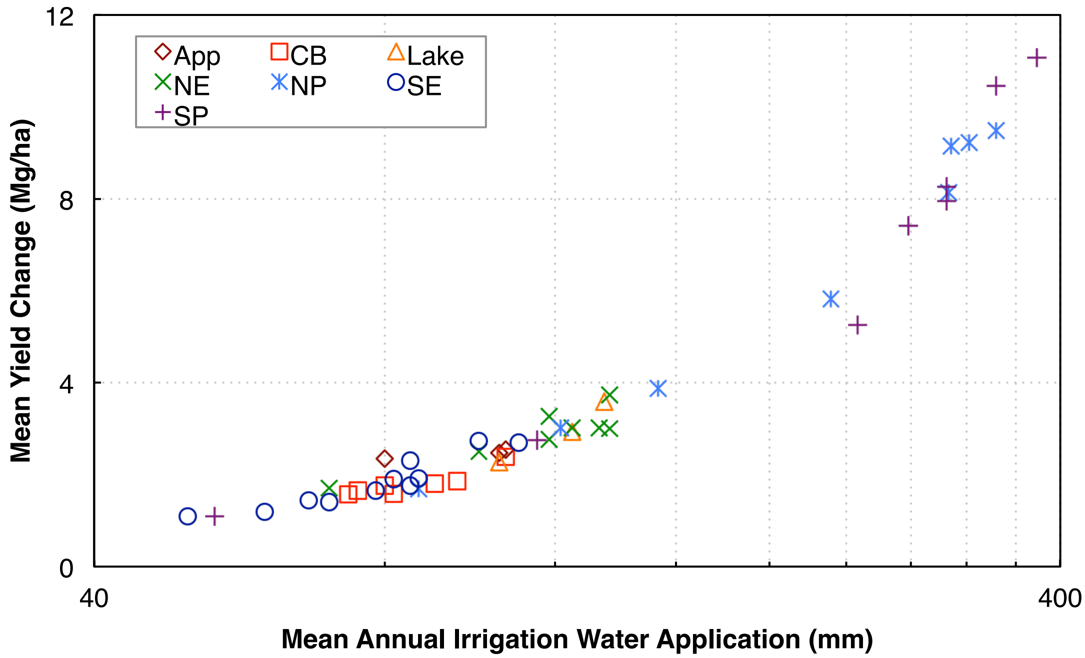


Figure 33. Comparison between absolute change in mean yield over 30 years and mean applied irrigation water (0.4 FAWHC criteria), categorized by POLYSYS yield region.
Note that the x-axis is logarithmic.

Figure 34 shows average annual irrigation data taken from the Agricultural Resource Management Survey undertaken by the Economic Research Service of the USDA [131]. The years shown are the only ones with irrigation data for the respective crops, so gaps represent no data, not zero. These results are annual average values applied over irrigated acres, not over all acres. In most years, somewhere between 150 and 350 mm of water is applied to irrigated corn, soybeans, and wheat. From about 2000 onwards, these crops have accounted for roughly 10, 6, and 3 million irrigated acres (with some fluctuations between reported years), so more water is used by corn than by soybeans and wheat combined. Irrigated acreage accounts for roughly 13% of corn acreage, 9% of soybean, and 14% of wheat. From these irrigation data from some primary US crops, it can be concluded that the 50 to 150 mm average annual water applied to switchgrass, which is generally assumed to be a rain-fed crop in the less water scarce states (such as in the Southeast or the Corn Belt) in order to manage the risk of switchgrass yield variability is comparable to irrigation water amounts applied to other key US crops. The amount of irrigation water necessary to grow switchgrass in an otherwise unfavourable location, such as the 250 to 400 mm necessary the Southwest, is not that much above the needs of these traditional irrigated crops.

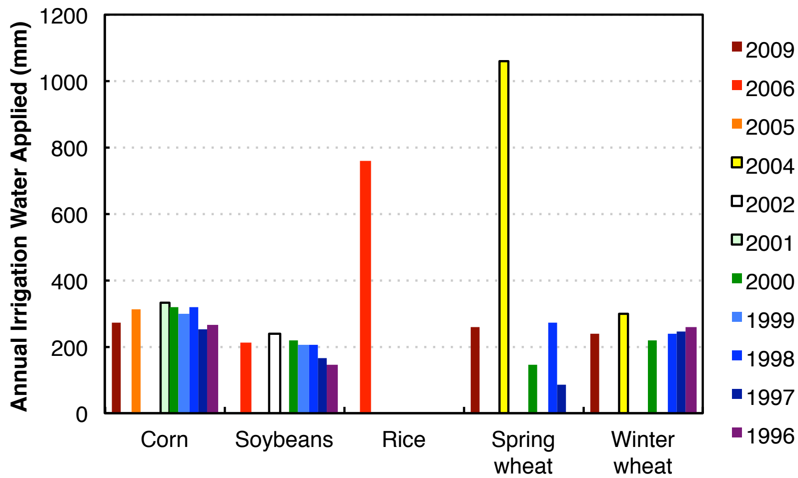


Figure 34. Irrigation water applied to key US crops.

4.4.5 Irrigation Costs Comparison

Of course, the increased switchgrass yields obtained though the application of irrigation water come at a cost. These costs are calculated using the methods described in Section 4.3.3 and Appendix A. Briefly, the costs for differences in the irrigated versus the non-irrigated system include irrigation infrastructure financing, irrigation system operating and maintenance, and potentially increased revenue from more productive irrigated lands. Figure 35 shows average annual cash flows for capital financing and operational costs, as well as the increased revenue from the sale of the additional switchgrass. Although this is not everything affecting the final after tax cash flow value, it is the cost of the system that drives the annual after tax cash flow values. Operating expenses are almost always less than financing expenses. Water costs are generally less than 10% of the total operating costs (given $20/acre-foot water costs), so water use is of little concern to the famer. The cash flows presented in Figure 35 are for a central pivot irrigation system. The trade-off between increased yields and comparative cash flow gains or losses is plotted in Figure 36. The changes are calculated as the difference in yields and after-tax cash flow values between otherwise equivalent irrigated and non-irrigated farms in each state.

The expected annual after tax cash flow difference between the irrigated and the non-irrigated farm is negative for 37 of 48 states (illustrated in Figure 35), and the average annual after tax flow values per state expressed as a dollar per acre on the top set of axes in Figure 36. These results mean that, for a state in which a negative cash flow value is calculated, a farmer in that state will expect to earn less money next year if irrigation is installed than if it is not. This suggests that investing in irrigation would not be viewed by a private, risk-neutral farmer as an effective risk mitigation measure to protect revenues in the face of drought. The risk tolerance of the farmer would impact how attractive the prospect of increased yields from irrigation might be, with a risk seeking farmer more likely to gamble on near-term high returns, and a risk averse farmer less likely.

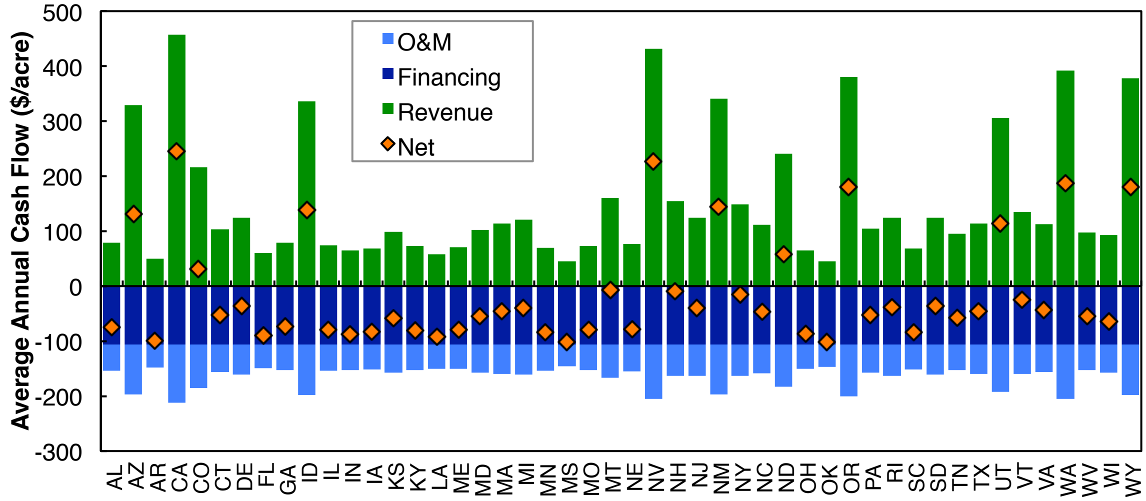


Figure 35. Key cash flow differences for each state using central pivot irrigation. Differences are between an irrigated farm and a non-irrigated farm.

The first panel in Figure 36, titled 'Base assumptions' shows essentially a linear relationship between mean annual cost difference per acre and yield change. When yield increases are greater, installing irrigation becomes increasingly attractive because, under crop and water price assumptions, spending between 5 and 20 cents on water yields $1 in increased switchgrass. For 11 of the 48 states modelled, the mean annual after tax cash flow value is greater if irrigation is installed at the expense of the farmer, meaning irrigation is used in most, if not all, years, so the increased yields (bought with cheap water) outweigh the capital costs. By and large, these states are all in the West. This result is consistent with the fact that corn is profitably grown with irrigation in Arizona, but not in Iowa. For the rest of the states, water is equally inexpensive, and switchgrass prices are equally high, but there is enough rainfall most of the time to suggest that irrigation generates a return on the investment for only a few years out of 30. In these states, farmers would not opt to install irrigation on their own because the expected annual cash flow for an irrigated acre is less than a non-irrigated acre. The trend here is that the states with small potential yield increases (i.e., the states where the yields are usually fairly high) such as Iowa, Arkansas or Missouri, show the biggest negative mean annual cost difference.

The smaller four plots (A to D) in Figure 36 explore the relationship between the expected annual after tax cash flow differences, switchgrass prices and water prices. The yield differences remain the same across all sensitivity plots because the amount of water applied (and all other yield model input parameters) remains constant. Dropping switchgrass prices by half to \$51/Mg (plot A) makes the average annual cash flow differences negative for all states. Not even in the Southwest, where large, irrigation-induced yield gains are had, can the cost of installing and operating irrigation be justified. The trend is still that the mean annual cost difference is much smaller for the water scarce regions where there is high potential for more water to bring great yield increases. In panel B, when water prices are increased to a point about halfway between agricultural and residential prices, and switchgrass is kept at \$102/Mg, the trend changes. Now to see \$1 in increased switchgrass production, more than \$1 must be spent on water. This trend is more pronounced with ever-higher water prices in panel C. When switchgrass prices are halved and water prices are set at \$100/acre-foot (panel D), the switchgrass return on water invested is about 1:1, with it being above some years and below others, so the relationship between yield gained and money lost clusters around the -\$120 to -\$130/acre range.

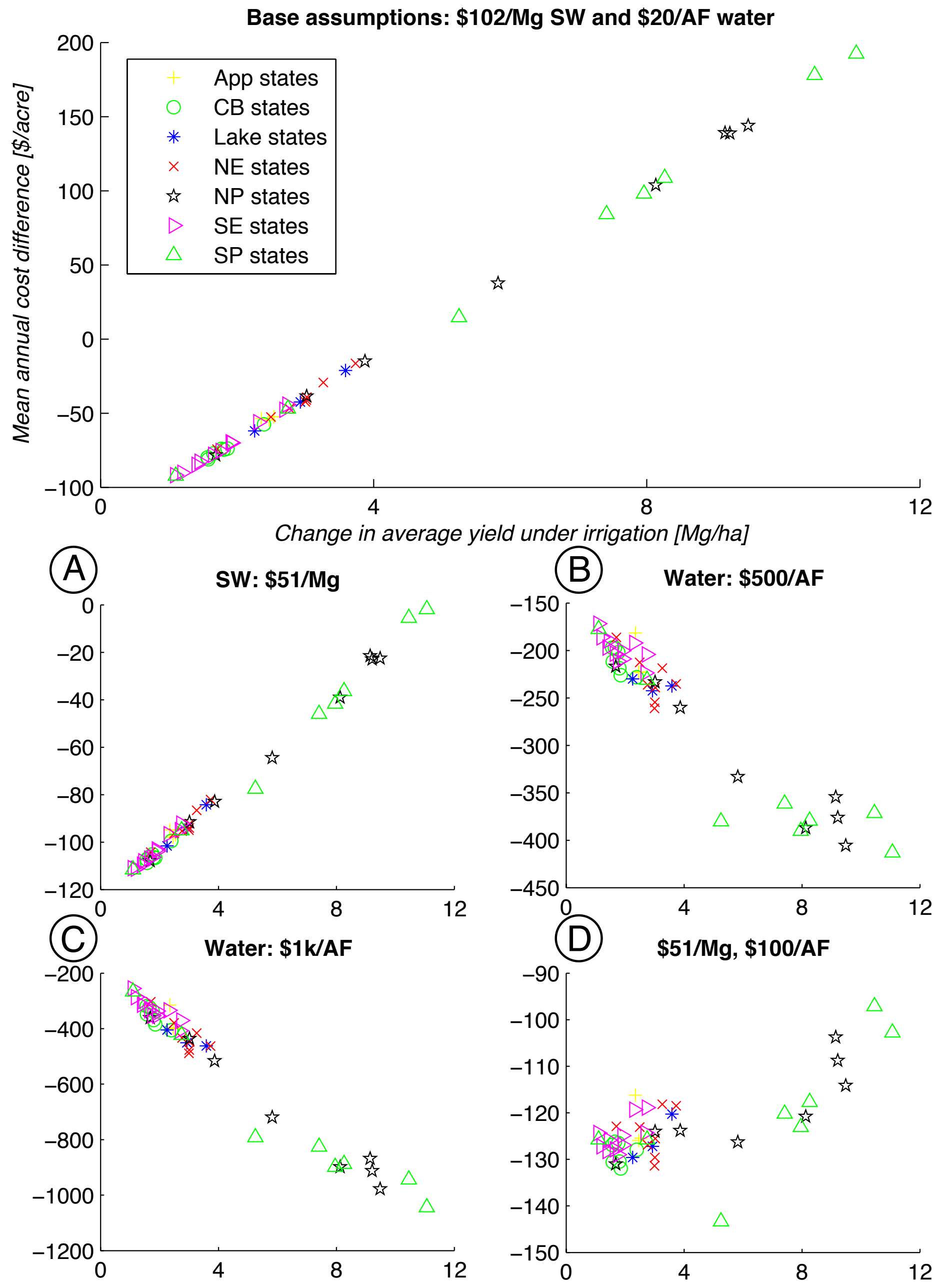


Figure 36. Mean annual cost differences (between irrigated and non-irrigated) farms in all states versus mean annual yield differences. Thirty years historical data used to model yields.

In practice, the farmer's decision to irrigate is not as straightforward as this. If the farmer has no irrigation equipment, a decision to install and begin irrigation (after dealing with acquiring a reliable source of water) must be made. Once irrigation is installed, there is a further decision not modelled this study regarding whether to use the water allocated to them, or to sell those water rights to a consumer who may be willing to pay more than the expected revenue increase from higher yields. This behaviour has been observed in California, where irrigation is given water rights priority. Farmers for whom irrigation provides relatively low added value are selling their water allocations to nearby industry or residential consumers [120]. This is important in this context. If farmers choose not to water their crop of switchgrass, but instead sell the water rights to the highest bidder, then switchgrass yields are not stabilized even with installed irrigation infrastructure. The government would not only have to overcome the negative expected annual cash flow values identified here to encourage switchgrass yield stabilization, but also the alternative markets for water. The conditions under which a farmer might decide to sell or lease water rights under drought conditions rather than irrigate to reduce crop losses would be driven by the value of the increased yields under irrigation, and the value of the water to another user (such as an industrial consumer). From an energy security standpoint, in order to ensure that irrigation is used to reduce switchgrass supply risks during drought, some measures would be needed to assure farmers irrigate rather than sell their water rights. This could mean water use restrictions, which could be very unpopular politically and socially, or possibly government payment in an amount competitive with what interested parties are offering for their water rights. Examining the relationship between water market prices and energy crop prices, alongside water rights and allocation as they vary by region, would be an excellent area for further research.

4.4.6 Subsidy for Supply Risk Reduction

From the previous section, it is apparent that, in states where studies (such as those based on the POLYSYS model) expect that rain-fed switchgrass will be grown (i.e., not the West or the Northeast, according to Figure 18), farmers will not be otherwise incentivized to install irrigation even with optimistic switchgrass prices and low water prices. This means yield variability caused by drought will not be taken care of by market-based private decisions unless an external incentive, such as a government subsidy, is provided. This could take the form of a tax credit, a loan guarantee, or some sort of direct payment to cover a portion of the irrigation installation (i.e., capital) expenses. The subsidy should not cover operating costs. If operating costs are effectively reduced, farmers might be less sensitive to water prices and use more water for irrigation than they would otherwise. Realistically, there is no simple way to ensure that farmers irrigate to the FAWHC 0.4 level (as presented in Section 4.4.4.1 and assumed to be the irrigation scenario in the following sections) rather than to the 0.7 level once irrigation infrastructure has been installed, but at the very least the subsidy design can avoid specifically incentivizing more water use. A second implementation issue is whether

Regardless of the specific mechanism, the subsidy has to cover the amount of money that the switchgrass farmer expects to lose if irrigation is installed and operated so that the decision to install and operate will be made by the private farmer. Based on the results presented above (see the first graph in Figure 36), this value varies by state. For example, farmers in Tennessee would expect to earn \$140/ha (or \$57/acre) less if irrigation was installed and operated than if it was not. So, the farmer would have to receive \$140/ha farmed through a subsidy program in order to decide to install and operate the irrigation system.

Biomass feedstock yield stability is related to energy security, and energy security is something that the government is willing to spend money to increase. For example, the US DOE estimates that \$3.50/barrel oil capital costs were invested for the US strategic petroleum reserve in Louisiana and Texas, which is currently filled to capacity at 727 million barrels, for which the US government paid an average of \$29.76/barrel oil each [132]. There is, then, reason to believe that irrigation could be subsidized to stabilize switchgrass yields and biofuel availability. Unlike with previous discussions in this study, which presents yields at a state location level, this requires yields and biomass availability to be aggregated to the national level, as national goals (such as EISA) drive the use of cellulosic ethanol.

To aggregate to a national level, some way of distributing acreage across the states must be set. A POLYSYS database distribution case that corresponds produces sufficient switchgrass to meet the EISA 2022 cellulosic ethanol target of 16 billion gallons (distribution shown in Figure 18) is used to calculate the relative distribution of switchgrass across all states (many of which produce zero switchgrass). Note that each distribution case is established based on three primary criteria in POLYSYS: a price for switchgrass, an ethanol demand level, and a switchgrass yield level ('expected' or 'high'). The set of input assumptions that result in sufficient switchgrass for 16 billion gallons is not unique. However, based on work by Wakeley, who showed that the choice of a specific POLYSYS scenario that yields 16 billon gallons of ethanol does not make a substantial difference in where the switchgrass is grown [133]. However, this assumption is an area for further investigation to see how the national aggregate yield varies based on how much switchgrass comes for each state to get an idea of how the national availability of switchgrass varies over time. This is not possible when using only point estimates for broad regions of the country as the POLYSYS database does. For the chosen POLYSYS case ($95/Mg switchgrass, high yield, high ethanol demand), 19 states grow some switchgrass. Instead of using the potentially ambitious and highly aggregated POLYSYS yields, the modelled switchgrass yields from previous sections here are used to calculate an annual, national, switchgrass production amount. The mass of switchgrass produced in each state in which the crop is planted is included in Table 11.

Table 11. Distribution of land among switchgrass producing states, and expected biomass production to generate 16 billion gallons ethanol.

State	Percent Area	Mean Yield (Mg/ha)	St. Dev.	Expected Biomass (10^6 Mg)
OK	12.9%	14.9	3.39	19.2
KY	10.7%	14.3	4.28	15.3
AR	9.4%	15.0	3.31	14.0
TN	8.7%	14.1	5.77	12.3
MO	8.2%	14.8	4.48	12.1
MS	7.1%	16.2	3.75	11.5
AL	6.0%	15.3	4.58	9.2
TX	7.1%	12.3	5.13	8.7
ND	5.6%	13.2	6.11	7.4
LA	4.2%	15.3	4.20	6.4
GA	3.9%	14.9	4.49	5.8
VA	4.0%	13.3	5.44	5.3
KS	3.1%	13.8	4.68	4.2
NC	2.1%	13.7	5.00	2.9
NY	1.8%	14.7	6.24	2.6
WV	1.3%	19.3	5.57	2.4
SC	1.6%	15.0	4.46	2.4
MN	1.2%	17.8	3.90	2.2
SD	1.2%	13.4	4.70	1.6

Two average national yield time series are plotted in Figure 37, one assuming no irrigation anywhere, and one assuming irrigation installed everywhere. The expected non-irrigated yields are always lower than the irrigated. The national aggregate non-irrigated case shows higher minimum yields than do the individual states involved (the low outliers shown in Figure 23), as not every state has record lows simultaneously. There is, however, still substantial variability at this aggregate level, with non-irrigated yields ranging from 9.9 to 19 Mg/ha with a mean of 14.6 Mg/ha; uncertainty as a percent of mean is 61%. When irrigation can be used everywhere (an upper bound for yields and stability) the variability is substantially reduced but certainly not eliminated, as mean yields range from 14 to 20 Mg/ha; uncertainty as a percent of mean is reduced to 33% with a mean of 16.6 Mg/ha. The error bars included here are not a standard error measure, but rather show the highest and lowest state values for each of the two scenarios (irrigated or not irrigated). As expected, the highest values of the error bars (both above and below the mean value) on the irrigation series are higher than the error bars on the non-irrigated series.

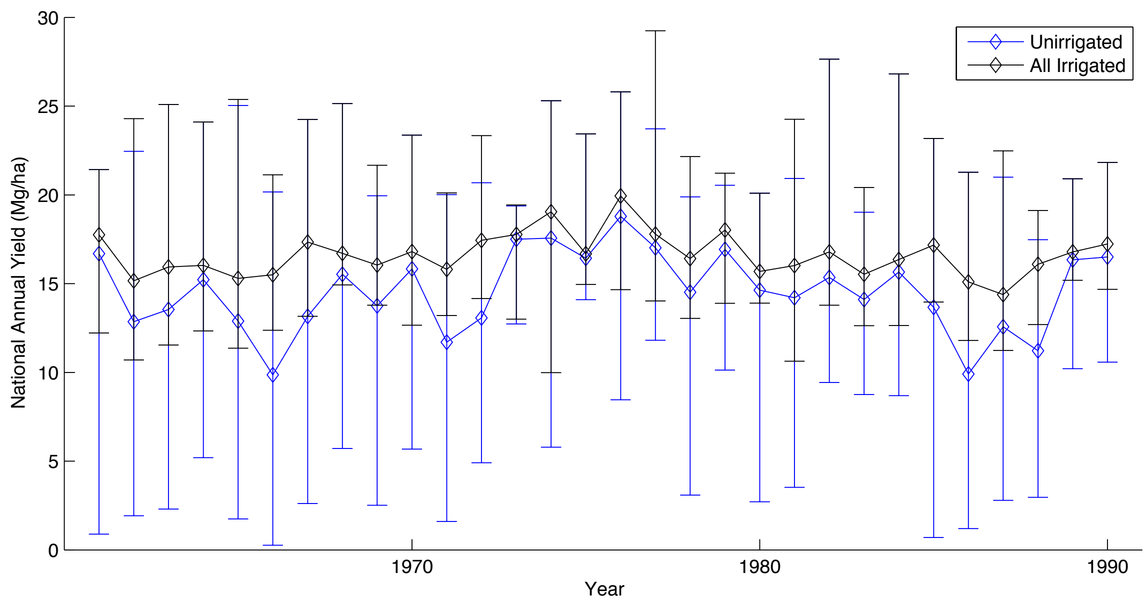


Figure 37. National average yields generated with historical data for no irrigation, and for complete irrigation coverage.
Error bars indicate the single highest and lowest yield each year out of the states included.

Of principal interest is how this yield variability, even when state yields are aggregated to a national level, affects the supply of ethanol. The last major assumption is how many acres are planted in each state, using the established relative distribution of acreage from the POLYSYS scenario excerpted (discussed above). If mean, 30-year unirrigated yields from each state are used, 24.7 million acres are required across the US to hit the EISA 16 billion gallon per year target. Using the unirrigated time series in Figure 37, there is insufficient switchgrass biomass produced to meet the hard EISA target 50% of the time. This is one data point plotted in Figure 38. Since irrigation increases yields and reduces variability, the likelihood of meeting the EISA target can be evaluated as a function of how much of the total area is irrigated, and under the assumption that the government would not necessarily seek to continually manage or mitigate all of the potential risk. Here, irrigation is applied as a percentage of the area in each state (as calculated above); the absolute area in each state that is irrigated is different because all states have different acreages planted with switchgrass, but the same percent of the total area planted with switchgrass for all states has irrigation infrastructure installed. If all of the switchgrass acres are irrigated, 97% of the time the ethanol volume target can be met.

If, alternatively, risk mitigation is done through planting more switchgrass acreage (i.e., if assumed yield values lower than mean are used to determine or predict acreage), then the likelihood of under producing ethanol goes down because more switchgrass tends to be produced every year. In Figure 37, the impacts of overplanting can be seen in the non-irrigated case (0% irrigation, or the y-intercept), as the likelihood of meeting the EISA target increases as more and more switchgrass acres are planted. The acres planted for each curve in this figure (which is based on a different assumed yield per acre) are summarized in Table 12. Additionally, the amount of irrigation needed in order to guarantee that sufficient switchgrass (and thus ethanol) will be available to meet the target decreases as the switchgrass acreage increases. Note that in the "overplanting" scenarios, if eventual yields in those years are higher than expected it could put downward pressure on market prices of switchgrass. This effect is not modelled here. In Figure 37, the curves step sharply upwards because only 30 years of data are used, and would be smooth with a longer time series. The 30 years of historical data, rather than yields from simulated weather data, are necessary to preserve the correlations in yields between states.

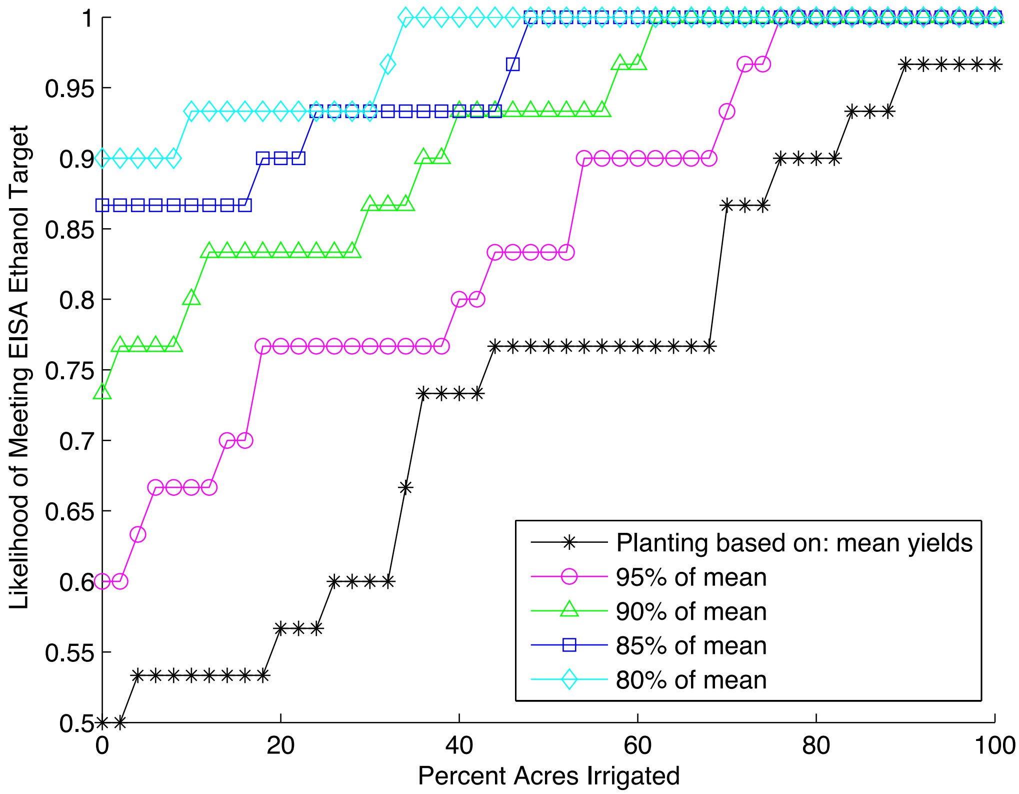


Figure 38. Percent of years (out of 30) during which the amount of ethanol is below the target 16 billion gallons due to yield variability.
Different series result from different mean values used to calculate switchgrass acreage per state.

One aspect of the trade-off that is not illustrated in Figure 38 is the total cost to the government from the subsidy required to get farmers to irrigate all of those acres. Recall that payment necessary to offset the cost of the irrigated system over the non-irrigated system varies by state (top panel in Figure 36). The total costs to install and operate irrigation over some fixed percentage of switchgrass acres increases with each planting acreage scenario (where each curve in Figure 38 represents one scenario), as more acres are necessary when you assume lower yields per acre while holding constant the necessary amount of biomass. The system subsidy costs are summarized in Table 12, assuming 100% of the acres are covered with irrigation infrastructure. It is highly unlikely that all of the acreage devoted to switchgrass would be irrigated, unless policy makers decide that they need to be guaranteed sufficient ethanol to meet a specific volume target. If this approach is taken, it is more likely that some level of risk would be tolerable, and that level of risk could be achieved though the combination of irrigation and overplanting. Using the curves in Figure 38 can assist in choosing how much of each irrigation or overplanting strategy to implement; a horizontal line at the desired risk level cuts through the various planting scenario curves at different irrigation levels. Each intersection point (defined by risk, planting level, and irrigation level) from this exercise would have a different system subsidy cost which would have to factor in to the decision making process. Because the percentage of switchgrass acreage covered by irrigation is modelled as consistent from state to state, while the total acres from state vary, the costs reported in Table 12 will scale linearly with the percent of acres covered by irrigation systems. This trade-off exercise illustrated in Figure 38 is most useful if the volume targets are strictly enforced. Currently, they are not. Cellulosic fuel targets have been waived since the RFS began because these fuels are not economically viable at a scale big enough to satisfy the volume targets, even with subsidies.

Table 12. Summary of annual system costs, acreage, and water use for 100% irrigated acres.

	Annual System Subsidy [billions]	Acres of Switchgrass [millions]	Annual Water Use [million acre-feet]
Mean yields	1.67	24.7	74.6
95% of mean	1.76	26.0	78.5
90% of mean	1.86	27.4	82.9
85% of mean	1.97	29.0	87.8
80% of mean	2.09	30.8	93.3

4.4.6.1 Cost Effectiveness of a Switchgrass Irrigation Subsidy Program

External financial support from the government is required, but that support translates to expected increases in yields (shown in Figure 36). As a result, a subsidy per gallon of ethanol can be calculated as a measure of policy cost effectiveness. Continuing with Tennessee as an example, a \$140/ha subsidy results in an expected switchgrass yield increase of 2.3 Mg/ha. Assuming 110 gallons of ethanol can be produced per Mg switchgrass [133], this means the cost effectiveness of the subsidy program in Tennessee is \$0.55/gallon ethanol. Distributions for these cost effectiveness values over all 19 likely switchgrass states are plotted in Figure 39, with a variety of different switchgrass and water price scenarios. The state with the least expensive subsidy would be New York, which requires \$52/ha to see an increase of 3.5 Mg/ha, which would cost \$0.13/gal ethanol. The second-to-least expensive state would be South Dakota, which needs \$95/ha to yield an increase of 3.0 Mg/ha. The cost effectiveness here would be \$0.29/gallon. Unfortunately, these two states are expected to have a low acreage percentage, at 1.8 and 1.2% respectively. In contrast, North Dakota farmers would be incentivized on their own to install irrigation, so no subsidy would be required as they expect \$93/ha returns on their own irrigation investment, and 5.6% of all switchgrass acres would be in that state.

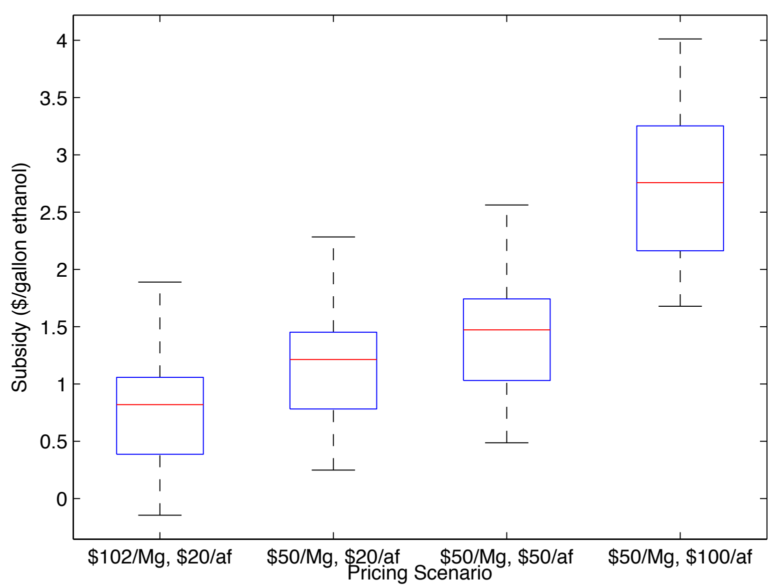


Figure 39. Distribution of government subsidy values across states growing switchgrass to satisfy EISA targets under various switchgrass and water price assumptions.

Generally, if the price of a gallon of gasoline is considered to be around the current 2012 $4/gallon mark (or $5.20/gallon ethanol to be energy equivalent), these additional costs seem quite high. To add some more relevant context to these values, first consider that another agricultural subsidy, crop insurance, pays out between $15 and $45/acre based on the data presented in Figure 5 for all causes. Recall the subsidy for irrigation for relevant states is somewhere between $90 and $200/acre. With the addition of irrigation, the drought portion of the crop insurance disbursement would not have to be paid, so the additional spending would be less than the calculated $90 to $200/acre because of this expected reduction in crop insurance payments.

Since the ethanol produced from this energy feedstock is replacing petroleum products, the externalities associated with oil consumption that are avoided through the increased consumption of ethanol are also relevant for comparison. This calculation is nicely detailed in a study by Michalek at al. [134], who draw from work done by others in the area. The oil premium is composed of three values: value related to oil supply disruptions avoided, as disruptions result in reduced economic output in the short term, value related to the US's monopsony of oil (reducing consumption will reduce world oil price, meaning the remaining oil purchased is cheaper), and finally value related to avoided military engagements in order to improve oil supply security. Ranges for each are $0.02 to 0.28, $0.03 to 0.45, and $0.03 to 0.16/gallon gasoline from [89], [135], [136]. The total oil premium, then, is $0.12 to 0.89/gallon gasoline. If the same impacts are assumed to extend to ethanol, at an energy equivalent level, this translates to $0.08 to 0.62/gallon ethanol. Taking data from the first boxplot in Figure 39, the cost effectiveness of the irrigation subsidy program (removing the negative subsidy state of North Dakota) range from about $0.10 to $1.90/gallon. Since there is substantial overlap in these two ranges, irrigating in select states could be a cost effective way to manage energy security risks.

4.4.7 Alternative Risk Mitigation Strategies

Though irrigation as a risk mitigation strategy was discussed extensively, there are certainly many other approaches that could be taken instead of, or in conjunction with, irrigation. Other alternatives may be more attractive than irrigation as water scarcity becomes increasingly important in the agriculture and energy sectors. One option is to aggressively pursue a research program aimed at increasing the drought tolerance of switchgrass and other cellulosic energy crops through crop breeding and genetics programs. Using an approach similar to that used earlier to compare irrigated to non-irrigated switchgrass, the willingness to pay for potential yield gains due to increased drought tolerance could be examined. The US DOE started a research program that included this goal through its Genomic Science Program [9]. In conjunction with strategic irrigation, there is potential for biomass supply risks to be substantially reduced in the future.

Another option is to store surplus biomass and/or ethanol during peak production years to help during lean production years. This would be particularly useful if the overplanting strategy discussed in Section 4.4.6, as the surplus switchgrass grown there is unused and essentially wasted. Unfortunately, this option is quite challenging to implement. Biomass has low energy density by volume, so it is expensive to transport and store unless it is dried and densified near where it is harvested. This, of course, adds a substantial cost into the supply chain. A study investigating co-firing of biomass with coal in electricity generating stations found that herbaceous biomass densification costs $16 to 22/dry Mg and storage would be an additional $18/dry Mg [137]. A non-densified storage option is simply to plant reserve acreage of biomass energy feedstocks that would be harvested only if necessary. Biomass is stored, living and aboveground. This hinges on the assumption of available land (using, for example, conservation reserve program land) and that these supplemental acres would have high enough yields, either despite drought conditions or poor soil conditions, that harvesting would be worth the expense.

If, instead, all of the switchgrass (or other cellulosic crop) is converted to ethanol during peak production years, the ethanol could be stored. This, too, is challenging because of difficulty in storing large quantities of ethanol, as it is volatile and hygroscopic. Unlike the strategic oil reserve, which is analogous to a strategic ethanol reserve, ethanol must be stored under controlled environmental conditions in fabricated stainless steel tanks rather than simply stored or left underground until the need to extract and process arises, as is the case with oil. This, of course, assumes that these commodities could be stored for potentially many years until needed, which does not seem feasible. To provide some context, expected Nth-generation ethanol plants modelled by McAloon and colleagues for the DOE and the USDA include 10 days worth of storage for the input feedstock, and 12 day of ethanol storage [69]. Storing on the order of years, rather than months, is well outside of what is currently practiced for either feedstock or finished product.

A flexible, rather than fixed, biofuel volume target changes what risks need to be mitigated. If the volume target is lowered in years of low ethanol production, compliance is not a concern, but satisfying transportation energy demand that would have been satisfied with cellulosic ethanol is. This could be done through increased ethanol imports, which are more attractive now that the import tariffs have lapsed. The economics of a sharp increase in US demand (such as would happen if one growing season was very poor due to drought) on international ethanol markets need to be considered in evaluating the merits of this response.

Alternatively (or additionally), oil imports or domestic production would have to increase in order to supplement ethanol production. This would likely have undesirable impacts on increasing oil prices. Under a high-ethanol future, it is possible domestic refineries will either downsize in response to decreased demand for petroleum products, or, reconfigure the relative amount of each petroleum product output as they optimizing production for non-transportation products in markets less affected by high ethanol use. In the event of an ethanol shortage in this scenario, there may be issues in producing enough gasoline or diesel to make up the energy shortfall. Note that the response scenario in which imported ethanol is used to supplement shortfalls in domestic production could have drastically different GHG emissions implications than the scenario in which oil is used. Even if the volume target is flexible, GHG emissions reductions are still a policy goal, so these impacts should be considered when evaluating the response scenario.

Uncertainty can be a guiding light

"Zooropa", U2

Chapter 5. Conclusions

5.1 Research Questions, Brief Answers

Chapter 2: Uncertainty in Life-Cycle Greenhouse Gas Emissions from Biofuels

1. *What is the quantitative uncertainty associated with life-cycle greenhouse gas emission estimates for current (corn ethanol) and proposed biofuels (switchgrass ethanol, butanol)?*

The life-cycle greenhouse gas emissions from the production of corn ethanol are estimated to range between 50 and 200 g CO_2e/MJ, from the production of corn butanol between 60 and 220 g CO_2e/MJ, from the production of switchgrass ethanol using fossil fuel for process heat, between -25 and 140 g CO_2e/MJ, and the production of switchgrass butanol using fossil fuel for process heat, between 10 and 180 g CO_2e/MJ.

2. *Which model input parameters (e.g., indirect land use change) are the most important in determining this range in output values?*

The emissions due to indirect land use change are far and away the most important in the uncertainty analysis, because the mean contribution is so great and the uncertainty surrounding the true value ILUC emissions is so great. The contribution to variance from ILUC for corn ethanol is 85%, and 66% for switchgrass ethanol. Production energy requirements are the second most important factor for fuels produced using switchgrass. The direct N_2O emissions factor is significant for corn and switchgrass fuels, contributing 3 to 4% of the variance. Unfortunately, of the factors listed here, only the production energy can be ascertained with enough certainty to be reduced to a point estimate. ILUC and N_2O emissions will best be represented as a distribution of values for the near future as the models from which those output values are taken are improved.

3. *Are there emissions reductions expected when shifting from bio-ethanol to bio-butanol?*

Even under optimistic production energy assumptions, the emissions that result from the energy necessary to produce and extract butanol outweigh the lower upstream emissions from the lower feedstock quantity needed per unit of energy output. So, no, there are not emissions reductions to be had from switching to butanol at this point. There are, of course, other advantages given butanol's increased compatibility with current engines and fuel distribution infrastructure when compared to ethanol.

Chapter 3: Uncertainty and Biofuel Policy Designs

1. *What is the probability that the revised Renewable Fuel Standard (based on deterministic life-cycle GHG emissions models) included in the Energy Independence and Security Act will succeed in reducing transportation emissions associated with the production of corn- and switchgrass-based biofuels?*

When the 'probability of failure' framework is applied to the Energy Independence and Security Act of 2007, there is a 10% probability that corn ethanol (including indirect land use change emissions) will meet the reduction targets, and a 40% probability that switchgrass ethanol will meet its more aggressive reduction target. If indirect land use change emissions are excluded from the system boundary, these fuels are much more likely to satisfy emissions reductions targets.

2. *What potential policy design incorporates uncertainty in emissions estimates (for the RFS and LCFS) so that the likelihood of emissions reductions occurring can be evaluated?*

Both the RFS and LCFS type policies can be modified to accommodate uncertainty in emissions estimates instead of only point estimates. For each, percent reduction targets could continue to play a central role in the policy, but the policy makers must additionally set a minimum desired probability of policy failure. In the case of the RFS, a fuel could be assessed on both criteria; one with an acceptable mean reduction and which has a low enough variability so as to pass the probability of failure test as well would be acceptable. In the case of the LCFS, one way to estimate a probability of policy failure is to generate a year-end (or other reporting period length) distribution representing the regional fuel mix. This is done by sampling distributions for each fuel used in the region based on how often it is used (or perhaps weighted by energy, or volume, depending on the functional unit of the study). Statistics of interest, including mean emissions, standard deviation, etc. can be considered alongside the expected reduction target. Using the reduction target and this PDF will produce a probability of failure statistic.

Chapter 4: Consequences of Uncertainty in Biofuel Feedstock Supply

1. *What are the weather-related supply risks to switchgrass grown in the continental United States? How do these risks change with future climate change?*

Using 30 years of historical data to simulate yields, there are several low yield years for each state (only 10 to 20% of expected yield in that year), suggesting that a deficiency in crop availability will happen chronically; it does not take a 1-in-100 year sort of situation for national yields to drop by 20 to 30%.

As the climate warms and is increasingly variable, yields will tend to decrease in many states, so using historical yield data in projections without adjusting for these changes in climate will lead to yield over-predictions. If these impacts are taken into account, increased acreage for cellulosic crops are necessary to maintain the same expected output.

2. *To what degree can these supply risks be mitigated with the use of irrigation? And at what cost?*

The drop in switchgrass supply due to unfavourable weather conditions can largely be addressed with the use of irrigation. All of the very low yields (something like 10% of the expected value) are addressed with irrigation in the states where switchgrass and other cellulosic crops are expected to be grown. Unfortunately, these yield gains come at a high social cost; $50 to \$100/acre (or \$0.12 to 1.90/gallon ethanol gained) given \$102/Mg switchgrass and \$20/acre-foot water prices. In comparison, the crop insurance program paid out between \$15 and \$45 and acre from 2000 to 2011, and energy security premiums associated with oil could be somewhere between \$0.08 and \$0.62/gallon of ethanol.

3. *How does this variability affect biofuel system recommendations and policy compliance based on point estimates?*

Modelling cellulosic biomass yields based on point values that have been aggregated over space and over time obviate important risks related to depending on biomass for transportation energy. If variability is not a central part of modelling, no attention is drawn to the possibility for substantial drops in available ethanol compared to what is expected, and the need to think about consequences, mitigation strategies, and contingencies just never arises. Unless many surplus acres of cellulosic crops are planted, under rain-fed conditions there will be insufficient ethanol to meet the EISA targets 10 to 25% of the time. Thinking in terms of yield ranges, not point estimates, is essential in planning a long-term energy system dependent on biomass.

5.2 Discussion

The recommendation that comprehensively assessing uncertainty and variability in making recommendations to policy makes has certainly been discussed before, and in more detail (see [138] and [65] for excellent discussion). That said, biomass offers an interesting case study, providing concrete examples of the challenges that the analyst faces in how to model a system in as detailed and complex a way as necessary to capture what is known and what is not yet known, and the challenges that policy designers face in how to make a policy that does recognize uncertainty in the specific benefits the policy will achieve while still setting specific, actionable targets. Monte Carlo simulation paired with assessing the likelihood of some policy target failing, or the 'probability of policy failure' framework discussed earlier and implemented through this dissertation, is a reasonable way to balance these two demands.

A theme through this dissertation is assessing and synthesizing work done by others to evaluate how increasing model complexity (where necessary) allows for a more comprehensive evaluation the merits of biomass energy. It is essential that the modelling community periodically assess how simplifying assumptions made early in research efforts of biomass (e.g., setting the system boundary to exclude land use changes, or assuming cellulosic feedstocks will be rain-fed) to make sure that recommendations to decision makers continue to be robust. This is particularly relevant in the case of biofuels because the science and understanding behind models has evolved fairly quickly. In conjunction with this, it is necessary for policy to be allowed to address potentially rapid changes in things like greenhouse gas emissions requirements built into energy policy. There is a role here, for the modelling community, to assist on this front as well.

5.3 Future Work

Like any involving academic endeavor, the research for this thesis revealed more new and worthwhile questions than it answered. Below are some of the more interesting issues raised during the course of this dissertation that could be addressed by future work.

1. Indirect land use change is the single greatest contributor to life-cycle GHG emissions from the production of corn ethanol, and it is also the least certain. One challenge to policy makers trying to counteract these emissions is that they occur primarily in other parts of the world, so US policy cannot directly affect the decisions that lead to indirect land use change. One strategy is to offset the carbon release in other countries with carbon uptake in the US through a targeted biomass planting effort. Areas with low soil carbon and minimal

aboveground biomass might offer the greatest potential for carbon storage. This program could be implemented at the national or the state jurisdiction, depending on which public lands would be pulled into use for this program. National goals (EISA targets) are driving corn ethanol production, so it seems more likely that federal money, rather than state, would be spent on this program.

2. Increased ethanol consumption causes US gasoline consumption to decrease. This applies downward pressure to the price of oil globally, which in turn induces increased oil consumption. As discussed previously based on the literature, this indirectly increases GHG emissions (a rebound effect) and should be considered as an additional indirect impact of biofuel usage. Another indirect GHG emissions impact that should be evaluated is the impact of increased biofuel production on food prices and food consumption. As mentioned, food price increases can partially be attributed to increases in biofuel production. The next step would be to link food price changes to changes in consumption habits. For example, if DDGS used as animal feed increases in price, meat will increase in price, and final consumers may shift away from meat consumption. The opposite could also happen, where DDGS become less expensive as more is available, causing meat to become cheaper. Existing literature on GHG emissions from different dietary choices (such as the study published by Weber and Matthews [139]) could be used to estimate GHG emissions changes due to changing dietary choices indirectly induced by biofuel production increases.
3. Many issues of water are very important in thinking about how to mitigate crop loss due to drought. While these are acknowledged here, they are not treated quantitatively. Coupling water availability data (or projections) with the irrigated crop yield model would provide a more realistic idea of how much risk could actually be mitigated during drought years, and

what fraction these yields make up out of the technical potential. The yield model could be run with some sort of water budget as an additional criterion to satisfy during the growing season. Coupled with this would be to have supply-sensitive water prices in the model. These data may be more difficult to come by.

4. Though challenging, the nuances of water rights allocation and management across different parts of the country would add a lot of depth to this analysis. Understanding this system would allow for a farmer's decision between irrigating and selling water rights to other demands to be modelled, making the decision model more complex and more realistic.
5. An economic analysis of price volatility of biofuels that result from supply variability should be compared to oil price volatility to actually get at one of the primary motivations for biofuels: energy security in the form of price stability.
6. The irrigation subsidy is only roughly defined in this dissertation. Several desired characteristics of a subsidy, such as infrastructure being supported rather than operating costs, are mentioned, but many details need to be specified before further analysis of policy feasibility or effectiveness can be undertaken. Of particular importance is how to prioritize who gets subsidized, and when. The 'who' might be prioritized based on several categories: expected yield gains, expected variability before and after irrigation, risk tolerance of farmers, site specific conditions (which might allow for a less expensive system to be installed), and data on water sources and existing demands. Data for some of these have been generated during the course of this study, but many remain to be assembled. This issue of when the subsidy happens, whether it be upfront or uniform over time, may affect farmers' responses to a possible subsidy program. A fixed amount of money up front (to assist with the irrigation infrastructure installation) is generally viewed more favourable than an amount

spread over time due to discounting even if NPVs are equal between these two scenarios, so participation may be higher with an initial lump sum. This approach may also more clearly indicate that the financial support is for capital expenses, where an annual payment could easily be used to offset operating expenses. As previously discussed, this may lessen the impact of water prices on the irrigation decision, which can lead to unnecessarily and undesirably high water consumption.

7. Over-planting switchgrass (or other cellulosic crops) was discussed as an alternative risk mitigation strategy. A negative aspect of this approach mentioned previously is the downward pressure on switchgrass prices due to overproduction in some years. One way to address this aspect is to expand the demand for switchgrass through co-firing at coal electricity generating stations, where equipment can handle up to 10% biomass by mass. Drying and densification would have to occur before combustion, adding cost and emissions, but this approach may offer a beneficial use of surplus cellulosic crops. Work would need to be done to estimate how cost effective this strategy would be, and how the capacity to use biomass in coal plants compares to the expected amount of surplus switchgrass.

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Appendix A

Fuel Properties and Yields for Simple Alcohols, Alkanes

All biomass feedstocks contain polymeric sugars, where types and quantities vary across species. Lignin, ash and other chemicals are also present in most biomass feedstocks. Lignin is a complex grouping of molecules that cannot be readily broken down and provides structure, rather than energy storage, for the plant. In lignocellulosic fuel production, it is an important source of process energy.

In the case of starchy feedstocks such as corn, the major sugar polymer (starch) is relatively easy to hydrolyze. In the case of lignocellulosic feedstocks such as switchgrass, there are two primary sugar polymer types: cellulose and hemicellulose. Cellulose is difficult to monomerize due to its crystalline structure [1]. Hemicellulose saccharification is more difficult than that of starch but easier than cellulose due to its lower degree of organization. Sugar types in each of these polymers are listed below.

Table 1. Sugar polymer compositions for starch, hemicellulose, and cellulose listed in increasing order of hydrolysis difficulty.

Sugar Polymer Classification	Component Polymer/Monomer	Role in Model
Starch	Starch/Glucose	Assumed sole source of sugar from corn.
Hemicellulose	*Six-Carbon Sugars:* Mannan/Manose Galactan/Galactose *Five-Carbon Sugars:* Arabinan/Arabinose Xylan/Xylose	Assumed source of sugar from switchgrass.
Cellulose	*Six-Carbon Sugar:* Glucan/Glucose	Assumed source of sugar from switchgrass.

Sugar content of some promising domestic feedstocks are presented in Figure 1. Feedstocks are primarily C6 sugars, with total sugar content ranging from 0.67 to 0.78 kg sugar/kg feedstock [2]. Based on sugar content, less corn is required per MJ than switchgrass.

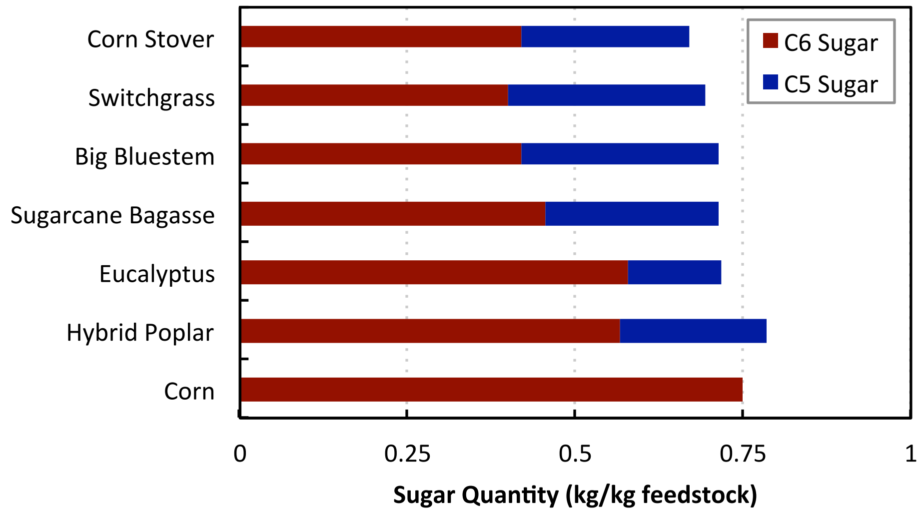

Figure 1. Sugar content of some promising domestic feedstocks are presented in SI Figure 1. Feedstocks are primarily C6 sugars, with total sugar content ranging from 0.67 to 0.78 kg sugar/kg feedstock. Based on sugar content, less corn is required per MJ than switchgrass.

Batch, industrial production processes are limited by carbon, energy or reducing equivalents (electrons). In bioprocess engineering, yields of cells and metabolic products can be modeled by balancing the flow of these elements. Depending on the process (aerobic or anaerobic) carbon can come from organic molecules or CO_2, and electrons from organic or inorganic molecules. Electrons flow from donor to a terminal acceptor, generating energy for cell synthesis and for product formation in the process [3].

When a sugar is used to produce a simple alcohol, it functions as both carbon source and electron donor. Figure 2 shows reactions of glucose to ethanol (C_2H_6O) and to butanol ($C_4H_{10}O$). The reactions are exothermic (not requiring additional energy). An excess of carbon is indicated by CO_2 as reaction product.

Glucose half reaction: $6\ CO_2 + 24\ e^- + 24\ H^+ \dashrightarrow 1\ C_6H_{12}O_6 + 6\ H_2O$

Ethanol half reaction: $\underline{2\ CO_2 + 12\ e^- + 12\ H^+ \dashrightarrow 1\ C_2H_6O + 3\ H_2O}$
Complete reaction: $C_6H_{12}O_6 \dashrightarrow 2\ C_2H_6O + 2\ CO_2$ ΔG_{rxn}= -212 kJ/mol
Yield (%w): 51.1%

Butanol half reaction: $\underline{4\ CO_2 + 24\ e^- + 24\ H^+ \dashrightarrow 1\ C_4H_{10}O + 7\ H_2O}$
Complete reaction: $C_6H_{12}O_6 \dashrightarrow C_4H_{10}O + 2\ CO_2 + H_2O$ ΔG_{rxn}= -275 kJ/mol
Yield (%w): 41.1%

Figure 2. Electron balancing for ethanol and butanol from glucose. Excess energy and carbon are demonstrated in the complete reactions. Energies calculated using the method in [4].

Opposite trends in mass yield and energy density are apparent for simple alcohols and alkanes. Combining these data reveal kg feedstock/MJ fuel output values that vary by approximately 1%. This result indicates that no particular fuel type offers an advantage in minimizing upstream emissions. Relative production emissions per MJ will have the largest impact in determining which fuel may have lower life-cycle emissions.

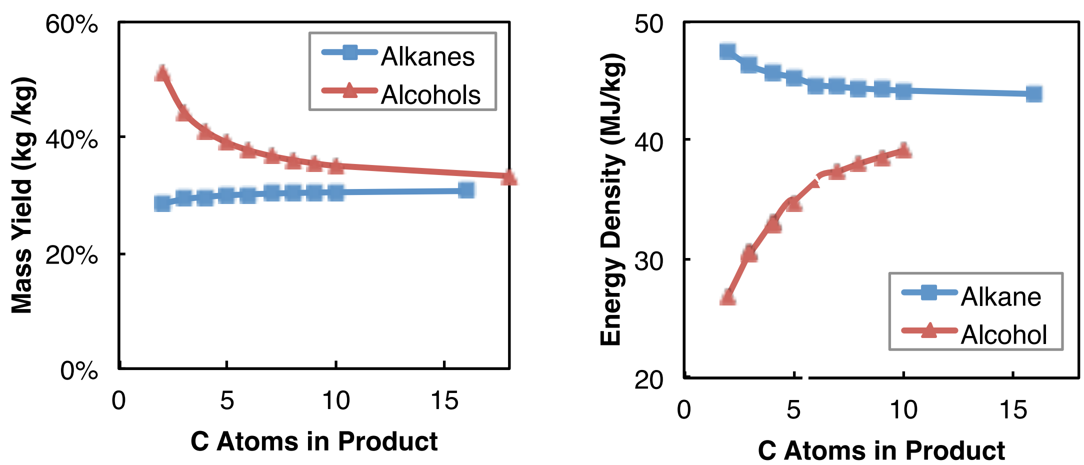

Figure 3. Comparison of mass yield and energy density trends for alcohols and alkanes. Alcohols have superior yields, while alkanes have superior energy density.

Table 2. Parameter estimates for the biofuels life-cycle greenhouse gas emissions model.

Parameter	Value	Unit	Data Source(s) and Notes
Parameters Common to Both Feedstocks			
Emissions Factor, Direct N_2O	0.01		Factor in direct N_2O calculations using IPCC 2006 methodology [5]
Emissions Factor, Indirect N_2O	0.01		Factor in indirect N_2O calculations using IPCC 2006 methodology [5]
Land use change emissions time frame	30	year	Common to [6], [7]
Ethanol yield from C5 and C6 sugars	0.511	kg/kg	Calculated value.
Butanol yield from C5 and C6 sugars	0.411	kg/kg	Calculated value.
Ethanol energy density	21.4	MJ/L	LHV, [8]
Butanol energy density	28	MJ/L	LHV, [8]
Gasoline life-cycle emissions	0.086	kg CO_2e/MJ	[8]
Diesel life-cycle emissions	0.091	kg CO_2e/MJ	[8]
LPG life-cycle emissions	0.082	kg CO_2e/MJ	[8]
Natural gas life-cycle emissions	0.060	kg CO_2e/MJ	[8]
Residual Oil life-cycle emissions	0.093	kg CO_2e/MJ	[8]
Electricity production emissions	0.197	kg CO_2e/MJ	[8], US national grid average
Parameters for Corn as Feedstock			
Corn Yield	9.8	Mg dm/ha	Average of USDA corn-for-grain 2007 county-level data for Midwestern states (IL, IN, IO, KA, MI, MN, MO, NE, ND, OH, SD, WI) [9]
Corn starch content	67.3	%w	[10]
Indirect Land Use emissions	5.5	Mg CO_2e /ha/year	[11]

Parameter	Value	Unit	Data Source(s) and Notes
Direct Land Use emissions	0.3	Mg CO_2e /ha/year	[11]
Nitrogen Application	150	kg N/ha	[12]
Truck transport distance with feedstock	40	mi (one way)	[8]
Truck transport emissions	1713	Btu/ton-mi	[8], Diesel fuel type combusted
Production electricity, ethanol	0.038	MJ/MJ etOH	[10]
Production heat, ethanol	0.42	MJ/MJ etOH	[10]
Production electricity, butanol	0.041	MJ/MJ buOH	[13]
Production heat, butanol	0.66	MJ/MJ buOH	[13]
Co-product credit (DDGS)	15	g CO_2e/MJ	[8], [14]
Parameters for Switchgrass as Feedstock			
Switchgrass yield	17	Mg dm/ha	Yield data for sample plots from [15] used to calculate appropriate distribution mean. Distribution shape parameters assumed the same as from USDA 2007 corn data .
Glucan	34.4	%w	[2]
Xylan	22.9	%w	[2]
Mannan	0.32	%w	[2]
Galactan	1.0	%w	[2]
Arabinan	3.01	%w	[2]
Lignin	19.2	%w	[2]
Indirect Land Use emissions	1.7	Mg CO_2e /ha/year	[11]
Direct Land Use emissions	2	Mg CO_2e /ha/year	[11]
Carbon sequestration	1.95	Mg CO_2e /ha/year	[16]
Nitrogen Application rate	74	kg N/ha	[17]
Production energy, ethanol	0.52	MJ/MJ etOH	[18]
Percentages to electricity, heat	10/90%		[18]
Production energy, butanol	0.82	MJ/MJ buOH	[13], [18]
Percentages to electricity, heat	7/93%		[13], [18]
Production plant boiler efficiency	68%		[18]
Production plant turbine efficiency	85%		[18]
Lignin energy content	21.8	MJ/kg	[18]
Non-sugar, non-lignin components' energy content	10	MJ/kg	[18]

Point estimates of emissions for each of the life-cycle stages are included below in Figure 4. Upstream emissions (including the switchgrass credit for soil carbon sequestration) are consistent across fuel types. Feedstock quantity drives upstream emissions, and feedstock demand per MJ ethanol and butanol are approximately equal (see 'Determining Fuel Yields' section above), resulting in similar upstream emissions. This is an important factor to consider going forward in developing new fuels, particularly since upstream emissions are the majority of life-cycle emissions. A particular fuel type's relative candidacy as 'renewable' or 'low carbon' will depend mostly on production emissions for any given feedstock amount required.

Differences between feedstocks for one fuel type are apparent throughout the life cycle. Corn fuels shows greater life-cycle emissions than corresponding switchgrass in all stages except DLUC. New land is expected to be used for switchgrass as biofuel feedstock, whereas existing corn is expected to be diverted to fuel production. Even if corn process energy were produced from switchgrass (SWf) instead of fossil energy sources (FF), the two cases modeled for the switchgrass fuels, upstream emissions would still push total corn emissions higher than switchgrass (SW)-based fuels.

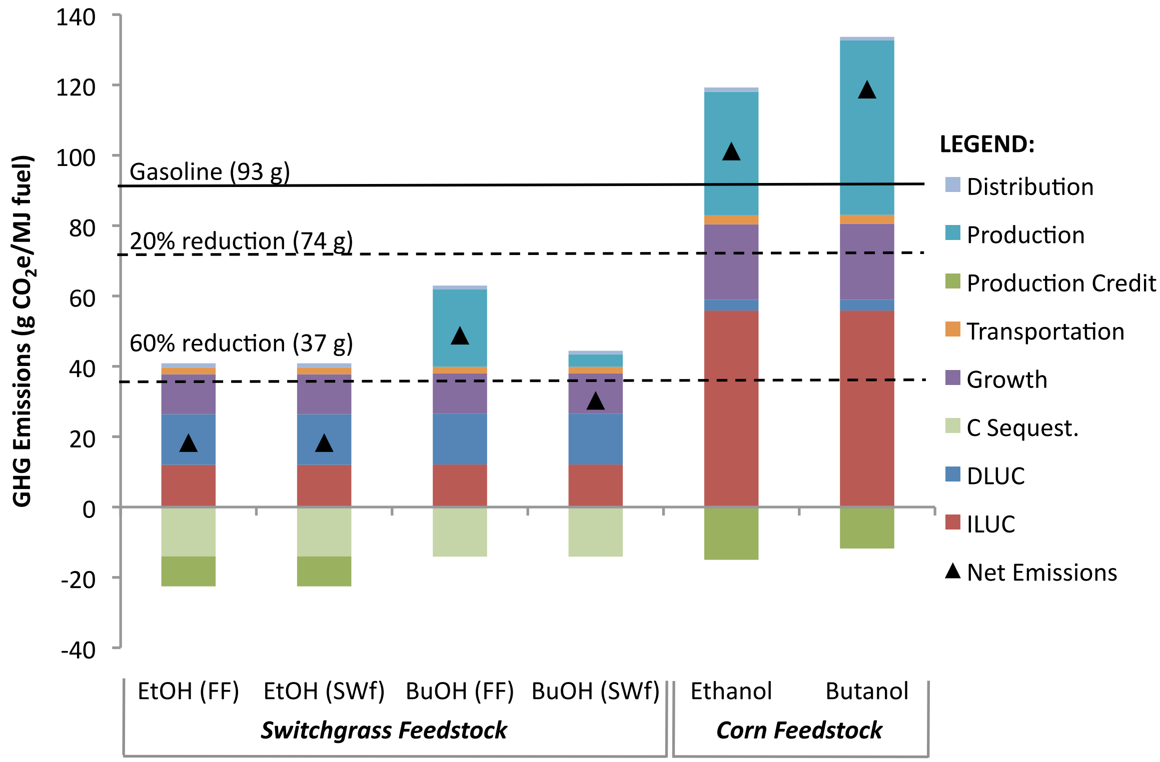

Figure 4. Life-cycle emissions by stage/source using point estimates for parameters and emissions factors. Horizontal lines show EISA gasoline emissions (93 g) and 20% and 60% reduction values. Results are grouped by feedstock type, with horizontal axis labels listing shorthand for fuel type and fuel production energy source (if needed) as listed in Table 1. Production credit results from system expansion allocation; surplus grid electricity for switchgrass, and DDGS credit for corn.

The following results (Table 3 Table 4) summarize the output from the Monte Carlo simulation.

Table 3. Distribution statistics for the base case Monte Carlo simulation as output by Crystal Ball modeling software.

Statistic	Corn buOH	Corn etOH	SW buOH FF	SW buOH SWf	SW etOH FF	SW etOH SWf
Trials	10,000	10,000	10,000	10,000	10,000	10,000
Mean	0.131	0.112	0.09	0.076	0.049	0.048
Median	0.129	0.111	0.088	0.07	0.047	0.046
Mode	'---	'---	'---	'---	'---	'---
Standard	0.029	0.028	0.034	0.036	0.033	0.032

Statistic	Corn buOH	Corn etOH	SW buOH FF	SW buOH SWf	SW etOH FF	SW etOH SWf
Deviation						
Variance	0.001	0.001	0.001	0.001	0.001	0.001
Skewness	0.2754	0.2805	0.251	0.6	0.3084	0.3468
Kurtosis	2.93	2.9	2.83	3.02	2.82	2.88
Coeff. of Variability	0.2211	0.2518	0.3762	0.4711	0.6584	0.6649
Minimum	0.056	0.039	-0.01	-0.01	-0.052	-0.052
Maximum	0.265	0.248	0.225	0.244	0.17	0.169
Mean Std. Error	0	0	0	0	0	0

Table 4. Sensitivity results for butanol.

Parameter	Corn butanol		SW buOH FF		SW buOH SWf	
ILUC emissions factor	82.5%	0.89	61.8%	0.77	78.7%	0.87
DLUC emissions factor			4.2%	0.20	5.8%	0.24
Soil C sequestration factor			2.5%	-0.15	2.4%	-0.15
Direct N2O emissions factor	4.0%	0.20	2.3%	0.15	3.0%	0.17
Feedstock yield	6.6%	-0.25	1.5%	-0.12	2.0%	-0.14
Production energy	3.5%	0.18	26.3%	0.50	7.4%	0.27
Glucose conversion efficiency	2.1%	-0.14				
Hydrolysis efficiency						

Irrigation Cost Model

Table 5. Capital and operating cost assumptions based primarily on Kansas data, confirmed (generally) from other state data.

Costs (2011)		
	Farm	*Per acre*
Getting water		
Well (300 ft)	$32,000	
Pump & gearhead (8", 245 ft.)	$27,500	
Power unit (NG)	$12,500	
Water meter	$1,350	
Connectors	$2,500	
TOTAL	$75,850	$607
Irrigation system		

Central pivot		
7-tower pivot system	$62,000	
Pipe, electrical, etc.	$9,815	
TOTAL	$71,815	$575
Flood	$5,125	
TOTAL	$5,125	$41
SDI		
System components	$184,192	
Equipment use, labour	$18,425	
TOTAL	$202,617	$1,621

Table 6. Cash flow model input assumptions. Blue values indicate the specific number will change based on either changing irrigation system type (central pivot, flood, or subsurface drip) or water source (well or surface). Capital costs are detailed in Table 5 below.

ASSUMPTIONS			
	Value	*Unit*	*Notes*
Financing			
Irrigation loan period	15	years	
Well loan period	25	years	
Interest rate	6%		
Tax rate	15%		
Insurance percentage	2%		
Irrigation maintenance	0.50%		
Power unit maintenance	3%		
Discount rate	12%		
Depreciation period	Same as loan period for each type of equipment		
Well capital cost	$75,850		
Irrigation system capital cost	$71,815		
Farm operations			
Size	125	acres	Central pivot size (Flood: 160 acres)
Well depth	300	ft	
Water use per irrigation event	1	in	
Labour	0.1	hr/acre/event	
Water per event	0.7	in/day/event	
Commodities			
NG price:	3.5	$/mcf	
Elec price:	0.06	$/kWh	

Water cost:	20	$/acre-foot	
Labour cost:	$13	/hour	
Switchgrass price	102	$/Mg	NAS break-even price

Switchgrass Yield Model

Below are listed the default values for various key input parameters according to the Grassini model definitions [19].

```
Tmin = 13;
Tmax = 42;
Topt = 33;        % [C] Grassini, cultivar characteristics
Rmax = 0.037;     % Blackwell cultivar, see Grassini Table 1
MAXLAI = 10;      % Value from within noted range of 7.5 to 17.7
RUE = 4.7;        % Grassini, from Kiniry et al. (1999)
SL1_depth = 150;  % [mm]
SL2_depth = 1450; % [mm] to give a total root depth of 1.6m
AWHC_SL1 = 0.15;  % Assumed soil characteristics
AWHC_SL2 = 0.12;  % Assumed soil characteristics
K_coeff = 0.48;   % Extinction coefficient for total incoming solar radiation
FAWHC_SL1 = 0.6;  % Default from Grassini
FAWHC_SL2 = 0.6;  % Default from Grassini
```

Table 7. Data related to the states modelled in the yield model.

FIPS	State	City	Elevation [m]	Region (Climate)	Region (POLYSYS)	Percent Area (POLYSYS)
1	AL	Montgomery	203	SE	SE	6.0%
2	AZ	Phoenix	1112	SW	SP	0.0%
3	AR	Little Rock	264	S	SE	9.4%
4	CA	Sacramento	26	W	SP	0.0%
5	CO	Alamosa	7536	SW	SP	0.0%
6	CT	Hartford	100	NE	NE	0.0%
7	DE	Wilmington	78	NE	NE	0.0%
8	FL	Tallahassee	69	SE	SE	0.0%
9	GA	Macon	360	SE	SE	3.9%
10	ID	Boise	2867	NW	NP	0.0%
11	IL	Springfield	613	C	CB	0.0%
12	IN	Indianapolis	807	C	CB	0.0%
13	IA	Mason	1224	ENC	CB	0.0%
14	KS	Dodge	2528	S	CB	3.1%
15	KY	Lexington	987	C	SE	10.7%
16	LA	Shreveport	259	S	SE	4.2%
17	ME	Caribou	623	NE	NE	0.0%
18	MD	Baltimore	154	NE	App	0.0%
19	MA	Worchester	987	NE	NE	0.0%
20	MI	Lansing	839	ENC	Lake	0.0%

21	MN	Rochester	1319	ENC	NP	1.2%
22	MS	Meridian	308	S	SE	7.1%
23	MO	Colombia	886	C	CB	8.2%
24	MT	Lewiston	4147	WNC	NP	0.0%
25	NE	Norfolk	1545	WNC	CB	0.0%
26	NV	Elko	5075	W	SP	0.0%
27	NH	Concord	345	NE	NE	0.0%
28	NJ	Newark	29	NE	NE	0.0%
29	NM	Albuquerque	5311	SW	SP	0.0%
30	NY	Syracuse	406	NE	Lake	1.8%
31	NC	Raleigh	439	SE	SE	2.1%
32	ND	Minot	1712	WNC	NP	5.6%
33	OH	Columbus	833	C	CB	0.0%
34	OK	Tulsa	676	S	SP	12.9%
35	OR	Salem	200	NW	NP	0.0%
36	PA	Harrisburg	348	NE	App	0.0%
37	RI	Providence	62	NE	NE	0.0%
38	SC	Colombia	227	SE	SE	1.6%
39	SD	Huron	1289	WNC	NP	1.2%
40	TN	Knoxville	981	C	SE	8.7%
41	TX	Waco	508	S	SP	7.1%
42	UT	Cedar City	5616	SW	SP	0.0%
43	VT	Burlington	341	NE	NE	0.0%
44	VA	Richmond	164	SE	SE	4.0%
45	WA	Spokane	2365	NW	NP	0.0%
46	WV	Elkins	1948	C	App	1.3%
47	WI	Madison	859	ENC	Lake	0.0%
48	WY	Cheyenne	6141	WNC	NP	0.0%

Sample Switchgrass Yield Under Irrigation

The first column lists years (out of 30) in which irrigation was used on at least one day. The second column lists the total number of days over the 30-year period where irrigation is used, and from which the total water amount is calculated.

Table 8. Irrigation use data, and yield improvement for three sample states.

	Years with irrigation	Irrigation days	Total water [m]	Change in Average Yield [%]	Change in Minimum Yield [%]
Criteria: 0.4					
Tennessee	13	51	2.25	14	90
Texas	18	69	3.45	18	83

Iowa	15	45	2.25	9	85
Criteria: 0.5					
Tennessee	20	81	4.05	19	91
Texas	23	106	5.30	23	85
Iowa	23	78	3.90	12	85
Criteria: 0.6					
Tennessee	23	108	5.40	21	92
Texas	25	141	7.05	26	86
Iowa	25	110	5.50	14	87
Criteria: 0.7					
Tennessee	26	138	6.90	23	92
Texas	28	176	8.80	28	86
Iowa	28	143	7.15	16	87

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Appendix B

```
function [C_eth SW_swf SW_ff] = biofuel_MC_fixed

% Biofuel GHG Emissions Model, Monte Carlo Simulation
% Kimberley Mullins
% Last update: April 30, 2011
%
% Organization:
%   Definition of variables and calculation of underlying model parameters (such as yield values)
%   Land use change emissions
%   Crop harvesting and transportation emissions
%   Fuel production and distribution
%
% Datasets:
%   Crops:  1. Corn
%           2. Switchgrass
%           3. Corn stover
%   Fuels:  !. Ethanol
%           2. Butanol


samples = 10000;

% TEST POINTS FOR NLCFS ANALYSIS
% Overwrite distributions with point values for select parameters
NLCFS = 1;

%%%% EMISSIONS FACTORS %%%%

% Unit: kg CO2e/MJ unless otherwise noted (elec)
EF.FFname = {'Gasoline'; 'Diesel'; 'LPG'; 'NG'; 'Resid Oil'; 'Elec_kg/MJ'; 'Elec_kg/kWh'};
EF.FFvalue = [0.086; 0.091; 0.082; 0.06; 0.093; 0.197; 0.71];
%EF.FFname = {'Gasoline'; 'Diesel'; 'LPG'; 'Coal'; 'Resid Oil'; 'Elec_kg/MJ'; 'Elec_kg/kWh'};
%EF.FFvalue = [0.086; 0.091; 0.082; 0.12; 0.093; 0.197; 0.71];

%%%% FUEL CHARACTERISTICS, YIELDS %%%%

% Unit: MJ/L
EtOH.MJperL = 21.4;
EtOH.MJperkg = 26.8;
EtOH.yield = 0.511; % by mass (g fuel/g sugar), from thermo calcs

BuOH.MJperL = 28;
BuOH.MJperkg = 33.11;
BuOH.yield = 0.4111; % by mass (g fuel/g sugar), from thermo calcs

% Hydrolysis
ConvEff.Glc.pt = 0.95;
ConvEff.Hyd.pt = 0.9;
ConvEff.Oth.pt = 0.85;

ConvEff.Glc.dst = unifrnd(0.85,1,samples,1);
ConvEff.Hyd.dst = unifrnd(0.85,0.95,samples,1);
ConvEff.Oth.dst = unifrnd(0.75,0.9,samples,1);

%%%% FEEDSTOCK CHARACTERISTICS %%%%

% Yield values

SW.yield.pt = 240; % Mg d.m./ha
C.yield.pt = [9.842 180]; % Mg d.m./ha then bu/acre

% Switchgrass yield distribution.  Beta [a=21.62, b=5.86, range [0,21.6]]
SW.yield.dst = (21.6-0)*betarnd(21.62,5.86,samples,1);
% SW.yield.dst = trirnd(5.2,12.9,21.6,samples);
% SW.yield.dst = 240*ones(samples,1);

% Corn yield distribution.  Beta [a=21.62, b=5.86, range [0,14.3]]
C.yield.dst = (14.3-0)*betarnd(21.62,5.86,samples,1);
% C.yield.dst = C.yield.pt(1)*ones(samples,1);

% Corn stover yield distribution. Based on 1:1 grain to stover ratio
% Adjusted to meet requirement to leave some stover on field (5 Mg/ha as
% calculated from Sheehan et al. (2004)
```

```
CS.yield.dst = C.yield.dst - 5;
for k = 1:samples,
    if CS.yield.dst(k) < 0,
        CS.yield.dst(k) = 0;
    end
end
clear k;

% Percentage feedstock composition

% C5 Sugars: Arabinan and Xylan, C6 sugars: Mannan, Galactan, Glucan
% Order:       Lignin Arabin. Xylan Mannan Galact. Glucan Else
SW.ptsugar = [0.192  0.03    0.229  0.003  0.01    0.344    0.192];
CS.ptsugar = [0.192  0.0238  0.1971 0.0048 0.0089  0.3643   0.2091];
%SW.PointSugar(7) = 1-sum(SW.PointSugar);

%  Energy content in MJ/kg
SW.sugarE =  [21.83  14.73   15.18 18.68  11.53   14.73  10.05];
SW.MJperkg.pt = SW.ptsugar*SW.sugarE';
CS.sugarE = SW.sugarE;
CS.MJperkg.pt = CS.ptsugar*CS.sugarE';

C.ptsugar =  [0      0       0     0      0       0.673  0.327];

% Based on data fit from Bioenergy Feedstock Composition Database

SW.composition(:,1) = trirnd(0.173,0.211,0.192,samples); % lignin
SW.composition(:,2) = unifrnd(0.026,0.034,samples,1); % arabinan
SW.composition(:,3) = trirnd(0.206,0.26,0.229,samples); % xylan
SW.composition(:,4) = trirnd(0.0029,0.0036,0.0032,samples); % mannan
SW.composition(:,5) = trirnd(0.0067,0.012,0.01,samples); % galactan
SW.composition(:,6) = trirnd(0.31,0.372,0.344,samples); % glucan
SW.composition(:,7) = zeros(samples,1)+1;
for i=1:6,
    SW.composition(:,7) = SW.composition(:,7)-SW.composition(:,i); % else
end

C.gluc = trirnd(0.626,0.72,0.673,samples);

CS.composition = zeros(samples,7);

for i=1:7,
    CS.composition(:,i) = CS.ptsugar(i) .* ones(samples,1);
end

%%%% TRANSPORTATION MODE CHARACTERISTICS %%%%

% Modal distribution for fuels
%      Perct. Dist  There        Back
%             (mi)  (Btu/ton-mi) (Btu/ton-mi)
Mode = [0.4,  520,   431,         328;
        0,    600,   253,         0;
        0.4,  800,   270,         0;
        0.2,  80,    1099,        1099;
        1,    30,    1099,        1099];

% Distribution of energy sources for each transportation mode
%          Barge Pipeline Rail Truck Truck2
Mode_FF = [0,    0,       0,   0,    0; % Gasoline
           0,    0.2,     1,   1,    1; % Diesel
           0,    0,       0,   0,    0; % LPG
           0,    0.24,    0,   0,    0; % NG
           1,    0.5,     0,   0,    0; % Residual Oil
           0,    0.06,    0,   0,    0; % Electricity
           0,    0,       0,   0,    0];% Elec (other unit)

% Emissions factors for each fuel
% Unit: g CO2e/MJ
for i=1:5,
    Mode_EF(i) = Mode(i,2)*sum(Mode(i,3:4))/(2000/2.2)/10^6*1055*(Mode_FF(:,i)'*EF.FFvalue);
end

% FUEL CONVERSION ENERGY FACTORS
```

```
% fuel production parameters
C.EtOH.ProductionElectricity.dst=trirnd(0.023,0.049,0.038,samples);     % MJ/MJ ethanol
C.EtOH.ProductionHeat.dst=trirnd(0.32,0.51,0.42,samples);               % MJ/MJ ethanol
C.BuOH.ProductionElectricity.dst=unifrnd(0.031,0.051,samples,1);        % MJ/MJ butanol
C.BuOH.ProductionHeat.dst=unifrnd(0.50,0.83,samples,1);                 % MJ/MJ butanol

SW.EtOH.ProductionEnergy.dst=unifrnd(0.44,0.72,samples,1);              % MJ/MJ ethanol
SW.BuOH.ProductionEnergy.dst=unifrnd(0.63,1.20,samples,1);              % MJ/MJ butanol

CS.EtOH.ProductionEnergy.dst=unifrnd(0.44,0.72,samples,1);              % MJ/MJ ethanol
CS.BuOH.ProductionEnergy.dst=unifrnd(0.63,1.20,samples,1);              % MJ/MJ butanol

% convert to single matrix to keep consistent with biofuel_point
% conventions
C.ProdE.dst=[C.EtOH.ProductionElectricity.dst C.EtOH.ProductionHeat.dst
C.BuOH.ProductionElectricity.dst C.BuOH.ProductionHeat.dst];
SW.ProdE.dst=[SW.EtOH.ProductionEnergy.dst SW.BuOH.ProductionEnergy.dst];
CS.ProdE.dst=[CS.EtOH.ProductionEnergy.dst CS.BuOH.ProductionEnergy.dst];

clear i;

% ALLOCATION FACTORS

mass_allocation = CS.yield.dst ./ (C.yield.dst + CS.yield.dst); % ratio of CS pulled off to total
mass
%energy_allocation =

if NLCFS == 1,
    %SW.yield.dst = ones(samples,1).*SW.yield.pt;
    %C.yield.dst = ones(samples,1).*C.yield.pt(1);

    ConvEff.Glc.dst = ones(samples,1).*ConvEff.Glc.pt;
    ConvEff.Hyd.dst = ones(samples,1).*ConvEff.Hyd.pt;
    ConvEff.Oth.dst = ones(samples,1).*ConvEff.Oth.pt;

    SW.composition(:,1) = ones(samples,1).*0.192; % lignin
    SW.composition(:,2) = ones(samples,1).*0.03; % arabinan
    SW.composition(:,3) = ones(samples,1).*0.229; % xylan
    SW.composition(:,4) = ones(samples,1).*0.003; % mannan
    SW.composition(:,5) = ones(samples,1).*0.01; % galactan
    SW.composition(:,6) = ones(samples,1).*0.344; % glucan
    SW.composition(:,7) = ones(samples,1).*0.192; % else
    C.gluc = ones(samples,1).*0.673;

    C.EtOH.ProductionElectricity.dst=ones(samples,1).*0.0408;     % MJ/MJ ethanol
    C.EtOH.ProductionHeat.dst=ones(samples,1).*0.4514;                % MJ/MJ ethanol
    C.BuOH.ProductionElectricity.dst=ones(samples,1).*0.0428;         % MJ/MJ butanol
    C.BuOH.ProductionHeat.dst=ones(samples,1).*0.6869;                  % MJ/MJ butanol
    SW.EtOH.ProductionEnergy.dst=ones(samples,1).*0.58;               % MJ/MJ ethanol
    SW.BuOH.ProductionEnergy.dst=ones(samples,1).*0.82;               % MJ/MJ butanol
    % convert to single matrix to keep consistent with biofuel_point
    % conventions
    C.ProdE.dst=[C.EtOH.ProductionElectricity.dst C.EtOH.ProductionHeat.dst
C.BuOH.ProductionElectricity.dst C.BuOH.ProductionHeat.dst];
    SW.ProdE.dst=[SW.EtOH.ProductionEnergy.dst SW.BuOH.ProductionEnergy.dst];

end


%% Hydrolysis Calculations

% For switchgrass, fuelyield in kg feedstock/MJ fuel

% Step1: SW.arabinan * 1000 / 132
% Step2: ... * 150 g/mol C5 sugar
% Step3: ... * 0.511 * hydrol eff * other sugar eff [g C5 sugar]
% Step4: ... /1000 * 26.8 MJ/kg

EtOH.kgSWperMJ.dst = 1./((EtOH.yield*EtOH.MJperkg).*(...
    (150/132).*sum(SW.composition(:,2:3),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*sum(SW.composition(:,4:5),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*SW.composition(:,6).*ConvEff.Hyd.dst.*ConvEff.Glc.dst));
```

```
BuOH.kgSWperMJ.dst = 1./((BuOH.yield*BuOH.MJperkg).*(...
    (150/132).*sum(SW.composition(:,2:3),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*sum(SW.composition(:,4:5),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*SW.composition(:,6).*ConvEff.Hyd.dst.*ConvEff.Glc.dst));

EtOH.kgCperMJ.dst =
1./((EtOH.yield*EtOH.MJperkg).*((180/162).*C.gluc.*ConvEff.Hyd.dst.*ConvEff.Glc.dst));
BuOH.kgCperMJ.dst =
1./((BuOH.yield*BuOH.MJperkg).*((180/162).*C.gluc.*ConvEff.Hyd.dst.*ConvEff.Glc.dst));

EtOH.kgCSperMJ.dst = 1./((EtOH.yield*EtOH.MJperkg).*(...
    (150/132).*sum(CS.composition(:,2:3),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*sum(CS.composition(:,4:5),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*CS.composition(:,6).*ConvEff.Hyd.dst.*ConvEff.Glc.dst));

BuOH.kgCSperMJ.dst = 1./((BuOH.yield*BuOH.MJperkg).*(...
    (150/132).*sum(CS.composition(:,2:3),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*sum(CS.composition(:,4:5),2).*ConvEff.Hyd.dst.*ConvEff.Oth.dst...
    + (180/162).*CS.composition(:,6).*ConvEff.Hyd.dst.*ConvEff.Glc.dst));

%% Land Use Change Emissions

time = 30; %years, consistent with other studies (EPA, Searchinger)

% ha domestic / MJ fuel value (vector)
% = Fuel yield MJ/kg divided by  kg / ha [Yield]
% From Hydrolysis,  From Yield Assumptions

% Emissions factors
C.ILUC_ef.dst = trirnd(0,351,165,samples); % Mg CO2e/ha corn harvested
C.DLUC_ef.dst = trirnd(0,135,9.1,samples);

% SW.ILUC_ef.dst = trirnd(0,450,50.1,samples); % Mg CO2e/ha switchgrass harvested
SW.ILUC_ef.dst = trirnd(0,450,70,samples);
SW.DLUC_ef.dst = trirnd(0,135,60,samples);
SW.Seq_ef.dst = -trirnd(21.9,120,58.5,samples);

CS.ILUC_ef.dst = zeros(samples,1); % Mg CO2e/ha corn stover harvested
CS.DLUC_ef.dst = (mass_allocation) .* trirnd(0,135,9.1,samples); % allocation by mass


% Emissions output (in g CO2e/MJ fuel)
% Mg CO2e/ha (30 year total) * kg feedstock/MJ * ha/kg feedstock(/d.m. conversion) / time

CEtOH.ILUC.MC = C.ILUC_ef.dst*10^6 .* EtOH.kgCperMJ.dst ./ (C.yield.dst.*1000./0.87) ./ time;
CEtOH.DLUC.MC = C.DLUC_ef.dst*10^6 .* EtOH.kgCperMJ.dst ./ (C.yield.dst.*1000./0.87) ./ time;
CBuOH.ILUC.MC = C.ILUC_ef.dst*10^6 .* BuOH.kgCperMJ.dst ./ (C.yield.dst.*1000./0.87) ./ time;
CBuOH.DLUC.MC = C.DLUC_ef.dst*10^6 .* BuOH.kgCperMJ.dst ./ (C.yield.dst.*1000./0.87) ./ time;

SWEtOH.ILUC.MC = SW.ILUC_ef.dst*10^6 .* EtOH.kgSWperMJ.dst ./ (SW.yield.dst.*1000) ./ time;
SWEtOH.DLUC.MC = SW.DLUC_ef.dst*10^6 .* EtOH.kgSWperMJ.dst ./ (SW.yield.dst.*1000) ./ time;
SWEtOH.Seq.MC = SW.Seq_ef.dst*10^6 .* EtOH.kgSWperMJ.dst ./ (SW.yield.dst.*1000) ./ time;
SWBuOH.ILUC.MC = SW.ILUC_ef.dst*10^6 .* BuOH.kgSWperMJ.dst ./ (SW.yield.dst.*1000) ./ time;
SWBuOH.DLUC.MC = SW.DLUC_ef.dst*10^6 .* BuOH.kgSWperMJ.dst ./ (SW.yield.dst.*1000) ./ time;
SWBuOH.Seq.MC = SW.Seq_ef.dst*10^6 .* BuOH.kgSWperMJ.dst ./ (SW.yield.dst.*1000) ./ time;

CSEtOH.ILUC.MC = CS.ILUC_ef.dst*10^6 .* EtOH.kgCSperMJ.dst ./ (CS.yield.dst.*1000./0.87) ./ time;
CSEtOH.DLUC.MC = CS.DLUC_ef.dst*10^6 .* EtOH.kgCSperMJ.dst ./ (CS.yield.dst.*1000./0.87) ./ time;
CSBuOH.ILUC.MC = CS.ILUC_ef.dst*10^6 .* BuOH.kgCSperMJ.dst ./ (CS.yield.dst.*1000./0.87) ./ time;
CSBuOH.DLUC.MC = CS.DLUC_ef.dst*10^6 .* BuOH.kgCSperMJ.dst ./ (CS.yield.dst.*1000./0.87) ./ time;

CEtOH.LUC.MC = CEtOH.ILUC.MC + CEtOH.DLUC.MC;
CBuOH.LUC.MC = CBuOH.ILUC.MC + CBuOH.DLUC.MC;
SWEtOH.LUC.MC = SWEtOH.ILUC.MC + SWEtOH.DLUC.MC + SWEtOH.Seq.MC;
SWBuOH.LUC.MC = SWBuOH.ILUC.MC + SWBuOH.DLUC.MC + SWBuOH.Seq.MC;
CSEtOH.LUC.MC = CEtOH.ILUC.MC + CEtOH.DLUC.MC;
CSBuOH.LUC.MC = CBuOH.ILUC.MC + CBuOH.DLUC.MC;

% clear time;

%% Feedstock Production Emissions - CODE: FeedP
%  Columns:
```

```
%  1. Nitrogen Fertilizer Production Emissions
%  2. Field-level N2O Emissions (converted to CO2e)
%  3. Farming Equipment Emissions

C.N.dst = trirnd(141,160,150,samples); % kg N/ha
SW.N.dst = trirnd(55,100,74,samples);
CS.N.dst = mass_allocation.*trirnd(141,160,150,samples);

if NLCFS == 1,
    C.N.dst = ones(samples,1).*150;
    SW.N.dst = ones(samples,1).*74;
end

% Nitrogen Fertilizer Production Emissions
%  g CO3e/kg N * kg N/ha land * ha/kg feedstock * kg feedstock/MJ fuel

EF.CO2perkgN = 3000; % g CO2e/kg N fertilizer produced
                     % same as in Point Estimate file

CEtOH.FeedP.MC(:,1) = EF.CO2perkgN .* C.N.dst .* EtOH.kgCperMJ.dst ./ (C.yield.dst*1000/0.87);
CBuOH.FeedP.MC(:,1) = EF.CO2perkgN .* C.N.dst .* BuOH.kgCperMJ.dst ./ (C.yield.dst*1000/0.87);

SWEtOH.FeedP.MC(:,1) = EF.CO2perkgN .* SW.N.dst .* EtOH.kgSWperMJ.dst ./ (SW.yield.dst*1000);
SWBuOH.FeedP.MC(:,1) = EF.CO2perkgN .* SW.N.dst .* BuOH.kgSWperMJ.dst ./ (SW.yield.dst*1000);

CSEtOH.FeedP.MC(:,1) = EF.CO2perkgN .* CS.N.dst .* EtOH.kgCSperMJ.dst ./
(CS.yield.dst*1000/0.87);
CSBuOH.FeedP.MC(:,1) = EF.CO2perkgN .* CS.N.dst .* BuOH.kgCSperMJ.dst ./
(CS.yield.dst*1000/0.87);

% Field-Level Emissions, CORN
%  g CO2e/MJ fuel

N2OEF_Dir.dst = trirnd(0.003,0.03,0.01,samples);
N2OEF_Indir.dst = trirnd(0.002,0.05,0.01,samples);
N2OEF_gasf.pt = 0.1; % consider adding trirnd(0.03,0.3,1,samples)

% direct emissions, N application
CN2O(:,1) = N2OEF_Dir.dst.*C.N.dst*1000; % g N2O-N/ha farmed
SWN2O(:,1) = N2OEF_Dir.dst.*SW.N.dst*1000;
CSN2O(:,1) = N2OEF_Dir.dst.*CS.N.dst*1000; % g N2O-N/ha farmed

% direct emissions, crop residues
%  F_cr = crop_yield*%_renew*(R_ag*N_ag*(1-%_removal) + R_bg*N_bg
CN2O(:,2) = ( C.yield.dst*1000*1*(1.09*0.006*(1-0)+0.22*0.007) ).*N2OEF_Dir.dst*1000; % g N2O-
N/ha
SWN2O(:,2) = ( SW.yield.dst*1000*1*(0.3*0.015*(1-0)+0.8*0.007) ).*N2OEF_Dir.dst*1000;
CSN2O(:,2) = ( CS.yield.dst*1000*1*(1.09*0.006*(1-0)+0.22*0.007) ).*N2OEF_Dir.dst*1000; % g N2O-
N/ha

% indirect emissions, N application
%  kg N/ha * indirect EF * some factor...
CN2O(:,3) = C.N.dst .* N2OEF_Indir.dst .* N2OEF_gasf.pt * 1000; % g N2O-N/ha
SWN2O(:,3) = SW.N.dst .* N2OEF_Indir.dst .* N2OEF_gasf.pt * 1000;
CSN2O(:,3) = CS.N.dst .* N2OEF_Indir.dst .* N2OEF_gasf.pt * 1000; % g N2O-N/ha

CEtOH.FeedP.MC(:,2) = sum(CN2O,2)*298*(44/28) .* EtOH.kgCperMJ.dst ./ (C.yield.dst*1000/0.87);
CBuOH.FeedP.MC(:,2) = sum(CN2O,2)*298*(44/28) .* BuOH.kgCperMJ.dst ./ (C.yield.dst*1000/0.87);
SWEtOH.FeedP.MC(:,2) = sum(SWN2O,2)*298*(44/28) .* EtOH.kgSWperMJ.dst ./ (SW.yield.dst*1000);
SWBuOH.FeedP.MC(:,2) = sum(SWN2O,2)*298*(44/28) .* BuOH.kgSWperMJ.dst ./ (SW.yield.dst*1000);
CSEtOH.FeedP.MC(:,2) = sum(CSN2O,2)*298*(44/28) .* EtOH.kgCSperMJ.dst ./
(CS.yield.dst*1000/0.87);
CSBuOH.FeedP.MC(:,2) = sum(CSN2O,2)*298*(44/28) .* BuOH.kgCSperMJ.dst ./
(CS.yield.dst*1000/0.87);


% farming machinery used
%  [1,196 g CO2e/bu corn * conv => kg CO2e/kg corn] * kg corn/MJ fuel
CEtOH.FeedP.MC(:,3) = (1196*(2.2/56)).*EtOH.kgCperMJ.dst;
CBuOH.FeedP.MC(:,3) = (1196*(2.2/56)).*BuOH.kgCperMJ.dst;

CSEtOH.FeedP.MC(:,3) = (1196*(2.2/56)).*EtOH.kgCSperMJ.dst;
CSBuOH.FeedP.MC(:,3) = (1196*(2.2/56)).*BuOH.kgCSperMJ.dst;
```

```
%  1394.4 MJ diesel/ha SW * kg CO2/MJ diesel * Mg SW/ha * kg SW/ MJ fuel
SWEtOH.FeedP.MC(:,3) = (1394.4*1000*EF.FFvalue(2)).*EtOH.kgSWperMJ.dst ./ (SW.yield.dst*1000);
SWBuOH.FeedP.MC(:,3) = (1394.4*1000*EF.FFvalue(2)).*BuOH.kgSWperMJ.dst ./ (SW.yield.dst*1000);

clear F_cr CN2O SWN2O CSN2O;

%% Feedstock Transportation Emissions

dist1 = 10; % miles
dist2 = 40;

CEtOH.FeedT.MC = (2*(1713*dist1 +
2199*dist2)/10^6/907.19*1055*EF.FFvalue(2)*1000).*EtOH.kgCperMJ.dst;
CBuOH.FeedT.MC = (2*(1713*dist1 +
2199*dist2)/10^6/907.19*1055*EF.FFvalue(2)*1000)*BuOH.kgCperMJ.dst;
SWEtOH.FeedT.MC = (2*(1713*dist2)/10^6/907.19*1055*EF.FFvalue(2)*1000).*EtOH.kgSWperMJ.dst;
SWBuOH.FeedT.MC = (2*(1713*dist2)/10^6/907.19*1055*EF.FFvalue(2)*1000).*BuOH.kgSWperMJ.dst;
CSEtOH.FeedT.MC = (2*(1713*dist2)/10^6/907.19*1055*EF.FFvalue(2)*1000).*EtOH.kgCSperMJ.dst;
CSBuOH.FeedT.MC = (2*(1713*dist2)/10^6/907.19*1055*EF.FFvalue(2)*1000).*BuOH.kgCSperMJ.dst;

clear dist1 dist2;

%% Fuel Production Emissions

% Corn
C.CoProdCredit = [-15        -11.8]; % (g CO2e/MJ fuel)

CEtOH.FuelP.MC = C.ProdE.dst(:,1).*EF.FFvalue(6)*1000 + C.ProdE.dst(:,2).*EF.FFvalue(4)*1000 +
C.CoProdCredit(1);
CBuOH.FuelP.MC = C.ProdE.dst(:,3).*EF.FFvalue(6)*1000 + C.ProdE.dst(:,4).*EF.FFvalue(4)*1000 +
C.CoProdCredit(2);

% Switchgrass
% Calculation of SW.wasteMJperkg brought over from biofuel_point model
% Max. potential sugar quantity
SW.maxsugar(1:2)=SW.ptsugar(2:3)/132*1000*150; %arabinose and xylose (g/kg SW)
SW.maxsugar(3:5)=SW.ptsugar(4:6)/162*1000*180; %mannose, galactose, glucose

% sum(SW.maxsugar(1:2)) % C5 sugars
% sum(SW.maxsugar(3:5)) % C6 sugars

% Unfermented polymeric sugars (lost at hydrolysis step)
SW.unfermentedpoly(1:2)=SW.ptsugar(2:3)*(1-ConvEff.Hyd.pt)*1000;
SW.unfermentedpoly(3:5)=SW.ptsugar(4:6)*(1-ConvEff.Hyd.pt)*1000;

% Unfermented monomeric sugars (lost at fermentation step)
SW.unfermentedmono(1:2)=(SW.ptsugar(2:3)*1000-SW.unfermentedpoly(1:2))*150/132*(1-
ConvEff.Oth.pt);
SW.unfermentedmono(3:4)=(SW.ptsugar(4:5)*1000-SW.unfermentedpoly(3:4))*180/162*(1-
ConvEff.Oth.pt);
SW.unfermentedmono(5)=(SW.ptsugar(6)*1000-SW.unfermentedpoly(5))*180/162*(1-ConvEff.Glc.pt);

C5energy=0.0049;
C6energy=0.0051;

SW.wasteMJperkg.pt = sum(SW.unfermentedpoly*SW.sugarE(2:6)'/1000) +
sum(SW.unfermentedmono(1:2))*C5energy ...
    + sum(SW.unfermentedmono(3:5))*C6energy;

EtOH.availE.dst=(SW.ptsugar(1)*SW.sugarE(1) + SW.ptsugar(7)*SW.sugarE(7) +
SW.wasteMJperkg.pt).*EtOH.kgSWperMJ.dst;
BuOH.availE.dst=(SW.ptsugar(1)*SW.sugarE(1) + SW.ptsugar(7)*SW.sugarE(7) +
SW.wasteMJperkg.pt).*BuOH.kgSWperMJ.dst;

%  Fraction of total input energy to electricity
SWetohElec = 0.1;
SWbuohElec = 0.0746;

%  Energy production efficiency values
boiler_eff = 0.68;
turbine_eff = 0.85;
```

```matlab
%  SW emissions factor
%   Units: g CO2e/kg SW used
SW.EF.dst = 1000*(SW.ILUC_ef.dst + SW.DLUC_ef.dst + SW.Seq_ef.dst)*1000/time./(1000*SW.yield.dst)
...
    + sum(SWEtOH.FeedP.MC,2)./EtOH.kgSWperMJ.dst ...
    + SWEtOH.FeedT.MC./EtOH.kgSWperMJ.dst;

SW_EF = SW.EF.dst;

%  ethanol energy requirements %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

EtOH.steam.reqd = SW.ProdE.dst(:,1).*(1-SWetohElec);
EtOH.steam.avail = EtOH.availE.dst.*boiler_eff;
EtOH.steam.surplus = EtOH.steam.avail - EtOH.steam.reqd;

EtOH.elec.reqd = SW.ProdE.dst(:,1).*SWetohElec;

% index iterated structures to reduce runtime
EtOH.elec.avail=zeros(samples,1);
EtOH.steam.SWneeded=zeros(samples,1);
EtOH.elec.surplus=zeros(samples,1);
EtOH.elec.SWneeded=zeros(samples,1);
EtOH.steam.FFemissions=zeros(samples,1);

for i=1:samples
    if EtOH.steam.surplus(i)>0,
        EtOH.elec.avail(i) = EtOH.steam.surplus(i)*turbine_eff;
        EtOH.steam.SWneeded(i) = 0;
    else
        EtOH.elec.avail(i) = 0;
        EtOH.steam.SWneeded(i) = EtOH.steam.reqd(i)/boiler_eff/SW.MJperkg.pt;
    end

    EtOH.elec.surplus(i) = EtOH.elec.avail(i) - EtOH.elec.reqd(i);

    if EtOH.elec.surplus(i)<0,
        EtOH.elec.SWneeded(i) = -EtOH.elec.surplus(i)/(boiler_eff*turbine_eff)/SW.MJperkg.pt;
    else
        EtOH.elec.SWneeded(i) = 0;
    end

    % emissions calculations
    if EtOH.steam.surplus(i)<0
        EtOH.steam.FFemissions(i) = -EtOH.steam.surplus(i)/boiler_eff*EF.FFvalue(4)*1000;
    else
        EtOH.steam.FFemissions(i) = 0;
    end
end

EtOH.elec.FFemissions = -EtOH.elec.surplus*EF.FFvalue(6)*1000;

%  butanol energy requirements %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
BuOH.steam.reqd = SW.ProdE.dst(:,2).*(1-SWbuohElec);
BuOH.steam.avail = BuOH.availE.dst*boiler_eff;
BuOH.steam.surplus = BuOH.steam.avail - BuOH.steam.reqd;

BuOH.elec.reqd = SW.ProdE.dst(:,2).*SWbuohElec;

% index iterated structures to reduce runtime
BuOH.elec.avail=zeros(samples,1);
BuOH.steam.SWneeded=zeros(samples,1);
BuOH.elec.surplus=zeros(samples,1);
BuOH.elec.SWneeded=zeros(samples,1);
BuOH.steam.FFemissions=zeros(samples,1);

for i=1:samples
    if BuOH.steam.surplus(i)>0,
        BuOH.elec.avail(i) = BuOH.steam.surplus(i)*turbine_eff;
        BuOH.steam.SWneeded(i) = 0;
    else
        BuOH.elec.avail(i) = 0;
        BuOH.steam.SWneeded(i) = -BuOH.steam.surplus(i)/boiler_eff/SW.MJperkg.pt;
    end
```

```
    BuOH.elec.surplus(i) = BuOH.elec.avail(i) - BuOH.elec.reqd(i);

    if BuOH.elec.surplus(i)<0,
        BuOH.elec.SWneeded(i) = -BuOH.elec.surplus(i)/(boiler_eff*turbine_eff)/SW.MJperkg.pt;
    else
        BuOH.elec.SWneeded(i) = 0;
    end

    % emissions calculations
    if BuOH.steam.surplus(i)<0
        BuOH.steam.FFemissions(i) = -BuOH.steam.surplus(i)/boiler_eff*EF.FFvalue(4)*1000;
    else
        BuOH.steam.FFemissions(i) = 0;
    end
end

BuOH.elec.FFemissions = -BuOH.elec.surplus*EF.FFvalue(6)*1000;

SWEtOH.FuelP.MC(:,1) = EtOH.elec.FFemissions + EtOH.steam.FFemissions;
for i=1:samples
    if (EtOH.elec.SWneeded(i)+EtOH.steam.SWneeded(i))>0,
        SWEtOH.FuelP.MC(i,2) = (EtOH.elec.SWneeded(i)  + EtOH.steam.SWneeded(i))*SW.EF.dst(i);
    else
        SWEtOH.FuelP.MC(i,2) = EtOH.elec.FFemissions(i);
    end
end

SWBuOH.FuelP.MC(:,1) = BuOH.elec.FFemissions + BuOH.steam.FFemissions;
for i=1:samples
    if (BuOH.elec.SWneeded(i)+BuOH.steam.SWneeded(i))>0,
        SWBuOH.FuelP.MC(i,2) = (BuOH.elec.SWneeded(i)  + BuOH.steam.SWneeded(i))*SW.EF.dst(i);
    else
        SWBuOH.FuelP.MC(i,2) = BuOH.elec.FFemissions(i);
    end
end


% Corn stover ----------------------------------------------------------
% Calculation of SW.wasteMJperkg brought over from biofuel_point model
% Max. potential sugar quantity
CS.maxsugar(1:2)=CS.ptsugar(2:3)/132*1000*150; %arabinose and xylose (g/kg SW)
CS.maxsugar(3:5)=CS.ptsugar(4:6)/162*1000*180; %mannose, galactose, glucose

% sum(SW.maxsugar(1:2)) % C5 sugars
% sum(SW.maxsugar(3:5)) % C6 sugars

% Unfermented polymeric sugars (lost at hydrolysis step)
CS.unfermentedpoly(1:2)=CS.ptsugar(2:3)*(1-ConvEff.Hyd.pt)*1000;
CS.unfermentedpoly(3:5)=CS.ptsugar(4:6)*(1-ConvEff.Hyd.pt)*1000;

% Unfermented monomeric sugars (lost at fermentation step)
CS.unfermentedmono(1:2)=(CS.ptsugar(2:3)*1000-CS.unfermentedpoly(1:2))*150/132*(1-
ConvEff.Oth.pt);
CS.unfermentedmono(3:4)=(CS.ptsugar(4:5)*1000-CS.unfermentedpoly(3:4))*180/162*(1-
ConvEff.Oth.pt);
CS.unfermentedmono(5)=(CS.ptsugar(6)*1000-CS.unfermentedpoly(5))*180/162*(1-ConvEff.Glc.pt);

CS.wasteMJperkg.pt = sum(CS.unfermentedpoly*CS.sugarE(2:6)'/1000) +
sum(CS.unfermentedmono(1:2))*C5energy ...
    + sum(CS.unfermentedmono(3:5))*C6energy;

EtOH.availE.dst=(CS.ptsugar(1)*CS.sugarE(1) + CS.ptsugar(7)*CS.sugarE(7) +
CS.wasteMJperkg.pt).*EtOH.kgCSperMJ.dst;
BuOH.availE.dst=(CS.ptsugar(1)*CS.sugarE(1) + CS.ptsugar(7)*CS.sugarE(7) +
CS.wasteMJperkg.pt).*BuOH.kgCSperMJ.dst;

%  Fraction of total input energy to electricity
CSetohElec = SWetohElec;
CSbuohElec = SWbuohElec;

% %  Energy production efficiency values
% boiler_eff = 0.68;
```

```matlab
% turbine_eff = 0.85;

%  SW emissions factor
%   Units: g CO2e/kg SW used
CS.EF.dst = 1000*(CS.ILUC_ef.dst + CS.DLUC_ef.dst)*1000/time./(1000*CS.yield.dst) ...
    + sum(CSEtOH.FeedP.MC,2)./EtOH.kgCSperMJ.dst ...
    + CSEtOH.FeedT.MC./EtOH.kgCSperMJ.dst;

CS_EF = CS.EF.dst;

%  ethanol energy requirements %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

EtOH.steam.reqd = CS.ProdE.dst(:,1).*(1-CSetohElec);
EtOH.steam.avail = EtOH.availE.dst.*boiler_eff;
EtOH.steam.surplus = EtOH.steam.avail - EtOH.steam.reqd;

EtOH.elec.reqd = CS.ProdE.dst(:,1).*CSetohElec;

% index iterated structures to reduce runtime
EtOH.elec.avail=zeros(samples,1);
EtOH.steam.CSneeded=zeros(samples,1);
EtOH.elec.surplus=zeros(samples,1);
EtOH.elec.CSneeded=zeros(samples,1);
EtOH.steam.FFemissions=zeros(samples,1);

for i=1:samples
    if EtOH.steam.surplus(i)>0,
        EtOH.elec.avail(i) = EtOH.steam.surplus(i)*turbine_eff;
        EtOH.steam.CSneeded(i) = 0;
    else
        EtOH.elec.avail(i) = 0;
        EtOH.steam.CSneeded(i) = EtOH.steam.reqd(i)/boiler_eff/CS.MJperkg.pt;
    end

    EtOH.elec.surplus(i) = EtOH.elec.avail(i) - EtOH.elec.reqd(i);

    if EtOH.elec.surplus(i)<0,
        EtOH.elec.CSneeded(i) = -EtOH.elec.surplus(i)/(boiler_eff*turbine_eff)/CS.MJperkg.pt;
    else
        EtOH.elec.CSneeded(i) = 0;
    end

    % emissions calculations
    if EtOH.steam.surplus(i)<0
        EtOH.steam.FFemissions(i) = -EtOH.steam.surplus(i)/boiler_eff*EF.FFvalue(4)*1000;
    else
        EtOH.steam.FFemissions(i) = 0;
    end
end

EtOH.elec.FFemissions = -EtOH.elec.surplus*EF.FFvalue(6)*1000;

% %  butanol energy requirements %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% BuOH.steam.reqd = SW.ProdE.dst(:,2).*(1-SWbuohElec);
% BuOH.steam.avail = BuOH.availE.dst*boiler_eff;
% BuOH.steam.surplus = BuOH.steam.avail - BuOH.steam.reqd;
%
% BuOH.elec.reqd = SW.ProdE.dst(:,2).*SWbuohElec;
%
% % index iterated structures to reduce runtime
% BuOH.elec.avail=zeros(samples,1);
% BuOH.steam.SWneeded=zeros(samples,1);
% BuOH.elec.surplus=zeros(samples,1);
% BuOH.elec.SWneeded=zeros(samples,1);
% BuOH.steam.FFemissions=zeros(samples,1);
%
% for i=1:samples
%     if BuOH.steam.surplus(i)>0,
%         BuOH.elec.avail(i) = BuOH.steam.surplus(i)*turbine_eff;
%         BuOH.steam.SWneeded(i) = 0;
%     else
%         BuOH.elec.avail(i) = 0;
%         BuOH.steam.SWneeded(i) = -BuOH.steam.surplus(i)/boiler_eff/SW.MJperkg.pt;
```

```
%     end
%
%     BuOH.elec.surplus(i) = BuOH.elec.avail(i) - BuOH.elec.reqd(i);
%
%     if BuOH.elec.surplus(i)<0,
%         BuOH.elec.SWneeded(i) = -BuOH.elec.surplus(i)/(boiler_eff*turbine_eff)/SW.MJperkg.pt;
%     else
%         BuOH.elec.SWneeded(i) = 0;
%     end
%
%     % emissions calculations
%     if BuOH.steam.surplus(i)<0
%         BuOH.steam.FFemissions(i) = -BuOH.steam.surplus(i)/boiler_eff*EF.FFvalue(4)*1000;
%     else
%         BuOH.steam.FFemissions(i) = 0;
%     end
% end
%
% BuOH.elec.FFemissions = -BuOH.elec.surplus*EF.FFvalue(6)*1000;
%
CSEtOH.FuelP.MC(:,1) = EtOH.elec.FFemissions + EtOH.steam.FFemissions;
for i=1:samples
    if (EtOH.elec.CSneeded(i)+EtOH.steam.CSneeded(i))>0,
        CSEtOH.FuelP.MC(i,2) = (EtOH.elec.SWneeded(i)  + EtOH.steam.CSneeded(i))*CS.EF.dst(i);
    else
        CSEtOH.FuelP.MC(i,2) = EtOH.elec.FFemissions(i);
    end
end
%
% SWBuOH.FuelP.MC(:,1) = BuOH.elec.FFemissions + BuOH.steam.FFemissions;
% for i=1:samples
%     if (BuOH.elec.SWneeded(i)+BuOH.steam.SWneeded(i))>0,
%         SWBuOH.FuelP.MC(i,2) = (BuOH.elec.SWneeded(i)  + BuOH.steam.SWneeded(i))*SW.EF.dst(i);
%     else
%         SWBuOH.FuelP.MC(i,2) = BuOH.elec.FFemissions(i);
%     end
% end

%% Fuel Distribution Emissions

CEtOH.FuelD.MC = Mode_EF*Mode(:,1) / EtOH.MJperkg *1000;
CBuOH.FuelD.MC = Mode_EF*Mode(:,1) / BuOH.MJperkg *1000;

SWEtOH.FuelD.MC = CEtOH.FuelD.MC;
SWBuOH.FuelD.MC = CBuOH.FuelD.MC;

CSEtOH.FuelD.MC = CEtOH.FuelD.MC;
CSBuOH.FuelD.MC = CBuOH.FuelD.MC;


%% Fuel Combustion Emissions

CEtOH.FuelC = 0;
CBuOH.FuelC = 0;
SWEtOH.FuelC = 0;
SWBuOH.FuelC = 0;
CSEtOH.FuelC = 0;
CSBuOH.FuelC = 0;

clear NLCFS;

%% Summary Statistics from MC Run

% Summary Table

disp('   C EtOH   C BuOH    SW EtOH    SW BuOH   CS EtOH');

Summary_MC_mean=zeros(8,4);

Summary_MC_mean(1,1)=mean(CEtOH.DLUC.MC);
Summary_MC_mean(1,2)=mean(CBuOH.DLUC.MC);
Summary_MC_mean(1,3)=mean(SWEtOH.DLUC.MC);
Summary_MC_mean(1,4)=mean(SWBuOH.DLUC.MC);
```

```
Summary_MC_mean(1,5)=mean(CSEtOH.DLUC.MC);

Summary_MC_mean(2,1)=mean(CEtOH.ILUC.MC);
Summary_MC_mean(2,2)=mean(CBuOH.ILUC.MC);
Summary_MC_mean(2,3)=mean(SWEtOH.ILUC.MC);
Summary_MC_mean(2,4)=mean(SWBuOH.ILUC.MC);
Summary_MC_mean(2,5)=mean(CSEtOH.ILUC.MC);

Summary_MC_mean(3,3)=mean(SWEtOH.Seq.MC);
Summary_MC_mean(3,4)=mean(SWBuOH.Seq.MC);

Summary_MC_mean(4,1)=mean(sum(CEtOH.FeedP.MC,2));
Summary_MC_mean(4,2)=mean(sum(CBuOH.FeedP.MC,2));
Summary_MC_mean(4,3)=mean(sum(SWEtOH.FeedP.MC,2));
Summary_MC_mean(4,4)=mean(sum(SWBuOH.FeedP.MC,2));
Summary_MC_mean(4,5)=mean(sum(CSEtOH.FeedP.MC,2));

Summary_MC_mean(5,1)=mean(CEtOH.FeedT.MC);
Summary_MC_mean(5,2)=mean(CBuOH.FeedT.MC);
Summary_MC_mean(5,3)=mean(SWEtOH.FeedT.MC);
Summary_MC_mean(5,4)=mean(SWBuOH.FeedT.MC);
Summary_MC_mean(5,5)=mean(CSEtOH.FeedT.MC);

Summary_MC_mean(6,1)=mean(CEtOH.FuelP.MC);
Summary_MC_mean(6,2)=mean(CBuOH.FuelP.MC);
Summary_MC_mean(6,3)=mean(sum(SWEtOH.FuelP.MC(:,1),2));
Summary_MC_mean(6,4)=mean(sum(SWBuOH.FuelP.MC(:,1),2));
Summary_MC_mean(6,5)=mean(sum(CSEtOH.FuelP.MC(:,1),2));

Summary_MC_mean(7,1)=mean(CEtOH.FuelD.MC);
Summary_MC_mean(7,2)=mean(CBuOH.FuelD.MC);
Summary_MC_mean(7,3)=mean(SWEtOH.FuelD.MC);
Summary_MC_mean(7,4)=mean(SWBuOH.FuelD.MC);
Summary_MC_mean(7,5)=mean(CSEtOH.FuelD.MC);

Summary_MC_mean(8,1)=CEtOH.FuelC;
Summary_MC_mean(8,2)=CBuOH.FuelC;
Summary_MC_mean(8,3)=SWEtOH.FuelC;
Summary_MC_mean(8,4)=SWBuOH.FuelC;
Summary_MC_mean(8,5)=CSEtOH.FuelC;

Summary_MC_mean

%%

CEtOH_final = CEtOH.ILUC.MC + CEtOH.DLUC.MC + CEtOH.FeedP.MC(:,1) + CEtOH.FeedP.MC(:,2)+...
    CEtOH.FeedP.MC(:,3) + CEtOH.FeedT.MC + CEtOH.FuelP.MC + CEtOH.FuelC;
CBuOH_final = CBuOH.ILUC.MC + CBuOH.DLUC.MC + CBuOH.FeedP.MC(:,1) + CBuOH.FeedP.MC(:,2)+...
    CBuOH.FeedP.MC(:,3) + CBuOH.FeedT.MC + CBuOH.FuelP.MC + CBuOH.FuelC;

SWEtOHFF_final = SWEtOH.ILUC.MC + SWEtOH.DLUC.MC + SWEtOH.Seq.MC + SWEtOH.FeedP.MC(:,1) + ...
    SWEtOH.FeedP.MC(:,2) + SWEtOH.FeedP.MC(:,3) + SWEtOH.FeedT.MC + SWEtOH.FuelP.MC(:,1) +
SWEtOH.FuelC;

SWBuOHFF_final = SWBuOH.ILUC.MC + SWBuOH.DLUC.MC + SWBuOH.Seq.MC + SWBuOH.FeedP.MC(:,1) +...
    SWBuOH.FeedP.MC(:,2) + SWBuOH.FeedP.MC(:,3) + SWBuOH.FeedT.MC + SWBuOH.FuelP.MC(:,1) +
SWBuOH.FuelC;

SWEtOHSWf_final = SWEtOH.ILUC.MC + SWEtOH.DLUC.MC + SWEtOH.Seq.MC + SWEtOH.FeedP.MC(:,1) + ...
    SWEtOH.FeedP.MC(:,2) + SWEtOH.FeedP.MC(:,3) + SWEtOH.FeedT.MC + SWEtOH.FuelP.MC(:,2) +
SWEtOH.FuelC;

SWBuOHSWf_final = SWBuOH.ILUC.MC + SWBuOH.DLUC.MC + SWBuOH.Seq.MC + SWBuOH.FeedP.MC(:,1) +...
    SWBuOH.FeedP.MC(:,2) + SWBuOH.FeedP.MC(:,3) + SWBuOH.FeedT.MC + SWBuOH.FuelP.MC(:,2) +
SWBuOH.FuelC;

CSEtOHFF_final = CSEtOH.ILUC.MC + CSEtOH.DLUC.MC + CSEtOH.FeedP.MC(:,1) +
CSEtOH.FeedP.MC(:,2)+...
    CSEtOH.FeedP.MC(:,3) + CSEtOH.FeedT.MC + CSEtOH.FuelP.MC(:,1) + CSEtOH.FuelC;
CSEtOHCSf_final = CSEtOH.ILUC.MC + CSEtOH.DLUC.MC + CSEtOH.FeedP.MC(:,1) +
CSEtOH.FeedP.MC(:,2)+...
    CSEtOH.FeedP.MC(:,3) + CSEtOH.FeedT.MC + CSEtOH.FuelP.MC(:,2) + CSEtOH.FuelC;
```

```
C_eth = CEtOH_final;
SW_ff = SWEtOHFF_final;
SW_swf = SWEtOHSWf_final;

% CSBuOH_final = CSBuOH.ILUC.MC + CSBuOH.DLUC.MC + CSBuOH.FeedP.MC(:,1) +
CSBuOH.FeedP.MC(:,2)+...
%     CSBuOH.FeedP.MC(:,3) + CSBuOH.FeedT.MC + CSBuOH.FuelP.MC + CSBuOH.FuelC;


%totals_mean=sum(Summary_MC_mean)

% Mean value for each of the final distributions (g CO2e/MJ fuel)
%       Ethanol           Butanol
totals=[mean(CEtOH_final) mean(CBuOH_final);         % Corn feedstock
        mean(SWEtOHFF_final) mean(SWBuOHFF_final);   % SW feedstock, FF production fuel
        mean(SWEtOHSWf_final) mean(SWBuOHSWf_final)] % SW feedstock, SW production fuel

% %% Stacked bar chart
% %  complicated because Matlab can't display negative values!
% %  still needs work to display the negative region properly
figure

ax1 = subplot(2,1,1,'XTickLabel',[]);
bar(Summary_MC_mean'.*(Summary_MC_mean'>0),'stacked')
ylabel('Life-cycle emissions, (g CO2e/MJ)')
ax2 = subplot(2,1,2 );
bar(Summary_MC_mean'.*(Summary_MC_mean'<0),'stacked')
lim1 = get(ax1,'YLim');
lim2 = get(ax2,'YLim');
pos = get(ax2,'position');
maxh = 1-2*pos(2);
posh = maxh*sum(abs(lim2))/sum(abs(lim1)+abs(lim2));
set(ax2,'position',[pos(1:3) posh])
set(ax1,'position',[pos(1) pos(2)+posh pos(3) maxh-posh])

legend('DLUC','ILUC','Sequestration','Farming','Feed. Transp.','Fuel Prod.','Fuel dist.','Fuel
Comb.',...
    'Location','NorthEast','Location',[0.6657 0.5568 0.235 0.3271])
xlabel('Fuel Pathway')
set(gca,'XTickLabel',{'Corn EtOH','Corn BuOH','SW EtOH','SW BuOH'})
% ylabh = get(gca,'YLabel');
% set(ylabh,'Position',get(ylabh,'Position') + [0 0 0.8]);

% %% Modify values for shifted lognormal distribution
%
% theta_CS_csf = (min(CS_csf)*max(CS_csf)-(median(CS_csf))^2) / (min(CS_csf)+max(CS_csf)-
2*(median(CS_csf)));
% theta_CS_ff = (min(CS_ff)*max(CS_ff)-(median(CS_ff))^2) / (min(CS_ff)+max(CS_ff)-
2*(median(CS_ff)));
% theta_SW_EF = (min(SW_EF)*max(SW_EF)-(median(SW_EF))^2) / (min(SW_EF)+max(SW_EF)-
2*(median(SW_EF)));
%
% mod_CS_csf = CS_csf - theta_CS_csf;
% mod_CS_ff = CS_ff - theta_CS_ff;
% mod_SW_EF = SW_EF - theta_SW_EF;
```

Appendix C

```
% % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % %
% Source: Grassini et al. Agrnomy Journ. 101 (3) 2009 pp. 564-571   %
% Switchgrass crop growth model                                     %
%                                                                   %
% Coded by: K. Mullins                                              %
% Last updated: June 7, 2012                                        %
% % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % % %

% Input units: T in C
%              R in MJ/m2 per day
%              AWHC in mm/mm

clear all;

% Read in data.  Years 1991 to 2005 correspond to year 1 to 15.
% Year 16 is all average year.
% Meteorological order, rows 5 to 10:
% precip (mm), mean temp (C), max temp (C), min temp (C), Solar (MJ/m^2 per
% day)
meteo_data_orig=csvread('data/IA_MC_basecase.csv',1,0);

year = 8;
start_row = 1 + 365*(year-1);
end_row = 365*year;
meteo_data_year = meteo_data_orig(start_row:end_row,6:10);

% Determine AGI given 365 days of temperature data
counter = 1;
while mean(meteo_data_year(counter:(counter+14),2)) < 13, % 13C requirement
    counter = counter + 1;
end

AGI_date = counter + 14;

% Extract only relevant data
rainfall = meteo_data_year(AGI_date:end,1);
T = meteo_data_year(AGI_date:end,2);
Thigh = meteo_data_year(AGI_date:end,3);
Tlow = meteo_data_year(AGI_date:end,4);
R = meteo_data_year(AGI_date:end,5);


% Global parameters that define various environmental, crop parameters for
% the simulation
global Tmin Tmax Topt Rmax MAXLAI RUE SL1_depth SL2_depth AWHC_SL1 AWHC_SL2 K_coeff Elev
ASE_count irr_amount;

Tmin = 13; Tmax = 42; Topt = 33; % [C] Grassini, cultivar characteristics
Elev = 551.7;      % [m]
Rmax = 0.037;      % Blackwell cultivar, see Grassini Table 1
MAXLAI = 10;       % Value from within noted range of 7.5 to 17.7
RUE = 4.7;         % Grassini, from Kiniry et al. (1999)
SL1_depth = 150;   % [mm]
SL2_depth = 1450;  % [mm] to give a total root depth of 2m
AWHC_SL1 = 0.15;   % WAG at this point... based on PowerPoint soil water lesson
AWHC_SL2 = 0.12;   % same...
K_coeff = 0.48;    % Extinction coefficient for total incoming solar radiation
FAWHC_SL1 = 0.6;   % Default from Grassini
FAWHC_SL2 = 0.6;   % Default from Grassini
ASE_count = 1;     % Counter for evapouration type [day]
irr_amount = 0;    % [mm]

% Initialize various counters, variables
day = 1;
dev_stage = 0;

while (dev_stage(day) < 1) && (day + AGI_date < 365),
    % Each iteration is one day in the development
                          % Loop runs until development stage = 1 (crop
                          % fully mature)

    % Calculate, output water stress factors, temperature stress factor
    [ WSF_LAI(day) WSF_RUE(day) TSF_RUE(day) ] = stresses(T(day), FAWHC_SL1(day),
```

```
FAWHC_SL2(day));

    % Calculate leaf area index
    LAI(day) = LAI_function( dev_stage(day), WSF_LAI(day) );

    % Calculate biomass growth
    biomass(day) = crop_growth(dev_stage(day), R(day), LAI(day), WSF_RUE(day),
TSF_RUE(day));

    % Calculate crop development progress as 'development stage' variable
    dev_stage(day+1) = crop_development(T(day), dev_stage(day));

    % Calculate soil-water balance
    [FAWHC_SL1(day+1) FAWHC_SL2(day+1) SL1_water(day) SL2_water(day) evap_track(day)
ETo_track(day) transp_track(day) overflow(day) canopy_track(day) runoff_track(day)
irr_track(day)] = ...
       soil_water_balance( LAI(day), rainfall(day), T(day), Tlow(day), Thigh(day),...
       R(day), FAWHC_SL1(day), FAWHC_SL2(day), biomass(day));

    ASE_track(day) = ASE_count;
    day = day + 1;

    if day + AGI_date > 365, % exit condition if crop never fully matures in the year
        display('Break condition met')
    end

end

for i = 1:length(biomass),
    cum_biomass(i) = sum(biomass(1:i));
end

% Final yield value, rainfall over growth period
biomass_Mg = cum_biomass(end)*10000/10^6;
display('calc.d biomass')

growth_rainfall = sum(rainfall(1:day-1));

display('growth rainfall')


% Extra stuff

% Change units from in to mm, F to C, extract only relevant data
% rainfall = temp1(AGI_date:end)*25.4;
% T = (temp2(AGI_date:end) - 32)*5/9;
% Thigh = (temp3(AGI_date:end) - 32)*5/9;
% Tlow = (temp4(AGI_date:end) - 32)*5/9;
% R = temp5(AGI_date:end);
```

```
function dev_stage = crop_development( T, dev_stage)
% Crop Development module

global Tmin Tmax Topt Rmax;

alpha = log(2)/log( (Tmax - Tmin)/(Topt - Tmin) );

f_T = (2*(T - Tmin)^alpha*(Topt - Tmin)^alpha - (T - Tmin)^(2*alpha))/(Topt-
Tmin)^(2*alpha);

if T <= Tmin,
    f_T = 0;
end

if T >= Tmax,
    f_T = 0;
end

r = Rmax*f_T; % daily growth rate

dev_stage = dev_stage + r;
```

```
end


function LAI = LAI_function( dev_stage, WSF_LAI )
% LAI Expansion module

global MAXLAI;

LAI = (1.27*exp(-4.51*exp(-2.94*dev_stage)))*MAXLAI*WSF_LAI; % dimensionless, [0, 1]

end
```

```
function [FAWHC_SL1 FAWHC_SL2 SL1_water SL2_water evaporation ETo transpiration overflow
canopy_loss runoff irr_track] = ...
    soil_water_balance( LAI, rainfall, T, Tlow, Thigh, R, FAWHC_SL1, FAWHC_SL2, biomass)

global SL1_depth SL2_depth AWHC_SL1 AWHC_SL2 K_coeff Elev ASE_count irr_amount;

% Water balance at the end of the day assumes the following happens in
% chronological order: rains, evaporation, then transpiration.

% How the day starts
SL1_water = FAWHC_SL1*AWHC_SL1*SL1_depth; % [mm]
SL2_water = FAWHC_SL2*AWHC_SL2*SL2_depth;

% Choice to irrigate
if FAWHC_SL2 < 0.6,                              %%% CHANGE HERE FOR SENSITIVITY ANALYSIS
    rainfall = rainfall + irr_amount;
    irr_track = 1;
else
    irr_track = 0;
end

% Module 1: Loss due to canopy interception
max_canopy_loss = 1; %mm
if rainfall > 0,
    canopy_loss = max_canopy_loss*(1-exp(-0.4*LAI)); % [mm]
else
    canopy_loss = 0;
end

% Module 2: Loss due to surface runoff
if (rainfall-canopy_loss) >= 200*0.1,
    runoff = ((rainfall - 200*0.1)^2)/(rainfall+800*0.1); % [mm]
else
    runoff = 0;
end

% Module 3: Evaporation
s = 2504*exp(17.27*T/(T+237.2))/(T+237.3)^2; % slope of vapour pressure saturation curve
[kPa/C]
lambda = 2.501 - 0.002361*T; % latent heat of vaporization [MJ/kg]
P_atm = 101.3*((293-0.0065*Elev)/293)^5.26; % atmospheric pressure [kPa]
gamma = 1.013E-3*P_atm/(0.622*lambda); % psychrometric constant [kPa/C]
rho = 1000; % density, kg/m^3
alpha = 1.26; % Priestley and Taylor (1972) []

ETo = alpha*s/(s+gamma)*R/(rho*lambda)*1000; % [mm] crop evapotranspiration
PSE = ETo*exp(-K_coeff*LAI); % potential evaporation

if FAWHC_SL1 > 0.5,
    evaporation = PSE; % actual evaporation (ASE in article)
    ASE_count = 1;
else
    evaporation = PSE*(sqrt(ASE_count)-sqrt(ASE_count-1));
    ASE_count = ASE_count + 1;
end

% Module 4: Transpiration
```

```
VPD = 0.611*exp(17.27*Thigh/(Thigh + 237.3)) - 0.611*exp(17.27*Tlow/(Tlow + 237.3)); %
vapor pressure deficit
transpiration = biomass/(7.44/(0.75*VPD)^-0.42); % [mm]
% note that biomass value already accounts for water and temperature stresses

% Module 5: Water "height" balance
% SL1 calculations first, with overflow going down to SL2
SL1_water = SL1_water + rainfall - canopy_loss - runoff; % water that soil layer 1 sees
FAWHC_SL1 = SL1_water / (AWHC_SL1*SL1_depth);

overflow = 0;

if FAWHC_SL1 > 1.1, % check for "saturation" (beyond alowable fraction)
    overflow = (FAWHC_SL1 - 1.1)*AWHC_SL1*SL1_depth; % if over 1.1, flows to second layer
    FAWHC_SL1 = 1.1;
    SL2_water = SL2_water + overflow;
    FAWHC_SL2 = SL2_water / (AWHC_SL2*SL2_depth);
end

if FAWHC_SL2 > 1.1, % if layer 2 saturated, water lost below roots
    FAWHC_SL2 = 1.1;
end

SL1_water = FAWHC_SL1*AWHC_SL1*SL1_depth;
SL2_water = FAWHC_SL2*AWHC_SL2*SL2_depth;

SL1_water = SL1_water - evaporation; % evaporation, only from layer 1
if SL1_water < 0,
    SL1_water = 0;
end

FAWHC_SL1 = SL1_water / (AWHC_SL1*SL1_depth);
FAWHC_SL2 = SL2_water / (AWHC_SL2*SL2_depth);

SL1_water = SL1_water - transpiration; % transpiration first from 1, then 2
if SL1_water < 0,
    SL2_water = SL2_water + SL1_water; % take deficit from previous calc.
    SL1_water = 0;
    if SL2_water < 0,
        SL2_water = 0; end
end

FAWHC_SL1 = SL1_water / (AWHC_SL1*SL1_depth);
FAWHC_SL2 = SL2_water / (AWHC_SL2*SL2_depth);

if FAWHC_SL2 > 1.1,
    FAWHC_SL2 = 1.1;
end

end
```

```
function biomass = crop_growth(dev_stage, R, LAI, WSF_RUE, TSF_RUE)
% Biomass production, [g/m^2 per day]

global RUE;

% Photosynthetically Active Radiation Intecepted
k = 0.65;  % extinction coefficient
PARINT = R*0.45*(1-exp(-k*LAI));
biomass = RUE*PARINT*WSF_RUE*TSF_RUE; % g dry matter

end
```

```
function [ WSF_LAI WSF_RUE TSF_RUE] = stresses(T, FAWHC_SL1, FAWHC_SL2)

global SL1_depth SL2_depth;

% Water stress factors
```

```
FAWHC_avg = (SL1_depth/(SL1_depth+SL2_depth)*FAWHC_SL1 +
SL2_depth/(SL1_depth+SL2_depth)*FAWHC_SL2)/2;
WSF_LAI = 1/(1 + 270*exp(-32.2*FAWHC_avg));
WSF_RUE = 1/(1 + 9*exp(-15.3*FAWHC_avg));

% Temperature stress factors
TSF_RUE = -0.42 + 0.067*T;

if T < 6.4,
    TSF_RUE = 0; end

if T > 21,
    TSF_RUE = 1; end

end
```