Comparative Lifecycle Analysis of BioEnergy Pathways:

Cellulosic Ethanol vs Biomass Electricity

By:

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Abstract

This research assesses the comparative environmental profiles of the bioenergy systems - biofuel (ethanol) and biomass electricity - derived from switchgrass. Switchgrass cultivation as a dedicated energy crop is an emerging practice. It has high yield with relatively low nutrient requirements and has a great potential to meet future energy needs.

The contribution of this research is twofold. First, the life cycle energy and GHG emissions of individual bioenergy pathways - producing cellulosic ethanol and biomass electricity - are analyzed in greater detail. In contrast with previous studies, we have not just used a single value of input parameters for different life cycle stages, but instead, have assessed the impact based on a probability distribution by incorporating a Monte Carlo analysis. This has helped to address the variability in the lifecycle impacts of bioenergy systems and establishing a range of energy and greenhouse gas (GHG) impacts, rather than previous single-valued estimates. Second, a framework to compare cellulosic ethanol and biomass electricity lifecycle energy and GHG emissions is provided. We propose the criterion for comparison should not be dictated by absolute emissions along a certain bioenergy pathway, such as producing biofuels or biomass electricity. Instead, we consider the savings in emissions from the displacement of fossil fuel by biomass along each pathway. Based on this criterion, we quantify the lifecycle GHG emissions impacts of each pathway, compare them to the reference fossil energy system and compare their land use efficiency.

The average lifecycle GHG emissions of ethanol are assessed as 35 g CO_2-eq/MJ of energy, with a minimum-maximum range of GHG emissions varying from 25 to 50 g CO_2-eq/MJ. Switchgrass yield, fertilizer application rates and conversion efficiency are important determinants in the overall variation in the GHG balance. For example, the GHG contribution from the agricultural stage of switchgrass varies over a large range from 500 to 1200 kg CO_2-eq/ha/year. A comparison between cellulosic ethanol and a gasoline system shows that on average 55 g CO_2-eq/MJ of energy are saved if gasoline use is replaced by cellulosic ethanol derived from switchgrass. The average life cycle GHG emissions from biomass electricity are 100 g CO_2-eq/kWh, with a minimum-maximum range of GHG emissions varying from 90 to 110 g CO_2 eq/kWh. In comparison to the U.S. grid electricity, 513 g CO_2-eq/kWh of energy are saved if biomass electricity from switchgrass displaces the grid electricity. Avoided emissions per unit of energy, however, are also dependent on regional factors, such as regional electricity grid mix.

When comparing these bioenergy systems in terms of land use efficiency, biomass electricity has a better environmental profile in terms of energy sue and GHG emissions than ethanol. 4.5 ton CO_2-eq/ha/year emissions are saved if we use all the switchgrass cultivated on a hectare of land to

produce ethanol. For biomass electricity, the annual GHG emissions saved are 10 ton CO_2-eq/ha/year. The GHG emissions offset from the best case of cellulosic ethanol is comparable to emissions offset from the worst case of biomass electricity.

We have also analyzed another case of the comparative environmental profile of these two bioenergy systems, formulated assuming a special case of biomass electricity use. In this case, all the biomass electricity produced is used to charge electric vehicles and ethanol is used to power Flex Fuel Vehicles (FFVs). 145 g CO_2-eq/km will be saved if we use ethanol is used instead of gasoline in FFVs. In the case of electric vehicles, 110 g CO_2-eq/km is saved if we use biomass electricity instead of the U.S. average grid power. Thus, biomass electricity is not a very effective alternative if the end goal of bioenergy policies is to use biomass only in the transportation sector. These findings are different from the previous bioenergy comparison studies, which have only estimated the offset of a biomass powered electric vehicle by comparing it to a gasoline-powered car. These studies concluded that biomass electricity has a better environmental profile than cellulosic ethanol.

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1. Introduction

Bioenergy systems have gained attention as an important source of alternative energy. The key drivers for development of alternative energy sources are diversification and security of fuel supply, as well as rising climate change concerns from greenhouse gas (GHG) emissions of conventional fuels. Bioenergy, especially that derived from cellulosic feedstocks such as agriculture waste and low maintenance energy crops, promises to reduce GHG emissions significantly [1]. Switchgrass, a perennial grass in North America, is one such promising cellulosic feedstocks which has been investigated under the DOE Bioenergy Feedstock Development Program (BFDP) since 1991 [2]. It has been proposed as an ideal herbaceous crop for energy because of its high yield, coupled with relatively low nutrient requirements. Although, switchgrass is currently only grown in buffer strips, not cultivated as a commodity crop, in the long run, switchgrass may be grown as a dedicated energy crop as envisioned by DOE Billion Ton Supply study [3] and in existing bioenergy plans such as Energy Independence and Security Act 2007 and state Renewable Portfolio Standards [10].

There are two main pathways to convert biomass into more usable forms of energy. It can be liquefied (e.g., ethanol) for use as a transportation fuel or it can be used for power generation. These two pathways have different environmental profiles as well as different economic and policy drivers. Currently, in the U.S., strong policy incentives exist to support biofuels' development. The Renewable Fuel Standards (RFS) policy of U.S. Environment Protection Agency (EPA) requires production of 36 billion gallons per year of renewable transportation fuels by 2022 [4]. Currently, ethanol, mostly derived from corn, powers approximately 3% of the nation's transportation sector (EIA, 2010) but consumes 25% of the nation's corn production [5]. The mass production of biofuels using food crops as feedstock has been criticized for a variety of reasons, including rising food prices [6], competing arable land, water resources stress, with food and fiber crops [7,8], and increasing GHG emissions [9]. Therefore, it is important to focus on biofuels derived from cellulosic sources such as agriculture waste and energy crops. The EPA mandates that the annual production of advanced fuels (i.e., biofuels other than ethanol derived from corn starch) should gradually increase to 21 billion gallons per year by 2022 [4]. The EPA also has specific thresholds for the lifecycle GHG emissions of the renewable fuels used to meet the 21 billion gallons per year mandate. In particular, cellulosic biofuels are required to achieve a 60% reduction in lifecycle emissions compared to the 2005 gasoline baseline [4]. This policy will help in reducing the GHG emissions from the transportation sector, which currently accounts for 28% of the total 6.5 billion metric tons of GHG emissions in the U.S. (Figure 1).

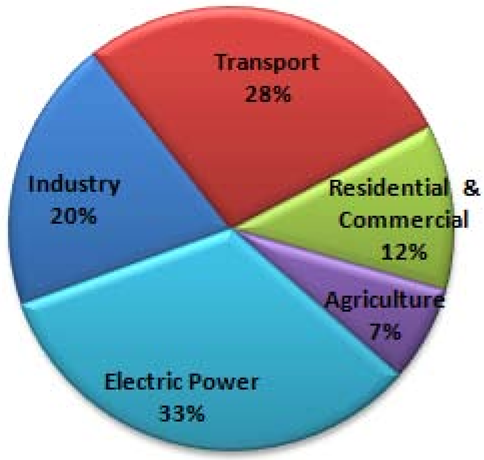

Figure 1: US Greenhouse Gas (GHG) Emissions by Sector
Source: Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990-2009 (EPA 2011)

On the other hand, GHG emissions for electricity are not being regulated at the national level. State governments are indirectly regulating these emissions through Renewable Portfolio Standards (RPS). As of 2009, a total of 33 states in the U.S. have a RPS in place [10]. There exists some diversity among different states with respect to the minimum requirements of renewable energy, implementation timing, and eligible technologies and resources. California has the most aggressive RPS targets, by requiring up to 33% of the total state electricity to be generated from alternative less carbon intensive sources by 2020 [10]. Biomass electricity along with solar and wind power can help to achieve these targets. Currently, electricity derived from biomass-based materials, mostly from wood waste and residue, contributes only about 1.5% of the U.S. electricity consumption (EIA, 2010) and has not reached large scale commercial production. Nationally, economic issues and market development for biomass supply are rated as the most significant barriers to biomass use for the electricity sector [11]. However, in the future, the market development of biomass supply for biofuels and economic incentives for clean electricity from carbon tax programs (such as in California) can promote the use of biomass for electricity generation. Pike Research predicts that its potential market value could reach $53 billion by 2020 [12] and could play a key role in America's renewable energy profile.

Some of the existing studies suggest that using biomass to produce electric power is better than using it to produce biofuels in terms of land use efficiency and lifecycle GHG emissions. Campbell et al. (2009) compared biofuel and biomass electricity for the transportation sector and found that biomass electricity can power approximately 81% more transportation mileage than cellulosic ethanol [13]. However, the scope of their study was limited, since they had restricted the use of biomass electricity exclusively for the transportation sector. Biomass electricity is generally used as a base load power [14] and hence logically will displace the fossil base load in the electricity sector.

The future development of biomass electricity will help in reducing the emissions from the electric power sector, which contributes, to about 33% of the total 6.5 billion metric tons of GHG emissions in the U.S. (Figure 1).

1.1.Motivation

This research has been undertaken to understand the comparative environmental profiles in terms of energy use and GHG emissions of the bioenergy systems - biofuel (cellulosic ethanol) and biomass electricity - derived from switchgrass. Switchgrass cultivation as a dedicated energy crop is an emerging practice. It has a high yield with relatively low nutrient requirements and is a promising feedstock to meet the future biofuels production and biomass electricity generation demands [2]. Moreover, the framework built in this research, for comparison of bioenergy systems is also applicable to other cellulosic sources, such as willow plant, corn stover.

Biofuel and biomass electricity production systems both require biomass, but the land area available for cultivation is limited. Therefore, given that the total supply is limited, it becomes important to decide on the amount of biomass that is allocated to each of these two pathways. To understand this optimal allocation, it is necessary to evaluate what the *relative* environmental impacts/benefits of these two bioenergy systems are. At a regional level there are additional factors, such as the existing energy mix and the logistics of supply, that play an important role in this appropriate allocation. This study compares the environment profile of these bioenergy systems to guide future bioenergy deployment policies at national and regional levels.

1.2.Contributions

The contribution of this research is twofold. First, the lifecycle energy and GHG emissions of individual bioenergy pathways - producing cellulosic ethanol and biomass electricity - are analyzed in detail. Any bioenergy system consists of a series of stages: biomass feedstock production, feedstock transportation and logistics, feedstock conversion to useful energy form, distribution and use of energy. In contrast with previous studies, this analysis does not use a single value of input parameters for different stages, but instead, assess impacts based on a probability distribution for them. This has helped in analyzing the importance of uncertain parameters and its impacts on overall life cycle analysis (LCA) results.

Second, we have provided a framework to compare cellulosic ethanol and biomass electricity given their lifecycle energy and GHG emissions. We propose that the criterion for comparison should not be dictated by absolute emissions associated with a specific energy conversion pathway since the unit energy from ethanol has altogether a different utility than unit energy from electricity. Ethanol will help in meeting alternative fuel demand in the transportation sector whereas biomass electricity is an alternative generation technology in the electric power sector. Instead, we consider the savings in GHG emissions from the displacement of fossil fuel by biomass along that specific pathway. Based on this criterion, we quantify the lifecycle GHG emissions impacts of each pathway as compared to the reference fossil energy system. A reference energy system is chosen that is both realistic and likely to be displaced by the bioenergy system. Cellulosic ethanol in the U.S. is most likely to replace gasoline use in internal combustion engine vehicles. Hence the reference system chosen for comparison of ethanol is gasoline. For biomass electricity choosing a reference system is somewhat challenging. Biomass electricity is most likely to replace electricity from base and intermediate load power plants [45]. However, these power plants GHG emissions are different in different regions. For the national level analysis, biomass electricity is compared with the U.S. grid average emissions. The regional variability in the grid electricity emissions and its effects on the comparison results are discussed in Section 4.6.

1.3. Thesis structure

This thesis explores the issue of comparison of lifecycle energy and GHG emissions for bioenergy systems derived from cellulosic biomass. Section 2 describes the existing literature in this area as well as literature in the field of uncertainty analysis in LCA of bioenergy systems. In Section 3, the methodology for life cycle analysis (LCA) of individual pathways and the aforementioned comparison framework is discussed. The use of a Monte Carlo approach for uncertainty analysis in LCA of bioenergy systems is also described. Section 4 presents the LCA results of individual pathways as well as a comparative performance of bioenergy systems. Finally conclusions, key findings, limitations of the current research and scope of future work, are discussed in Section 5.

2. Literature Review

The potential environmental impacts of bioenergy systems are typically quantified using a life cycle analysis (LCA) approach. LCA is an analytical tool that captures the environmental impacts of a product or service through various stages of its life cycle including raw material acquisition, manufacturing, transport, use, reuse (where applicable), recycling and final disposal [15]. A number of studies have been published which investigate the lifecycle impacts of biofuels derived from cellulosic feedstock such as switchgrass [16-20]. The potential use of the cellulosic feedstock to produce ethanol has been actively researched in the last decade, and has seen considerable advances in cellulosic biofuels production technologies. Thus, there is a focus among LCA researchers to understand the lifecycle impacts of rapidly evolving cellulosic biofuels processing technology [21-23]. The biomass agricultural phase and the logistics of biomass transportation are also important components of bioenergy lifecycle analysis, and there have been continuous efforts to model this supply chain [24, 25].

Compared to the number of LCA studies for cellulosic ethanol, there are relatively few studies involving biomass electricity. The life cycle assessment entitled *Biomass Gasification Combined-Cycle System*, a technical report published by NREL in 1997, is the first and most extensive study of biomass electricity derived from energy crops [26]. Thereafter, researchers have published a few other biomass electricity LCA studies [27-28]. This trend can be attributed to several factors. First, the technology for converting biomass to electricity is already established and not evolving at as fast a pace as the production technology for cellulosic biofuels. Therefore, there is little interest in further investigation of biomass electricity LCA. However, this alone does not offer the complete picture. There have been no recent studies exploring issues such as impacts of direct and in-direct land use change on LCA results of biomass electricity. These issues are being actively researched and debated in the case of biofuels production [9]. The lack of interest for research in the biomass electricity sector can also be attributed to other economic and policy factors. There is no direct policy stimulus to promote biomass electricity generation. Nationally, economic issues and market development for biomass supply have been identified as the most significant barriers to biomass use for the electricity sector [11]. However, with economic incentives such as carbon taxes and the development of a biomass supply chain with biofuel industry development, biomass electricity can be a viable low carbon option for the future.

Given the limited land area for biomass cultivation and the various policy incentives promoting bioenergy use, it is important to compare the relative environmental impacts of different bioenergy pathways such as producing biofuel and biomass electricity. The next subsection discusses some of the existing literature on comparison of bioenergy systems. The succeeding subsection discusses the uncertainty and variability analysis in the LCA of bioenergy systems.

2.1. Comparing LCA of different bioenergy systems

There are a few published studies comparing the environmental impacts of different bioenergy pathways such as producing biofuels and biomass electricity. Campbell et al.'s (2009) publication is an early study in this field. It compares the energy and GHG offset from bioelectricity and ethanol for the transportation sector. In 2011, Rowe et al. published a systematic review and comparison of current LCA studies for bioenergy systems. In the same year 2011, International Energy Agency (IEA) also published their guidelines for the comparison of bioenergy systems. In the following section, we have discussed these studies in detail.

Campbell et al. (2009) studied the use of biofuel (ethanol) and biomass electricity for the transportation sector [13]. Their study suggests that using biomass to produce electricity and using it in electric vehicles is a better option than using biomass to produce biofuels in terms of efficiency and life cycle GHG offset. According to their analysis, biomass electricity used in electric vehicle can power approximately 81% more transportation mileage than cellulosic ethanol. The lifecycle GHG emissions offsets of biomass electricity are approximately 108% more than those of cellulosic ethanol, on a per unit area of cropland basis. However, there are limitations of using these results to support national and regional policies for deploying bioenergy in the U.S. In their analysis, the authors have restricted the use of biomass electricity for electric vehicles only. However, that might not be the case in real world since biomass electricity generally displaces the grid electricity in a region. Thus, using 100% of biomass electricity to charge electrical vehicles is an arbitrary restriction. In addition, electric vehicles technology is still evolving. While the federal government has an ambitious vision of putting one million electric vehicles on the road by 2015, electrifying the transportation sector can be challenging. Therefore comparing these two bioenergy pathways as per the Campbell et al. methodology does not provide the relevant information to policy makers at the regional and national level. We have addressed this gap in our analysis by choosing a more realistic reference framework for the comparison of different bioenergy pathways.

Rowe et al.'s (2011) study provides a systematic review of the current life cycle assessments studies for heat and power and liquid biofuels from a variety of cellulosic and non-cellulosic feedstocks [29]. They have reviewed a wide range of studies from European and North American regions. The energy use and GHG emissions has been compared for a MJ of bioenergy from different biomass pathways (heat -power and liquid biofuels). Across all literature, on average, a MJ of energy from cellulosic biofuels has higher GHG emissions and fossil energy requirements than a MJ of bioenergy from the heat and power pathway. They have also compared bioenergy systems with their respective fossil fuel equivalents. GHG emissions for the biofuel production chains are found to be at least 64% lower than fossil fuel equivalents (petrol/diesel). In the case of heat and power generation, GHG emissions for heat and power from biomass are found to be at least 91% lower than from coal power generation.

Rowe et al.'s publication is a good systematic review study, compiling all the recent bioenergy LCA literature. However, this study provides only partial information with respect to the policy support information for bioenergy deployment in the United States since the land use efficiency of different bioenergy pathways is not discussed. They have expressed the results of comparison of bioenergy pathways only in terms of percentage reduction from fossil fuel system. Since the land area available to grow biomass is limited, it is important to perform the comparison in terms of land use efficiency. In our analysis, we have proposed a two-step comparison framework to address this limitation. In addition, Rowe et al. have results of comparison of bioenergy systems averaged over a very large geographical region (European- North American). Thus, the variation in comparison results due to regional factors are not reflected. In our analysis, we have focused on the energy derived from switchgrass and have performed a comparison of these bioenergy systems at national as well as at a regional scale, taking into account the regional variables such as energy mix, switchgrass yield. Hence, the results of our analysis are more relevant to the decision makers of bioenergy deployment policies in the United States.

The IEA technical report (2011) provides guidelines for comparing different bioenergy systems using a life cycle approach [47]. It is suggested that in order to determine the comparative environmental impact of bioenergy systems, the bioenergy should be compared with a *reference case- fossil energy system*. A reference energy system should be chosen which is realistically likely to be displaced by the bioenergy system. The system boundary should be defined such that the bioenergy and reference fossil systems provide equivalent products and services. In our analysis, we have followed these guidelines while performing the comparison of different bioenergy systems

2.2.Uncertainties in LCA of bio-energy systems

There are some inherent uncertainties and variability in the LCA results of bioenergy systems. Over the last few years, the environment sustainability and the variability analysis of bioenergy systems has received wide spread attention. Thus, in our analysis we have performed a detailed analysis of individual bioenergy pathways, incorporating sources of variation, highlighting areas of uncertainty. Whitaker et al. (2011) published a systematic review of sources of variation in bioenergy systems LCA and have identifies three broad categories of variation [32]:

1. The first category can be called ‘real’ variation. This category illustrates the relative importance of cultivation, transport and conversion processes in biofuel production; where each component can have a significant impact on the complete lifecycle of GHG emissions and energy requirements.
2. The second category of variation can be called ‘methodological’. It reflects how the mechanics of calculating lifecycle GHG emissions and energy requirements can change the interpretation, introducing variability in LCA estimates and comparisons; this category includes the setting of LCA system boundaries, the methods of coproduct allocation and the format used to present data.
3. The third category can be described as variation caused by ‘uncertainty’. This category of variation comprises variables which are often omitted from LCAs because they are poorly understood or difficult to quantify

In this analysis we have focused on the first – ‘real variability’ and the third - ‘uncertainty’ category. Within the category of ‘real’ variation, agronomy is both the major source and contributor to variation. Variations in crop yields and fertilizer application rates are important ‘real’ determinants of both the GHG and energy balance. In addition, the fuel source and technology used for the fuel conversion also causes a significant source of variation in the GHG and energy balance. Though we recognize that the second category of variation, caused by ‘methdological’ factors, has significant contribution to the overall lifecycle impacts and uncertainty of bioenergy systems, quantifying this category of variation is very challenging. The divergence is generally attributable to different assumptions and methodological choices made by LCA analysts. Hence, the nature of uncertainty involves subjective choices to define the problem analyzed or how the model results are interpreted [48]. LCA researchers are working to address the areas of unresolved LCA methodology such as disagreements over how to estimate market mediated effects such as indirect land use change and how to handle co-products [31].

We have reviewed three studies in detail for uncertainty analysis in bioenergy LCA results. They were chosen for their availability, publication date, and whether they have information regarding the uncertainty analysis results for bioenergy derived from switchgrass. All of the studies discussed here have performed uncertainty analysis with respect to biofuels only. In our analysis, we have further extended uncertainty analysis to the biomass electricity sector and later use it to compare different bioenergy pathways.

In 2001, Argonne National Laboratory (ANL) collaborated with General Motors (GM) to apply the Greenhouse Gases, Regulated Emissions and energy Use in Transportation model (GREET) to a range of fuels produced and consumed in the U.S. [33]. During this project, the ability was added to run the GREET LCA model under the Crystal Ball software, to perform a Monte Carlo analysis, and distributions were defined for 700 model parameters. For GHG emissions, ANL established probability distributions. They developed subjective distribution functions based on the range of values for the parameter from published results (GREET report Vol3 pg.37). All input parameter were assumed to follow the normal distribution curve except in a few cases. The development of parameter probability distribution functions using subjective estimations might seem a rudimentary approach, however, this is the best approximate approach, given the lack of significant amount of GHG datasets to computationally generate probability distribution functions. While ANL study provides an extensive analysis of variety of fossil and non-fossil energy sources, it provides limited information with respect to bioenergy derived from energy crops such as switchgrass. Probability distributions of a few bioenergy input parameters are defined. Also, in the last decade the technology of processing of cellulosic ethanol and logistics of switchgrass supply have improved considerably. Thus in our study, using the contemporary literature we undertook the task of revising and adding more input probability distributions for life cycle analysis of switchgrass bioenergy systems.

Groode's (2008) dissertation work, available at DOE bioenergy KDF library [30] assessed GHG impacts of ethanol produced from three feedstocks; corn grain, corn stover, and switchgrass. Life-cycle assessment with an integrated Monte Carlo uncertainty analysis is applied to each of these three bioethanol pathways. Their report, however, lacks detailed information regarding the derivation of probability distribution functions for input parameters. In addition, the assumptions regarding the lifecycle stages such as ethanol process technology and logistics are the same as the 2001 GREET uncertainty study [33]. Hence the LCA results for switchgrass ethanol are similar to the 2001 GREET uncertainty study, which is quite old.

Plevin (2010) has extensively studied the uncertainty and variability issue of biofuel from a policy perspective [31]. He has examined uncertainties in estimates of the GHGs directly emitted across the biofuel supply chain as well as the uncertainty in estimates of emissions from indirect land use changes induced by the expanded production of biofuels. In the case of direct emissions, the N_2O emission rate of fertilizer and the N fertilizer application rate are identified to be the top contributors to biofuels uncertainty (part V pg 78). They contribute to about 62% of biofuels system uncertainty. In our analysis, we have focused on uncertainties from the direct emissions from biofuels and have given special consideration to model the above-mentioned variables.

3. Methodology

This section describes the methodology for analyzing the fossil energy consumption and GHG emissions of switchgrass bioenergy systems, i.e. cellulosic ethanol and biomass electricity, as well as an approach to compare these two pathways. A few common terms used in the analysis are as follows:

<u>System Boundary:</u> It is the theoretical boundary to a life cycle analysis beyond which impacts are not recorded. In this study, we define the system boundary as shown in Figure 2. The boundary includes agricultural input production and transport, farm equipment energy use, feedstock production, feedstock collection and transport, biorefinery chemical use, feedstock conversion, ethanol distribution and end use. Fossil energy use and GHG emissions are accounted for within the system boundary. We have accounted only for the direct GHG emissions, while GHG fluxes associated with indirect land use change (ILUC) impacts are not considered. While recognizing that ILUC has contributions to the overall lifecycle and its uncertainty for bioenergy systems, quantifying this impact is quite challenging. LCA researchers are working to quantify the ILUC impact using various economic allocation and market models [31]. In our analysis, we restrict the system boundary to capture only direct effects. The GHG fluxes from ILUC are in addition to the direct GHG emissions and ILUC results do not affect the relative/comparative environmental profile for bioenergy systems, which is an essential part of our analysis.

<u>Functional Unit:</u> The lifecycle GHG emissions from the ethanol pathway are expressed in units of grams CO_2-equivalents per megajoule of energy (g CO_2-eq/MJ). The lower heating value (LHV) of ethanol is used to convert it from volumetric to energy units (MJ of energy). Using MJ instead of volumetric units makes it easy to compare ethanol with gasoline system. In the case of biomass electricity, the LCA results are expressed on a per kWh basis. It is a convenient unit to compare biomass electricity with other reference electricity systems such as the U.S. grid electricity or coal power plants. Appropriate conversion factors used in this analysis are given in Appendix 1.

<u>Reference case:</u> It refers to a fossil fuel alternative to which a biomass production chain is compared. For example, the reference case for ethanol is gasoline. In the case of biomass electricity, choosing a reference case is more complex. Biomass electricity is most likely to replace average grid electricity in a region. However, the environmental profile of grid electricity varies from region to region. For the national level analysis, comparison is made between biomass electricity and the U.S. grid average emissions. In the later sections, we discuss the regional variability in the average grid electricity emissions and its effect on the comparison results.

Monte-Carlo method for LCA: Instead of using a single average value for different input parameters of life cycle analysis, we define a domain of possible inputs using probability distributions. Then we use a Monte Carlo simulation approach to perform the lifecycle analysis. This approach generates inputs randomly from a probability distribution over the domain, performs deterministic computation on the inputs and aggregates the results. MATLAB is used to perform these simulations. A sample MATLAB program for the LCA of the agricultural subsystem is given in Appendix 2. The total life cycle GHG emissions are the sum of the emissions at each stage.

The Net Energy Ratio (NER) is estimated using following equation:

$$NER\left(\frac{MJ_{fuel}}{MJ_{input}}\right) = \frac{Output\ Energy\ (MJ_{fuel})}{Input\ Energy\ (MJ_{input})}$$

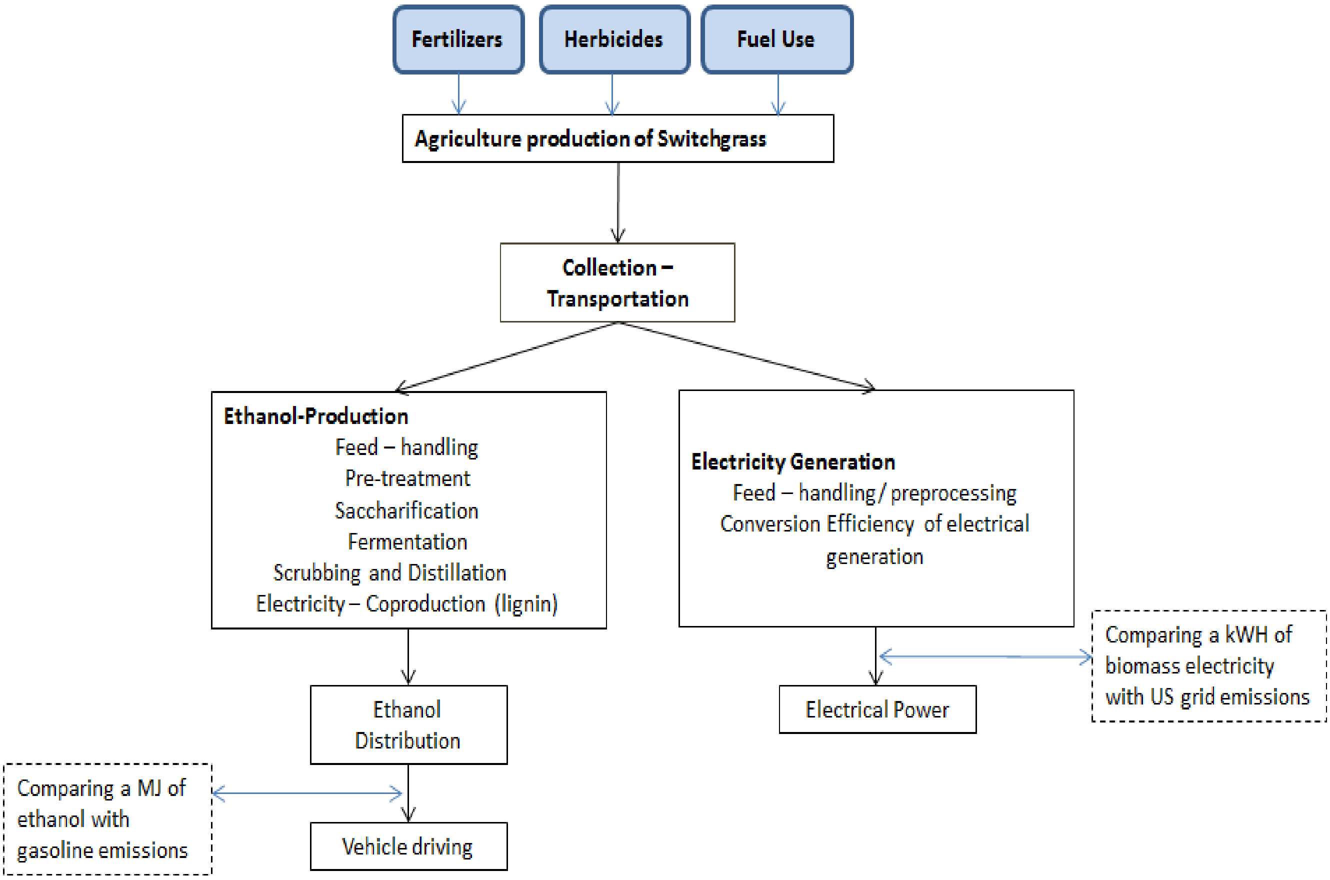

Figure 2: System boundary of bioenergy systems life cycle analysis

3.1.Life Cycle Analysis (LCA) of individual pathways

The main stages for LCA of individual pathways are as follows:

Cellulosic Ethanol

a. Switchgrass Agriculture

b. Biomass collection and transportation

c. Bio-refinery process

d. Ethanol distribution

e. Ethanol End Use in flex-fuel vehicles

Biomass Electricity

a. Switchgrass Agriculture

b. Biomass collection and transportation

c. Biomass electricity generation

The following section discusses our approach to derive the mean value and the probability distribution of various input parameters.

3.1.1. Switchgrass Agriculture

Switchgrass, is a native to North America and survives in a wide variety of climatic conditions. It is found in regions ranging from Mexico to Quebec [2]. It has been studied under the DOE Bioenergy Feedstock Development Program (BFDP) since 1991 and is proposed as an ideal herbaceous crop for energy because it has high yield, coupled with relatively low nutrient requirements. Although switchgrass currently only grown in buffer strips and not cultivated as a commodity crop, in the long-run, switchgrass may be grown as a dedicated energy crop as envisioned by DOE Billion Ton Supply study [3] and in existing bioenergy plans such as Energy Independence and Security Act 2007 and State Renewable Portfolio Standards [10]. Switchgrass has a ten year plantation cycle, meaning it is planted once at the beginning of year one but harvested annually over a ten-year period [36]. Eliminating an annual planting cycle has the advantage of reducing the annual energy use to cultivate this feedstock as well as reduces soil loss and soil degradation. We gathered the switchgrass agricultural process data from a variety of published papers and reports [2, 30, 36, 37]. The agricultural system boundary for switchgrass production includes:

a. Yearly switchgrass yield

b. Nitrogen fertilizer application rates

c. Herbicides application rates

d. Farm machinery fossil fuel consumption

Switchgrass Yield:

The switchgrass yield is an important parameter in the agricultural subsystem LCA. However, reported empirical data of the switchgrass yield is quite variable as switchgrass cultivation is still an emerging practice. Switchgrass yield is also dependent on other variable factors such as soil quality, climatic conditions and switchgrass ecotype. In our analysis, we have derived switchgrass yield data from the most recent ORNL's publication for the switchgrass yield and potential in the U.S.[37]. This study has collected and analyzed a large number of field observations for the switchgrass yield (1400 observations across 200 sites in the U.S. - Appendix 3). Switchgrass yield estimates vary considerably, from less than 1 ton/ha to 40 ton/ha (yield data are expressed on a dry mass basis). The most frequently observed yield class across all cultivars, soils, and management practices is between 10 and 12 ton/ha. In our analysis, we represent the yield of switchgrass by a normal distribution graph with a mean value of 12 ton/ha. The standard deviation (σ) of yield is found to be 5 ton/ha such that ± 2σ covers approximately 95% of the yield values. The input yield graph used for our analysis is as shown in Figure 3.

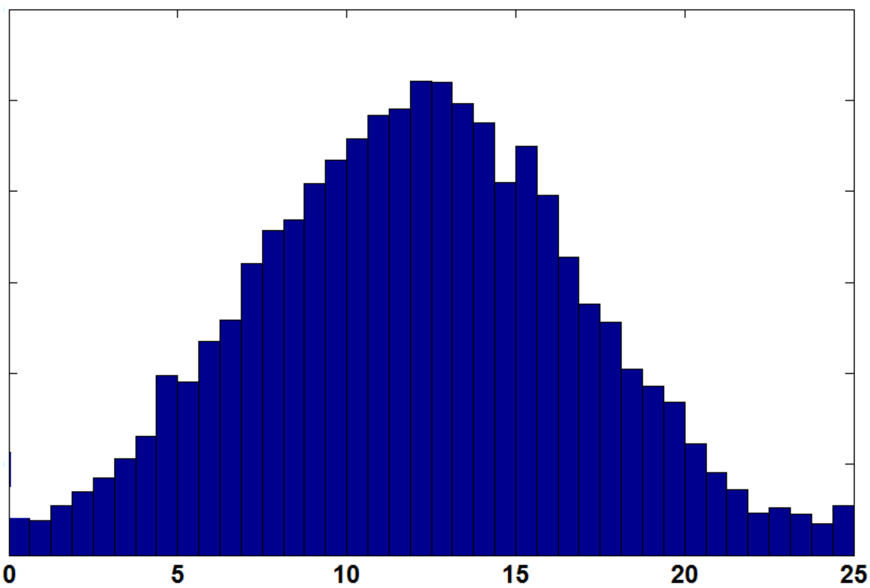

Figure 3: Switchgrass Yield distribution (mean – 12 ton/ha; σ – 5 ton/ha)

Nitrogen Fertilizer Application Rate:

Application rate of nitrogen (N) fertilizer is one of the major contributors to the overall uncertainty in the LCA results of the switchgrass agricultural subsystem. There is a very high variability in N application rate for switchgrass agriculture. In addition, there is not a strong correlation between the switchgrass yield and the use of nitrogen fertilizer [37] (Appendix 3). The ORNL's empirical study suggests that optimum N fertilizer application rate is 90 kg/ha/year. Nevertheless, there are several cases where zero fertilizer planting did as well as fertilized stands. Very high levels of fertilizers use also do not result in increased switchgrass production. Thus, in absence of clear consensus around the N fertilizer use topic, we have assumed the switchgrass yield is an independent parameter from the N fertilizer application rate. In our study we found the mean N application rate to be 90 kg/ha/year. The standard deviation (σ) for the N application rate is found to be 40 kg/ha/year such that ± 2σ covers approximately 95% of the N application values.

N_2O Emissions: N fertilizer is also responsible for direct N_2O emissions [35]. According to Pelvin's study [31], N_2O emissions are the major contributor to the overall uncertainty of biofuels' LCA. The global warming potential (GWP) of N_2O is approximately 300 times that of CO_2. In our analysis, we have referred IPCC 4th Assessment Report [50] and have applied the GWP value of N_2O as 296 times that of CO_2 (Appendix2). Given the uncertainty regarding the percentage of N fertilizer converted to N_2O, we have modeled this parameter with as a triangular distribution. The lower and upper limits of triangular distribution are 0.8% to 1.8% N to N_2O conversion respectively (same as modeled in GREET uncertainty study [33]).

Herbicide application rate:

The herbicide application rate is only applicable to the first two years of switchgrass cultivation. We have averaged this value for the 10 year switchgrass production cycle. The average herbicide application rate for this study is found to be 1.6 kg/ha/year. The standard deviation (σ) for herbicide application rate is found to be 0.6 kg/ha/year [30].

Farm machinery fossil fuel consumption:

Farm machinery is used for soil preparation, planting seeds, irrigation and other farm jobs. The fuel consumption for on farm activities is higher in the first two years of switchgrass cultivation as compare to the rest of the switchgrass cultivation years. Once the switchgrass crop reaches maturity, two years after the plantation, the energy required for farm operation reduces. The mean fuel use rate in farm machinery is found to be 16.4 (liters) l/ha/year. The standard deviation (σ) for the fuel use rate in farm machinery is found to be 3.3 l/ha/year [30].

Table 1 summaries the mean and standard deviation value of the major LCA input parameters in the switchgrass agricultural phase.

Table 1: Mean and standard deviation of the major LCA input parameters in the switchgrass agricultural phase. These are average values per year for a 10 year plantation cycle.

	Mean	**Standard Deviation**
Switchgrass Yield	12 ton/ha	5 ton/ha
N Application Rate	90 kg/ha	40kg/ha
Herbicide Rate	1.6 kg/ha	0.6 kg/ha
Farm Machinery Fuel Use Rate	16.4 l/ha	3.3 l/ha

Assumptions in LCA of Agriculture Subsystem:

a. *Carbon neutrality* of bioenergy systems is assumed. This is when combustion of the biomass releases the same amount of CO_2 as captured by the plant during its growth [34]. Thus in our analysis we have not accounted for the CO_2 sequestered during the switchgrass cultivation phase as well as CO_2 emissions during biomass/biofuels combustion phase. We have only accounted for the external fossil fuel energy inputs and associated GHG emissions during various lifecycle stages. However, the land use change may lead to a change in carbon stored above and below ground called soil organic carbon. This may disturb the carbon neutrality of the bioenergy system. In our analysis, we have assumed that equal portions of Conservation Reserve Program (CRP) land and land growing conventional crops are converted to the switchgrass cultivation. Converting conventional crop land to switchgrass cultivation is associated with net positive sequestration of carbon in the soil [35]. However, converting fallow CRP land to switchgrass cultivation is associated with release of soil organic carbon [35]. Thus, the resulting net carbon flux to the atmosphere from the land use change is balanced.

b. Energy use in manufacturing of the farm machineries is not taken into account. Their contribution to overall energy use is less than 5% of the total energy use in agricultural stage [51]. Moreover, switchgrass can be cultivated, managed and harvested using conventional farming equipment. Therefore, it does not require purchasing of new equipment for farming of switchgrass only.

c. Appropriate energy use and GHG emissions factors for inputs such as production and transportation of fertilizer, herbicides, fossil fuel energy use are taken from the GREET 1.8 model. Appendix 1 summaries all the GREET factors used in this study.

d. Energy use and GHG emissions associated with some of the input parameters such as seeds, and chemicals, used only in the first year of the switchgrass plantation, are not taken into account. Their contribution to overall energy use and GHG impact is less than 5% of overall contributions [30].

3.1.2. Biomass collection and transportation

Switchgrass collection and transportation- encompassing harvest, storage, and delivery – is an integral part of the overall life cycle analysis of bioenergy systems. However, accounting for this stage is quite challenging, as switchgrass cultivation is an emerging practice and it is not grown anywhere for this purpose. Thus, a modeling approach is used to predict LCA impacts of this stage. Majority of existing LCA studies account for the energy and GHG emissions of this stage using a simplified model. The fuel consumption for the roundtrip of a truck used for the transportation of biomass, from the agricultural farm to the processing plant, is accounted. The modeled distance for the cost effective transportation of biomass ranges between 50 to 100 miles [30]. However, the actual energy use and GHG emissions associated with the switchgrass handling and transport can be quite large. Being a low-density material more energy is needed to transport switchgrass than other feedstocks such as corn grains for the same mass. Also, the energy associated with loading, unloading, grinding is significant [24].

Integrated Biomass Supply Analysis and Logistics (IBSAL) model developed at Oak Ridge National Laboratory (ORNL) provides an extensive analysis of the switchgrass logistics [24]. Using advanced computational tools, they have estimated the cost, energy use, and GHG emissions for different collection and transportation options for switchgrass. The details of this model relevant to our study are discussed in Appendix 4. In our analysis, we have used the results of the ISBAL model for switchgrass to assess energy and GHG emissions in the collection and transportation stage. The switchgrass logistics energy use and GHG emissions are dependent on the volume of biomass required per day or the size of biorefinery - electricity plant. The size of biorefinery – electricity plant is in fact dependent on other factors such as demand for the biofuel/ biomass electricity, availability of the biomass in the region and upfront capital investment available. In absence of clear information regarding the future viable economic size of biomass plants and daily requirement of biomass, we have used an average value of 2500 dry ton/day for our analysis.

According to the ISBAL model, the fossil energy use and the GHG emissions in the collection and transportation for a ton of switchgrass is 1100 MJ/ton and 85 kg CO_2-eq/ton respectively. These reported energy and GHG emissions are much higher as compared to a simple accounting model for a 100 mile round trip with a 40 short ton truck capacity (94 MJ/ton and 8.3 kg CO_2-eq/ton respectively [30]). The energy and GHG emissions in the processes such as baling, loading, unloading and grinding are significant and should be carefully accounted in the logistics phase of switchgrass.

3.1.3. Bio-refinery process

Lignocellulosic feedstocks such as switchgrass are mainly composed of cellulose, hemicellulose, lignin and other inorganic minerals. Production of cellulosic ethanol via biological conversion consists of three critical steps: pretreatment of biomass, hydrolysis of sugar polymers (cellulose, hemicellulose etc.) to sugar monomers and fermentation of sugar monomers to ethanol [22]. A generic cellulosic ethanol production process is shown in Figure 4.

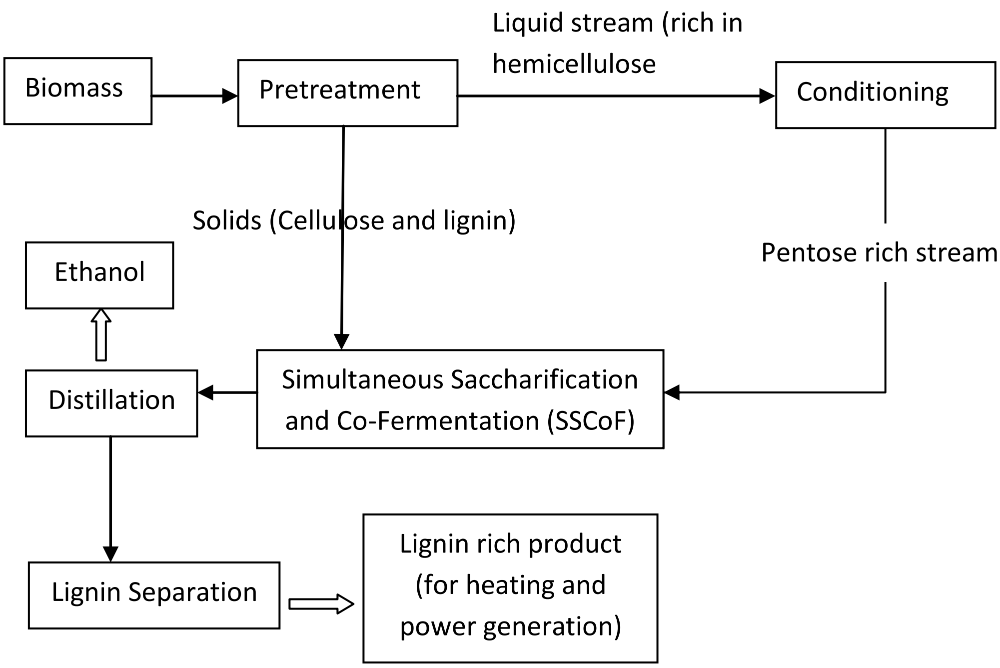

Figure 4: Biological Cellulosic ethanol production process (source: D.Kumar et. al. 2012 [22])

The ethanol yield and energy and chemical used in the bio-refinery phase are the important parameters contributing to the LCA of cellulosic ethanol. The following section discusses the methodology to estimate these parameters for the cellulosic ethanol LCA study.

<u>Ethanol yield</u>

The cellulosic ethanol yield is expressed in units - liters of ethanol produced / dry ton of biomass (l/ton). It is determined by the following factors [30]:

a) Mass fraction of cellulose and hemicelluloses in biomass feedstock

b) Efficiency of the pretreatment process

c) Efficiency of the enzymatic breakdown of cellulose and hemicelluloses

d) Efficiency of the fermentation process

Mass Fraction of cellulose / hemicellulose- Switchgrass

The physical properties of switchgrass such as cellulose, hemicellulose, and lignin mass fractions are estimated by feedstock properties databases from the U.S. DOE [38]. Table 2 shows these parameters mean and variation values.

Table2: Mass fraction of Cellulose/Hemicellulose in Switchgrass

Switchgrass Mass Fraction	Mean	Std deviation
Cellulose	33.6 %	1.3 %
Hemicellulose	26.2 %	0.1 %
Lignin	18.7 %	1.6 %

Efficiency of pre-treatment, enzymatic breakdown and fermentation process

The ethanol conversion process is being researched widely and scientists are working to improve conversion efficiencies. The 2011 techno-economic report by NREL [39], provides the most recent and comprehensive information regarding the conversion efficiencies for lignocellulosic biomass. The analysis by NREL is for a bioethanol plant using dilute acid pretreatment process with simultaneous saccharification and cofermentation hydrolysis and fermentation (DA-SSCF) process. The efficiencies of different conversion steps is shown in table 3. These conversion efficiencies have significantly improved over last ten years. The 2002 report by NREL estimated the Xylan to Xylose and Cellulose to Glucose process efficiencies as 67.5% and 63.5 % respectively [40].

Table 3: Cellulosic Ethanol Conversion Efficiencies

Process	2012 Yield
Xylan (hemicellulose) to Xylose	90%
Cellulose to Glucose	90%
Xylose to Ethanol	90%
Glucose to Ethanol	95%
Ethanol stoichiometric yield	50%

Source: Aden et all, NREL study 2011 [39]

Taking into account the composition of switchgrass feedstock and the process yield of switchgrass ethanol, we estimate the yield for ethanol production. Figure 5 shows the probability distribution of ethanol yield for the above discussed process efficiencies.

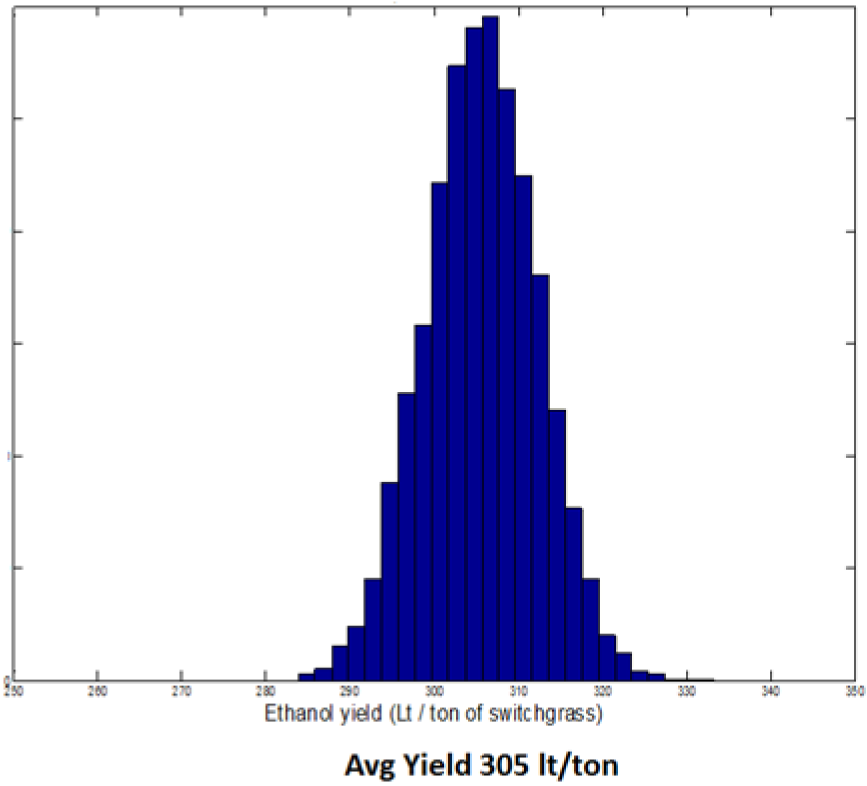

Figure 5: Probability distribution of ethanol yield (l/ton)

Energy Use in Producing Cellulosic Ethanol

Another important factor contributing to the LCA of cellulosic ethanol process is energy and chemical use in the ethanol processing stage.

Bio-refinery Utilities

Bioethanol facilities require a large amount of process steam at various temperatures and pressures (For example, low pressure steam at 152°C and 502 kPa and high pressure steam at 242°C and 3464 kPa [22]). Lignin stream is a co-product generated in cellulosic ethanol process. It is estimated that the waste lignin (co-product) can provide the entire processes steam requirement for production processes of cellulosic ethanol [22]. Moreover, steam generated from waste lignin stream is more than the steam required for the cellulosic ethanol production process. Thus, excess steam can be used to generate on-site electricity [39].

Assumptions: In our analysis of the biorefinery process, we have assumed that all process steam and electricity is obtained through the burning the lignin onsite. Hence, there are no extra energy or GHG emissions burdens from the energy use/utilities in the bio-refinery process. The excess electricity generated from waste lignin stream can be fed into the grid and can add a positive credit for biofuel process. According to the NREL techno-economic feasibility report (2011) [39], 30% of the total onsite generated electricity from lignin is in excess than what is required for ethanol production and can be fed into the grid [39]. However, the amount of excess electricity available is variable and depends on the process design. Thus, to keep the lifecycle accounting for the cellulosic ethanol on a conservative side we have not accounted for this co-product.

Bio-refinery Chemical/Enzyme Use

Ethanol production is through a biochemical processes utilizes chemicals for pretreatment, hydrolysis, and fermentation. Enzymes (proteins that catalyze biochemical reactions) assist with liquefaction, saccharification, and fermentation and are associated with other process benefits in ethanol production [23].

Most of the existing cellulosic ethanol LCA studies do not account for process chemicals and enzymes. However, with the present cellulosic process technology, these chemicals and enzymes can have a significant contribution to overall LCA results. Spatari and Maclean (2007) comprehensively analyzed this part of life cycle analysis [23]. The chemicals and enzymes contribute about 9 g CO_2-eq/MJ of ethanol energy derived from the switchgrass feedstock using DA-SSCF and AFEX-SSCF conversion technologies. Table 4 shows the contribution of chemicals and enzymes to the overall lifecycle of cellulosic ethanol for these two conversion processes.

Table 4: Contribution of individual chemical and enzyme inputs used in ethanol conversion to GHG emissions (gCO_2-eq /MJ of ethanol)

Feedstock Process	**Switchgrass - DA SSCF**	**Switcgrass - AFEX CBP**
Enzymes	3.3	3.6
Sulfuric acid	0.13	0.59
Lime	0	4.7
Ammonia	5.4	0
Nutrients	0.21	0.21
Total GHG emissions	9.3	9.8

Source: Spatari and Maclean study (2007)

3.1.4. Ethanol Transport and Distribution

The distance between the bioethanol plant and ethanol retail station location plays an important role in determining the energy and GHG emissions in this stage. Since these plants are currently not in existence, but will be built in future, a modeling approach is used to determine the optimal locations of these plants across the U.S. According to the GREET model the emissions in the distribution stage are approximately 40 g CO_2-eq/l (liter) of ethanol. Another study by Morrow et al., optimizes the bio-refinery location across the U.S. such that cost of ethanol distribution is minimum and estimates the emissions from the distribution stage to be 20 g CO_2-eq/lt [41]. In our analysis, we have taken that the average emissions from the distribution stage are 30 g CO_2-eq/l of ethanol.

3.1.5. Ethanol Use in Flex Fuel Vehicle (FFVs)

In this stage of the life cycle analysis of biofuels, combustion of the fuel in the vehicle and associated GHG emissions are accounted for. Ethanol fuel has a lower energy density compared to gasoline. Thus Flex-Fuel Vehicle (FFVs) typically suffer a loss in apparent fuel economy (miles per gallon of fuel, mpg) when running on E85 (nominally 85% ethanol, 15% gasoline). In our analysis, we use the fuel economy for ethanol a typical mid-sized FFV vehicle to be 20 mpg (using ORNL Federal Test Procedure [42]). The fuel economy for gasoline for this category of vehicle is 25 mpg [42]. These fuel economy values are used to estimate life cycle GHG emissions per kilometer (km) of vehicle drive. Assuming the carbon neutrality of the bioenergy we have not accounted for any additional GHG emissions from this stage. Thus for cellulosic ethanol, all the life cycle GHG emissions are from upstream stages only. However in the case of gasoline emissions from combustion phase are approximately 80% of total fuel cycle GHG emissions [46].

3.1.6. Biomass Electricity Conversion Process

Biomass feedstocks are used to generate electricity using conversion technologies such as direct firing, integrated gasification and co-firing with coal. The potential environmental impact of the biomass electricity generation system is dependent on the chosen technology option for conversion. The common types of biomass electricity generation systems are:

a. Direct-fired biomass power plant using biomass residue (woody residue, primarily)

b. Biomass-fired integrated gasification combined cycle (IGCC) system using a biomass energy crop (willow, switchgrass)

c. Co-firing biomass residue with coal (10-15% biomass by heat input)

Direct-fired is at present the most common method of converting biomass resources into power in the United States. A direct-fired system burns the biomass to generate hot flue gas, which is fed into a boiler to generate steam. Direct-fired biomass facilities have a conversion efficiency of 15% to 35%, depending upon the manufacturer [43]. Gasification systems- instead of directly burning the fuel to generate heat -convert biomass into a combustible gas, which is a mixture of carbon monoxide, hydrogen and other gases. The integrated gasification combined cycle (IGCC) technology can use energy crops such as willow tree and switchgrass as feedstock. However, this is not widely deployed biomass electricity generation method at present [43]. Gasification technology to generate electricity is still considered to be in the development and demonstration phase. The conversion efficiency of IGCC is higher than direct-fired. Conversion efficiencies for gasification technology have been reported as 37.2% by NREL and 36% by EPRI [27]. Recent constructed biomass gasification plants in Europe have conversion efficiencies varying from 25% to 43% [52].

In this report, we analyze both the direct-fired and the biomass-fired IGCC system to convert switchgrass to electricity. Based on the current state of technology in the U.S. [45] and assuming that the new dedicated biomass power developed will deploy the most efficient conversion technology option; we have found the mean value conversion efficiency to be 35%. The average standard deviation is found to be 5% such that ±2σ covers the majority of the conversion efficiency range for the direct fired and the IGCC technology. This conversion efficiency distribution range also helps accounting for the variance in the conversion efficiencies due to other external factors such as moisture content in biomass.

Assumptions: In this analysis we have assumed carbon neutrality of the biomass energy. It is considered a closed-loop process, in which power is generated using a feedstock (switchgrass) which is grown specifically for the purpose of energy production. The carbon sequestered in the growing of switchgrass offsets the emissions from the biomass combustion phase during the electricity generation stage. The energy and emissions associated with commissioning and decommissioning of the biomass electricity plant are not taken into account. These GHG emissions may contribution upto 10% of overall GHG emissions of the biomass electricity LCA [26]. However, this assumption is same for commissioning or decommissioning of the bio-refinery and thus there is no impact on the comparison results of the two-bioenergy use pathways.

3.2.Framework for Bioenergy Systems Comparison

One of the main aims of this study is to assess the relative land use efficiency and climate change mitigation potential of biomass use for the transport sector versus biomass use for electric power. We propose the criteria for comparison should not be dictated by absolute emissions along a certain bioenergy use pathway, as considered by some previous studies [13]. Energy from ethanol has altogether a different utility than energy from electricity. Ethanol helps with meeting the demand of alternative fuel for the transportation sector, whereas biomass electricity helps in reducing the fossil fuels (coal/natural gas) consumption in the electric power sector. We consider the savings in emissions of bioenergy systems from the displacement of fossil fuel along that pathway. Based on this criterion, it becomes important to quantify the lifecycle GHG emissions impacts of each pathway as compared to the reference case - fossil energy system. A reference case energy system is chosen that is realistically likely to be displaced by the bioenergy system.

In the case of cellulosic ethanol in the U.S., it is most likely to replace gasoline use in internal combustion engine vehicles. Hence, the reference case system chosen for comparison of cellulosic ethanol is gasoline. Lifecycle impacts of gasoline fuel from upstream processing and fuel combustion stages are well quantified with detailed LCA reports (such as GREET 1.8 model). The average total fuel cycle emissions from gasoline are 90 g CO_2-eq/MJ of fuel energy (Appendix1). In the case of biomass electricity, choosing a reference case system is more complex. Biomass electricity is most likely to replace average grid electricity in a region. However, the environmental profile of grid electricity varies from region to region. For the base case analysis, we have compared biomass electricity with the U.S. grid average emissions. In the later section, we have discussed the regional variability in the average grid electricity emissions and its effect on the comparison results.

3.2.1. Comparison - Emissions offset per hectare (ha) of land

We follow a two-step approach to compare the environmental profile of bioenergy pathways. In the first step, the life cycle GHG emissions impacts of each pathway are compared with the reference case - fossil energy system (Figure 7). The functional unit for comparison of ethanol to gasoline is MJ of energy and for electric power is kWh .

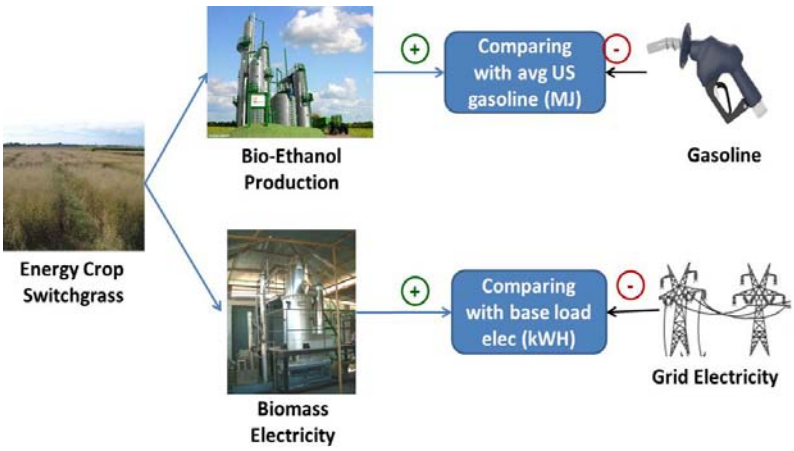

Figure 7: Step 1 – Comparing bioenergy systems with reference case fossil energy

In the second step, the environmental performance of bioenergy pathways is evaluated in terms of land use efficiency. We assume that 100% of switchgrass produced in a year from a hectare of land is either used to produce ethanol or biomass electricity, and estimate the emissions saved from a hectare of land using either of pathways. The following equations describe the calculation of land use efficiency for each bioenergy systems.

$$Let, annual\ switchgrass\ yield = x\ (ton/ha)$$

$Cellulosic\ ethanol\ yield\ = y\ (l/ton)$

$Biomass\ electricity\ conversion\ efficiency = z\ (kWh/ton)$

We have mean values and probability distributions for these parameters from section 3.1.1, 3.1.3 and 3.1.6

$Let, GHG\ offset\ of\ cellulosic\ ethanol\ compared\ to\ gasoline\ = e_1\ (CO_2eq/MJ)$

$2eq/kWh$

Values of e_1 and e_2 values can be estimated from the step 1 of this comparison

Then we can estimate GHG offset from bioenergy systems per hectare of land as follows:

$GHG\ offset\ for\ cellulosic\ ethanol = x * y *\ e_1 * LHV(ethanol)\ (CO_2eq/ha/year)$

$GHG\ offset\ for\ biomass\ electricity = x * z *\ e_2\ (CO_2eq/ha/year)$

3.2.2. Comparison - Emissions offset per kilometer (km) driven

Another method used to compare the environmental profile of bioenergy systems is formulated assuming a special case of biomass electricity use where all the biomass electricity produced is used to charge electric vehicles. Ethanol is used to power Flex Fuel Vehicles (FFVs). Figure 8 shows the schematic used for comparison. We have only accounted for the fuel cycle GHG emissions in this comparison. The fuel economy of Flex fuel Vehicles is discussed in section 3.1.6. The lifecycle impacts associated with vehicle manufacturing are not taken into account.

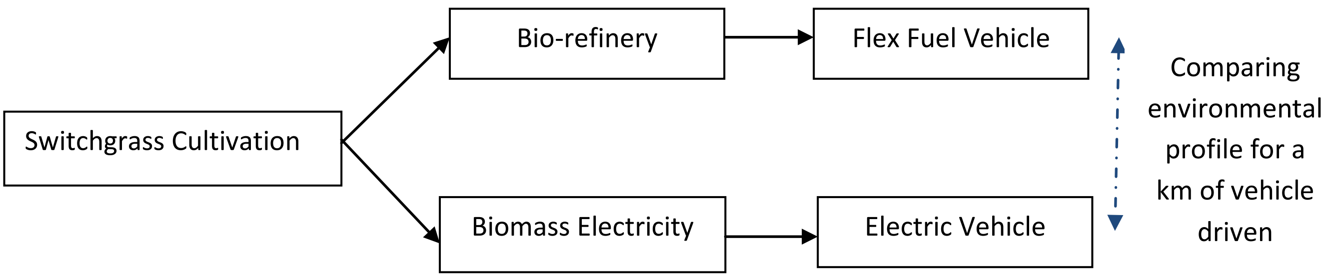

Figure 8: Schematic for bioenergy systems comparison (on basis of a km driven)

4. Results

Box and Whisker representation: Energy use and GHG emissions are represented by a white box symbol with whiskers. The red line in the white box represents the mean, with the top line as 75th percentile and the bottom line as 25th percentile of a certain output parameter (energy use/GHG emissions). The end of whiskers represents the minimum and maximum value of an output parameter excluding outliers.

4.1.Switchgrass Agriculture - Energy Use & GHG Emissions

Figure 9 and Figure 10 display the fossil energy use and GHG emissions from the agricultural inputs for switchgrass agriculture per hectare of land per year. The fossil energy use for switchgrass agriculture is further broken down as energy use in different agricultural inputs. All of the agricultural stage inputs cumulatively consume on average 5630 MJ/ha/year of fossil energy, with a minimum value of energy use is 4000 MJ/ha/year and maximum is 8000 MJ/ha/year. Nitrogen fertilizer use is responsible for the greatest fossil energy use per hectare. TheERG biofuel analysis meta model estimates the total energy consumption in switchgrass agriculture as 7411 MJ/ha/year [44]. Another biofuel LCA study estimates switchgrass farm energy input as 4800 MJ/ha/year[30]. Thus, the range of variability in this analysis captures the previous single-valued estimates.

The GHG emissions are also broken down by source for agricultural production. Appropriate emissions factors were taken from the GREET 1.8 model for each agriculture input (Appendix1). The cumulative average GHG emissions from the agriculture stage are 830 kg CO_2-eq/ha/year. The minimum system emissions are 450 kg CO_2-eq/ha/year and maximum 1200 kg CO_2-eq/ha/year. The energy use in production and transportation of nitrogen fertilizer as well as N_2O direct emissions have largest impact on the total GHG emissions from switchgrass agriculture stage. The ERG biofuel analysis meta model estimates the GHG emissions from switchgrass cultivation as 971 kg CO_2-eq/ha/year [44].

This analysis captures the first category of variation that is due to 'real' parameter variability (discussed in section 2.2.). Variation in the nitrogen fertilizer application rate is an important determinant of both the GHG and energy balance. However, this analysis doesn't capture the second category of variation that is due to 'methodological' factors. In our analysis, the system boundary for the agriculture subsystem considers a limited number of inputs. For example, the fossil energy use in farm machinery production and repair, labor energy are not considered. Thus defining system boundaries, as well accounting for co-products causes methodological variation. Since the source of 'methodological' variation is very subjective, we have not considered it in this analysis.

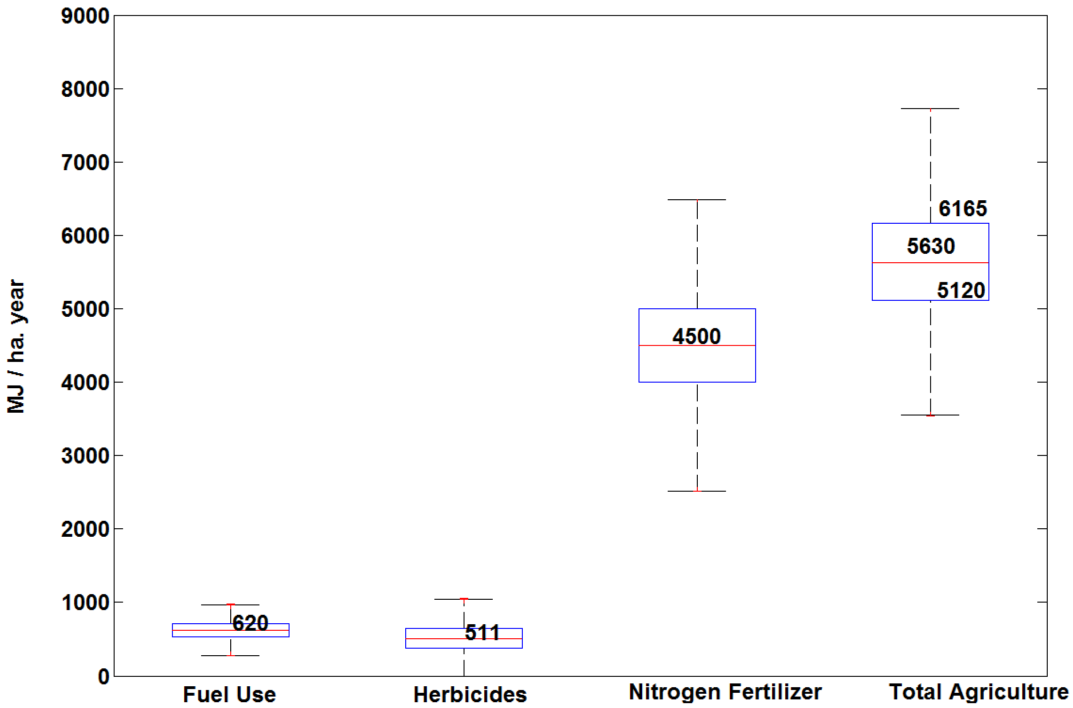

Figure 9: Switchgrass Agriculture- Fossil Energy Input (MJ/ha/year)

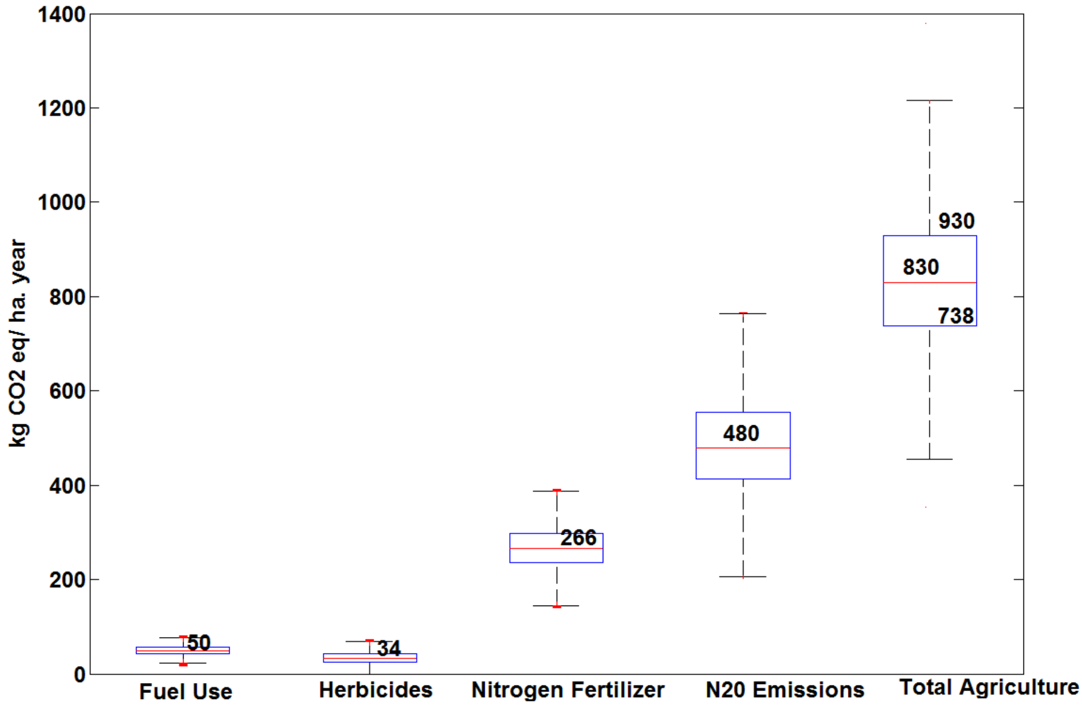

Figure 10: Switchgrass Agriculture- GHG Emissions (kg CO_2-eq/ha/year)

4.3.Ethanol –Net Energy Ratio & GHG Emissions

Figure 11 shows the life cycle GHG emissions for cellulosic ethanol production. The average value of LCA emissions are 35 g CO_2-eq/MJ of energy, with a minimum-maximum range varying from 25 to 50 g CO_2-eq/MJ. The ERG biofuel analysis meta model estimates the GHG Emissions from cellulosic ethanol as 11 g CO_2-eq/MJ [44]. Other studies estimate GHG emissions from cellulosic ethanol from energy grasses to vary from 5 to 50 g CO_2-eq/MJ [29]. Thus the range of variability in this analysis captures the previous single-valued estimates to some degree.

This analysis captures two categories of variation, first that which is caused due to 'real' parameter variability and the second due to 'uncertain' parameters (discussed in section 2.2.). Variations in switchgrass yield, fertilizer application rates and conversion efficiency are important 'real' determinants of both the GHG and energy balance. For example, the contribution from the agricultural stage of ethanol production varies over a large range of 3 to 25 g CO_2-eq/MJ. The other category of variation caused by 'uncertainty' is captured in the collection and transportation and bio-refinery chemical use stage. In existing LCA studies, the contribution from these stages is poorly quantified. We have accounted for these stages by reviewing the most contemporary literature in the field. However, there exists a scope of research to improve the understanding and quantification of these parameters by advanced modeling approaches.

The Net Energy Ratio (NER) of cellulosic ethanol has an average value of 3.84 MJ_{output} / MJ_{input} and minimum – maximum range as 3.03 to 5.00 MJ_{output} / MJ_{input} . Cellulosic ethanol has a high NER as it is assumed that the unprocessed lignin will provide the cellulosic ethanol facilities energy for steam and electricity.

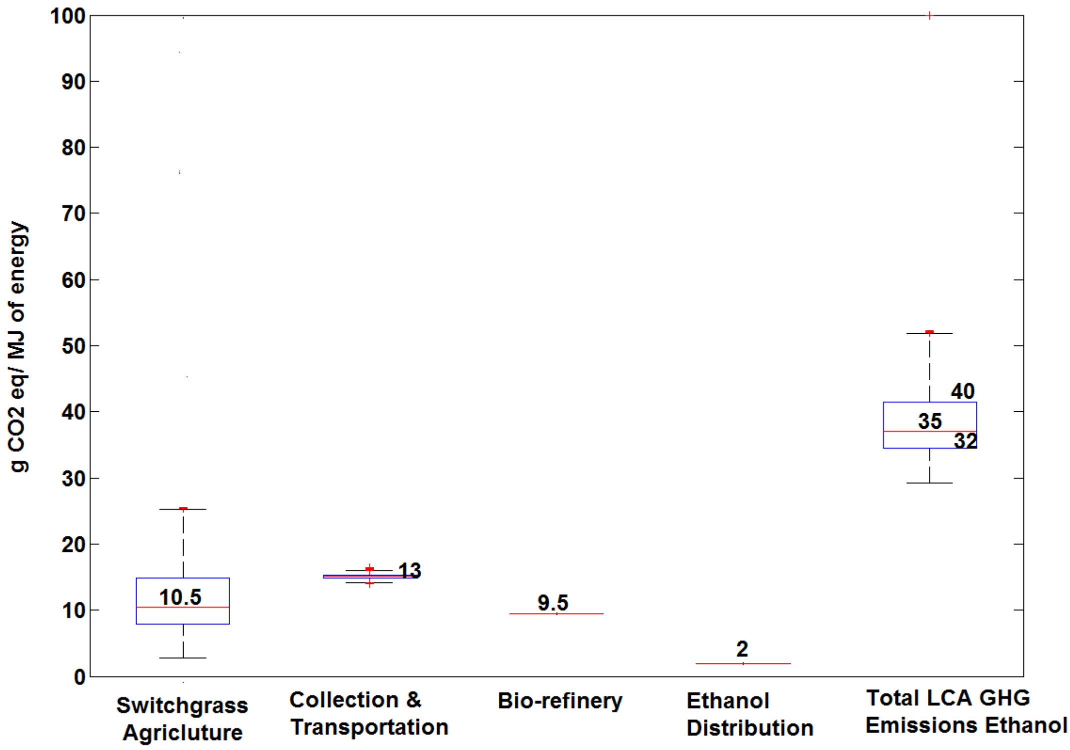

Figure 11: Lifecycle GHG emissions (g CO_2-eq/MJ) of cellulosic ethanol derived from switchgrass

4.3.Biomass Electricity: Net Energy Ratio and GHG Emissions

Figure 12 shows the life cycle GHG emissions for biomass electricity derived from switchgrass. The mean value of LCA emissions is about 100 g CO_2-eq/ kWh of energy, with a minimum-maximum range varying from 50 to 180 g CO_2-eq/ kWh. The NREL study estimates the GHG Emissions from biomass electricity as 45 g CO_2-eq/kWh [26]. Another dedicated biomass electricity LCA study estimates GHG emissions as 38 to 52 g CO_2-eq/kWh [27]. Thus, the average GHG emissions found in our analysis are higher than the previous estimated values. This discrepancy is due to the estimates from the logistics phase.

This analysis captures two categories of variation, first that which is caused due to 'real' parameter variability and the second due to 'uncertain' parameters (discussed in section 2.2.). Variations in switchgrass yield, fertilizer application rates and conversion efficiency are 'real' determinants for variation in GHG emissions. The contribution from agricultural stage of biomass electricity varies over a range from 10 to 100 g CO_2-eq/kWh. The other category of variation caused by 'uncertainty' is captured in the collection and transportation stage. In existing biomass electricity LCA studies, the contribution from these stages is poorly quantified. We have accounted for this stage by reviewing the most contemporary literature in the field (ISBAL model Appendix 4).

The NER of biomass electricity has an average value of 3.33 MJ_{output} / MJ_{input} and minimum – maximum range as 2.38 – 4.54 MJ_{output} / MJ_{input}.

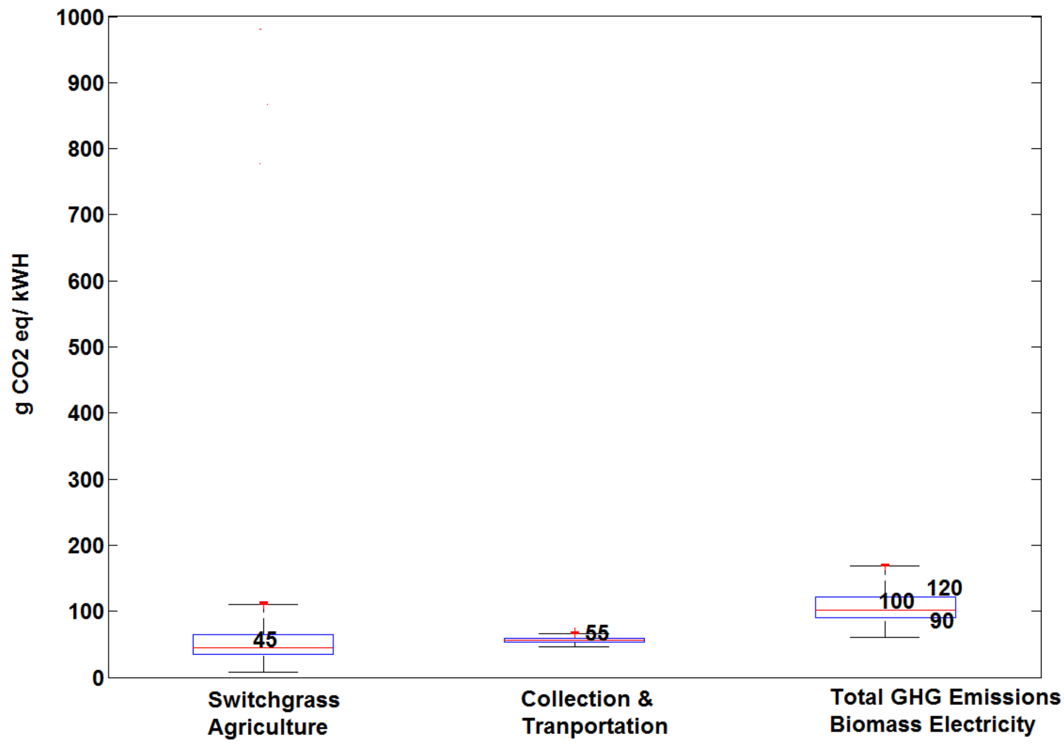

Figure 12: Lifecycle GHG emissions (g CO_2-eq /kWh) of biomass electricity derived from switchgrass

4.4.Comparison - Emissions offset per hectare of land

Thus far this study has modeled and assessed the fossil energy and GHG emissions of individual bioenergy pathways, i.e. ethanol production and electricity generation from switchgrass. Each of these pathways has a different energy and environmental profile. The goal of this section is to compare the different bioenergy pathways and highlight differences in GHG offset potential from a land use efficiency perspective. This is needed as the scale of bioenergy production depends on the optimal use of land.

As discussed in section 3.2.1, we have followed a two-step approach for evaluating land use efficiency. First, the lifecycle GHG emission impacts of each pathway are compared with the reference fossil energy system. Then we determine the GHG offset potential from a land use efficiency perspective. Figure 13 represents a comparison of cellulosic ethanol with gasoline system. Gasoline life cycle GHG impacts are estimated from GREET 1.8 model (Appendix 1). On average 55 g CO_2-eq/MJ of energy are saved if gasoline use is replaced by cellulosic ethanol derived from switchgrass. Figure 14 represents the comparison of biomass electricity with U.S. grid average and coal plant emissions. On average 558 g CO_2-eq/kWh of energy are saved if the U.S. average grid electricity use is replaced by biomass electricity from switchgrass.

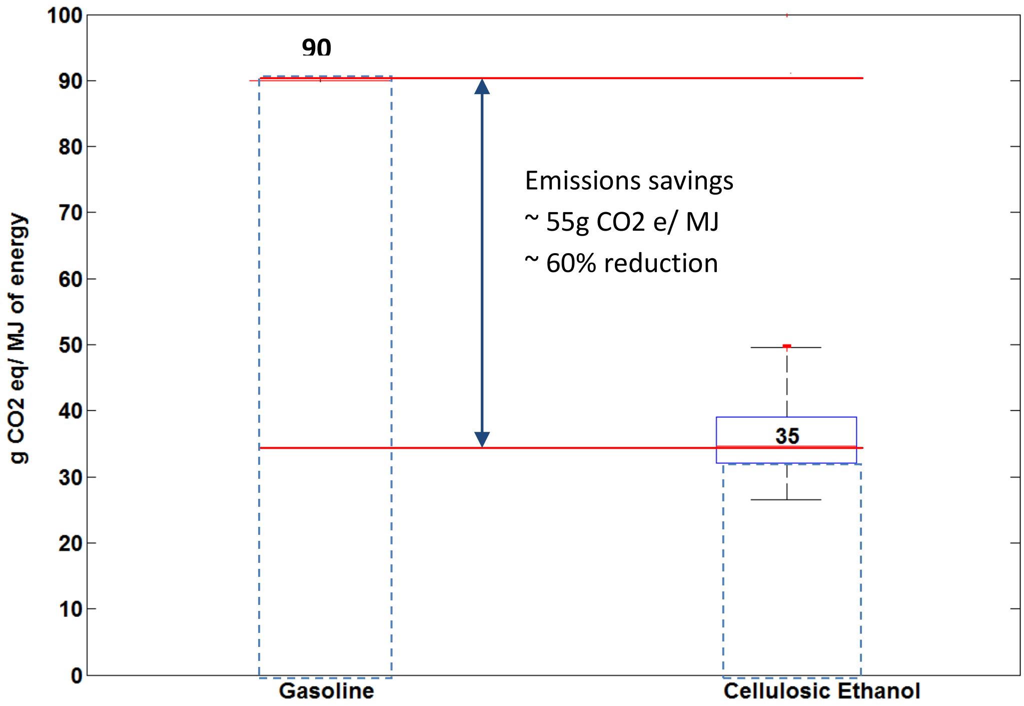

Figure 13: GHG emissions of cellulosic ethanol compared to gasoline (on basis of MJ of energy)

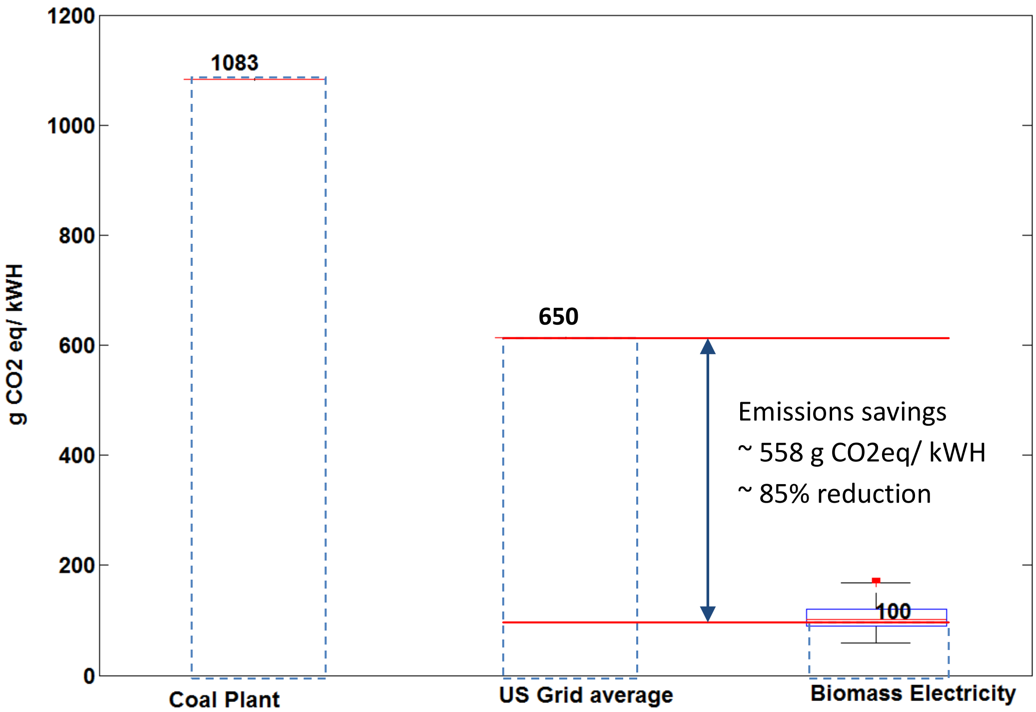

Figure 14: GHG emissions of biomass electricity compared to the U.S. grid average and coal plant emissions (on basis of a kWh of energy)

In step 2, the comparative environmental performances of bioenergy pathways is evaluated from a land use efficiency perspective. We assume that 100% of the switchgrass produced in a year from a hectare of land is either used to produce ethanol or biomass electricity (discussed in section 3.2.1). Figure 15 represents the comparison results for different bio-energy pathways. On average about 4.5 ton CO_2-eq/ha/year are saved if we use cellulosic ethanol instead of gasoline. In the case of biomass electricity the average GHG emissions saved are 9.5 ton CO_2-eq/ha/year if biomass electricity displaces U.S. average grid electricity. On average 18.3 ton CO_2-eq/ ha/year are saved if biomass electricity displaces coal electricity.

Thus, biomass electricity has a higher GHG offset potential than cellulosic biofuels in terms of land use efficiency. However, the results are sensitive to the regional electricity grid mix that biomass electricity displaces. In section 4.6, the GHG offset potential of bioenergy systems is assessed taking into account regionally variable parameters.

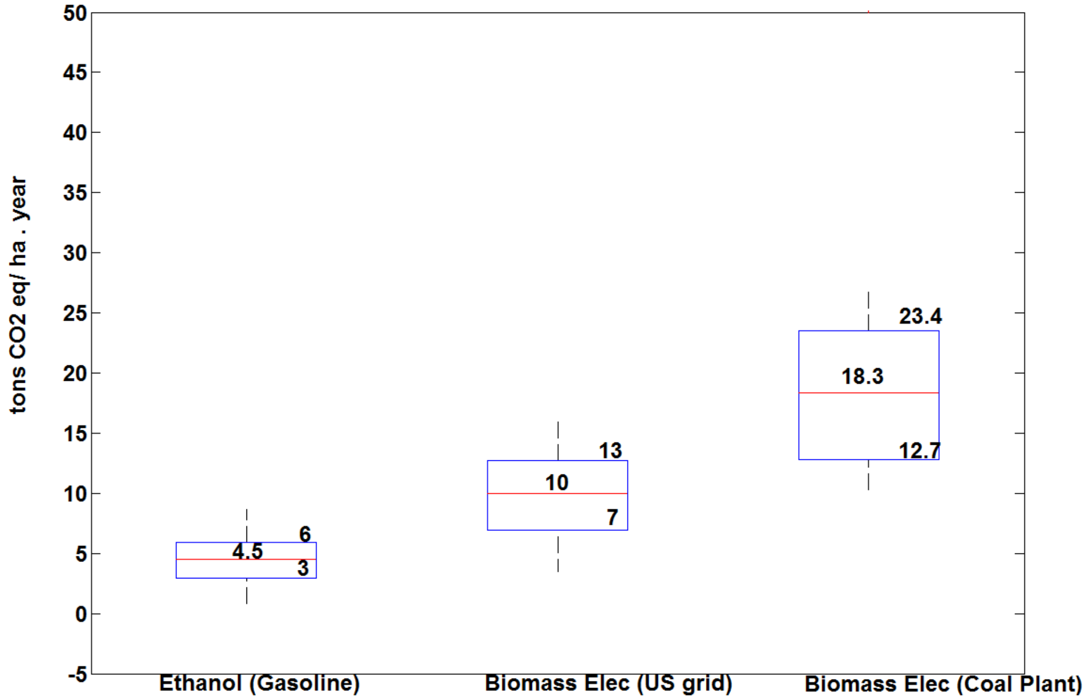

Figure 15. GHG emissions offset from different bioenergy systems in terms of land use efficiency (metric tonCO_2-eq/ ha/year)

4.5.Comparison - Emissions offset per kilometer (km) driven

This is another method used to compare energy and GHG aspects of the environmental profile of bioenergy systems. It is formulated assuming a special case of biomass electricity use where all the biomass electricity generated is used to drive electric vehicles. Ethanol is used to power Flex Fuel Vehicles (FFVs) (as discussed in section 3.2.2). The results of this comparison are shown in Figure 16.

Using the average LCA emissions for ethanol (35 g CO_2-eq/MJ) and the fuel economy of ethanol driven FFVs (20 mpg), we estimate the GHG emissions per km driven for ethanol-powered vehicles. It is 85 g CO_2-eq/km. Similarly, using the average GHG emissions of gasoline from the GREET 1.8 model (Appendix 1) and the fuel economy of gasoline powered FFVs (25 mpg - section 3.1.5) we estimate the emissions per km driven for a gasoline powered vehicle. It is 230 g CO_2-eq/km. Thus comparing the two systems results, on average 145 g CO_2-eq/km of GHG emissions are saved if we use cellulosic ethanol to drive FFVs instead of gasoline.

For an electric vehicle, assuming the average grid emissions (Appendix 1) and fuel economy of pure electric vehicle as 5.06 km/kWh [49], we have estimated the emissions per km driven. The electric vehicle average emissions are about 130 gCO_2-eq/km driven. If we use biomass electricity to power an electric vehicle, the emissions are about 20 g CO_2-eq/km driven. Therefore, 110 g CO_2eq/km emissions are saved per kilometer of an electrical vehicle driven. Similarly, if the electricity form coal power plants is used to charge an electric vehicle, the GHG emissions per kilometer of vehicle driven are 214 g CO_2-eq/km. Thus, comparing this scenario to the option where electric vehicle is charged exclusively by biomass electricity, on average 194 g CO_2-eq/km GHG emissions are saved per kilometer of an electrical vehicle driven.

Thus, biomass electricity may not be a very effective alternative in terms of GHG offset potential if the end goal of bioenergy policies is to use biomass for the transportation sector only. In the case where we consider an electric vehicle charged using biomass electricity and displacing average grid electricity, the GHG emissions offset per kilometer of vehicle driven are less than the alternative scenario of using biomass for producing cellulosic ethanol. However if the biomass electricity used to charge electric vehicle displaces the electricity from carbon intensive fossil sources such as coal, the GHG emissions offset per kilometer of vehicle driven are more than the scenario of using biomass for cellulosic ethanol. These findings are different from previous bioenergy comparison studies, which have estimated the offset of biomass powered electric vehicle by comparing it to a gasoline powered car only and concluded that biomass electricity has a better environment profile than cellulosic ethanol in all cases [13].

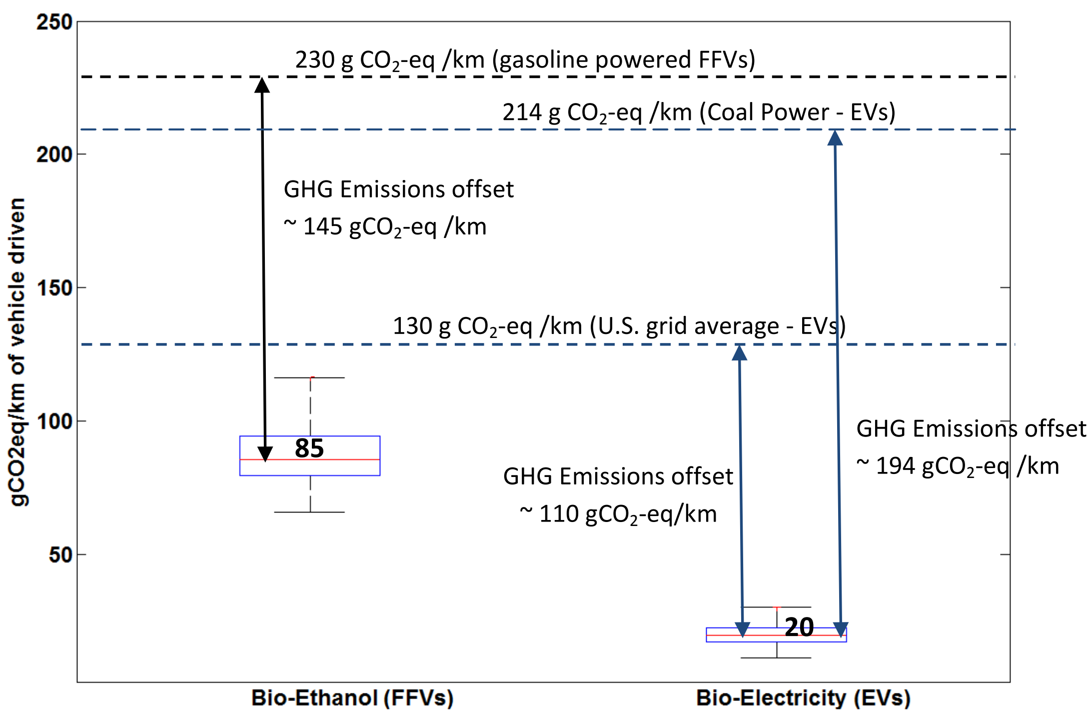

Figure 16: GHG emissions offset from different bioenergy systems (gCO_2-eq/ km of vehicle driven)

4.6. Regional Variability

Thus so far we have analyzed the comparative performances of bioenergy systems based on national average values. However, at a regional level there are some factors such as current energy mix, switchgrass yield and logistics which affect the overall environmental performance of bioenergy systems. In this section, we have analyzed three main geographic regions across the U.S., to understand the effect of regional variable parameters (Figure 17). The regions that have variation in the electric generation mix and have high potential for switchgrass cultivation are chosen for this analysis.

Electrical Grid Mix: The U.S. EPA, Emissions & Generation Resource Integrated Database (eGRID) is a comprehensive inventory that determines environmental attributes of electric power system across the nation [45]. It divides the U.S. into ten regions, according to their grid electricity mix. In our analysis, we have focused on Midwest Reliability Organization (MRO) – Region 1, Southwest Power Pool (SPP) – Region 2, and SERC Reliability Corporation (SERC) – Region3 (Figure 17). These regions also have high potential of switchgrass cultivation in the future. Table 5 shows the average electrical generation emissions for different regions.

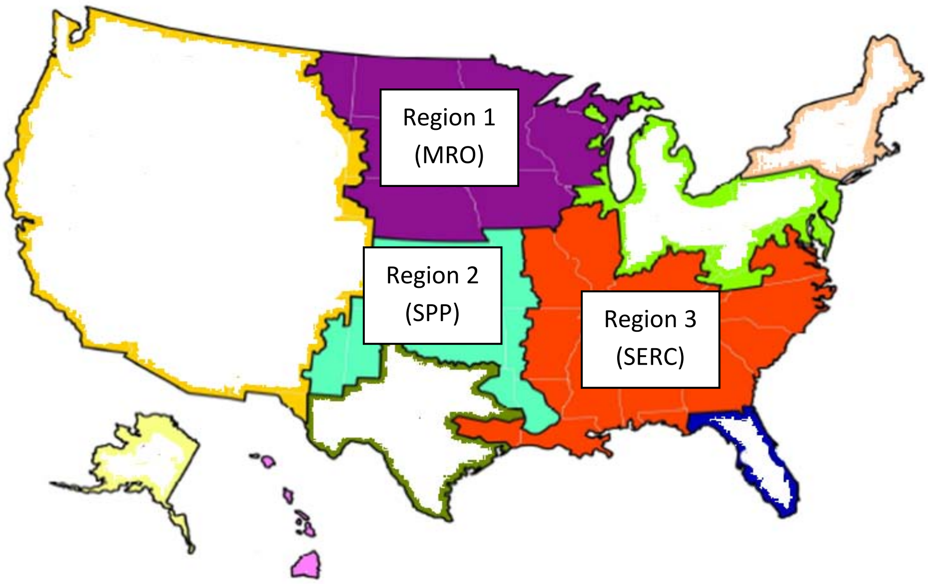

Figure 17: Different geographic regions considered for bioenergy systems analysis

Table 5: Electrical Grid Emissions (gCO_2-eq/ kWh)) across different geographic regions

	Grid Average Emissions (g CO_2 eq/ kWh)
Region 1 (MRO)	773
Region 2 (SPP)	756
Region 3 (SERC)	613
US Average	648

Source: eGRID 2007 [45]

Switchgrass Yield: The potential yield of switchgrass across all states in the U.S. is shown in Appendix 5 (U.S. DOE Billion Ton Study). The mean yield and variation across three regions chosen for our analysis are as shown in table 6.

Table6: Switchgrass yield (ton/ha) across different geographic regions

	Yield Average (ton/ha/year)	**Std Deviation (ton/ha/year)**
Region 1 (MRO)	9	2
Region 2 (SPP)	12	3
Region 3 (SERC)	15	5
US Average	12	5

Source: ORNL (2008) Exploring potential U.S. switchgrass production for lignocellulosic ethanol [37]

For the regional analysis, it is assumed that other parameters of LCA such as collection and transportation, biomass conversion efficiency and yield remain the same across all regions. A two-step approach is followed to determine the GHG offset potential from a land use efficiency perspective. (GHG emissions offset per hectare of land - section 3.2.1). Figure 18, 19 and 20 shows these results for region 1, 2 and 3 respectively. Table 7 summarizes the average value of these potential GHG offset results.

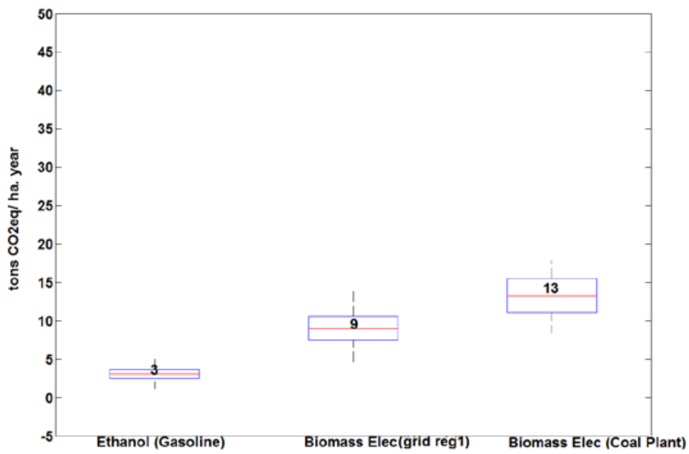

Figure 18: Region 1 (MRO) - GHG emissions offset from bioenergy systems (ton CO_2-eq/ha/year)

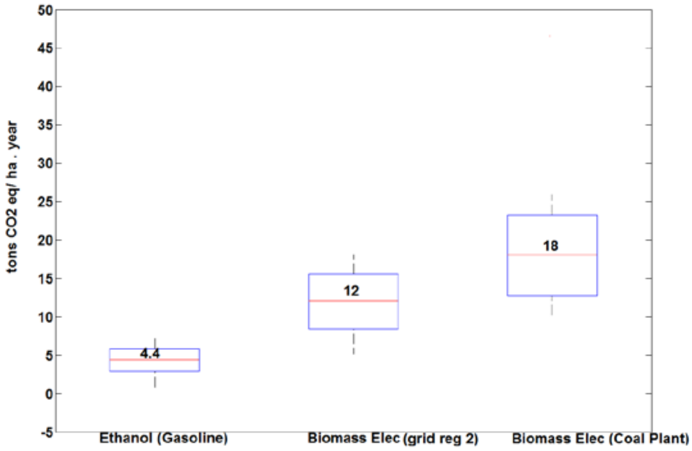

Figure 19: Region 2 (SPP) - GHG emissions offset from bioenergy systems (ton CO_2-eq/ha/year)

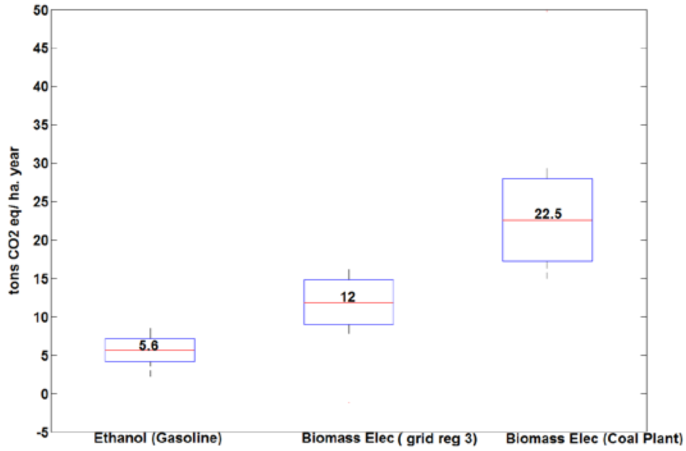

Figure 20: Region 3 (SERC) - GHG emissions offset from bioenergy systems (ton CO_2eq/ha/year)

Table 7: Average GHG emissions of offset from bioenergy systems across different regions (tonCO_2 -eq/ha/year)

	GHG offset (ton CO_2-eq/ha/year)		
	Ethanol (gasoline)	Biomass Elec (regional grid)	Biomass Elec (Coal Plant)
Region 1 (MRO)	3	9	13
Region 2 (SPP)	4.4	12	18
Region 3 (SERC)	5.6	12	22.5
US Average	4.5	10	18.3

Thus in the region 1 where the switchgrass yield is lower the GHG offset are lowest among all bioenergy systems. In region 3 where the switchgrass yield is highest and average grid emissions are lowest, the difference between ethanol and biomass electricity system environmental profile is the smallest.

Figure 21, 22 and 23 shows the comparison results for GHG offset potential for a kilometer of vehicle driven for region 1, 2 and 3 respectively regions. Table 8 summarizes the average value of these potential GHG offset results. The absolute emissions of biomass pathways are least in the region 3. This is because the switchgrass yield is highest in this region. However, relative GHG offset potential of both pathways is comparable for a kilometer of vehicle driven.

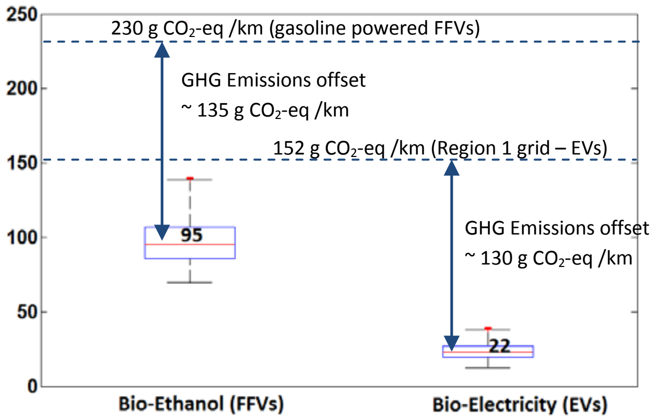

Figure 21: Region 1 (MRO) - GHG emissions offset for bioenergy pathways (gCO_2-eq/ km of vehicle driven)

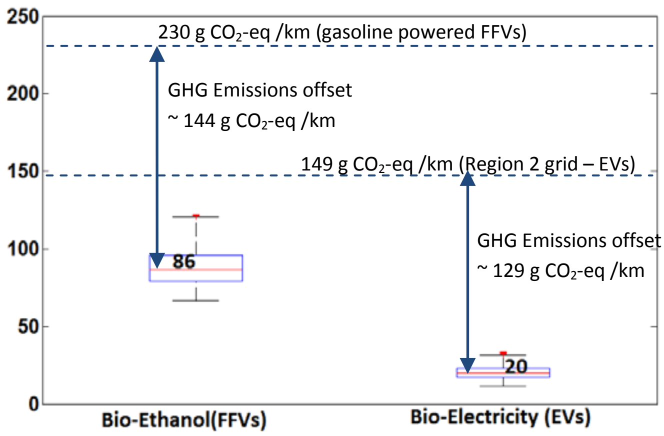

Figure 22: Region 2 (SPP) - GHG emissions offset for bioenergy pathways (gCO_2-eq/ km of vehicle driven)

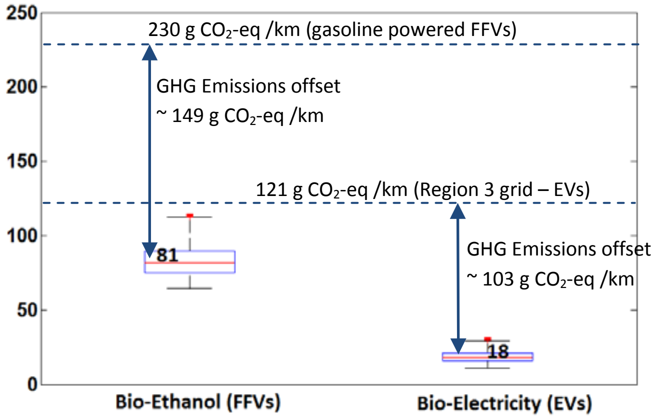

Figure 23: Region 3 (SERC) - GHG emissions offset for bioenergy pathways (gCO_2-eq/ km of vehicle driven)

Table 8: Average GHG emissions of offset from bioenergy systems across different regions (g CO_2-eq/ km of vehicle driven)

	GHG offset (g CO_2-eq/ km of vehicle driven)	
	Ethanol (FFVs)	Biomass Elec (regional grid)
Region 1 (MRO)	135	130
Region 2 (SPP)	144	129
Region 3 (SERC)	121	103
US Average	145	110

5. Conclusions

5.1. Key Findings

In this report the lifecycle energy and GHG emissions of individual bioenergy pathway, i.e. producing cellulosic ethanol and biomass electricity from switchgrass, are assessed. The results from this analysis provide a mean value for each life cycle metric as well as a range of possible outcomes.

Cellulosic ethanol average life cycle GHG emissions are 35 g CO_2-eq/MJ of energy, with a minimum-maximum range varying from 25 to 50 g CO_2-eq/MJ. Variations in switchgrass yield, fertilizer application rates and conversion efficiency are important determinants in overall variation in energy and GHG balance. For example, the contribution from the agriculture stage of switchgrass varies over a large range of 500 to 1200 kg CO_2eq/ha/year. The range of variability in this analysis captures the previous single-valued estimates for life cycle GHG emissions for ethanol derived from switchgrass [16-20]. While comparing cellulosic ethanol with gasoline system, on average 55 g CO_2-eq/MJ of energy are saved if gasoline use is replaced by cellulosic ethanol derived from switchgrass.

Biomass electricity average life cycle GHG emissions are 100 g CO_2-eq/kWh, with a minimum-maximum range varying from 90 to 110 g CO_2eq/kWh. The average life cycle GHG emissions accounted for in this analysis are higher than the previous estimated values for dedicated biomass electricity. This is because the energy use and GHG emissions values from the logistics and supply chain phase of biomass used in this study are much higher than previously used values in other LCA studies. In comparison to the U.S. grid electricity, on average 513 g CO_2-eq/kWh of energy are saved if biomass electricity from switchgrass displaces the average grid electricity. However, avoided emissions per unit of energy are dependent on the regional factors also, such as the regional electricity grid mix.

When comparing these bioenergy systems from land a use efficiency perspective, biomass electricity has better energy and GHG aspects of the environmental profile than ethanol. 4.5 ton CO_2-eq/ha/year are saved if we use all the switchgrass cultivated on a hectare of land to produce ethanol. In the case of biomass electricity, the annual GHG emissions offset are 10 ton CO_2-eq/ha/year. However, the emissions offset from the best case of cellulosic ethanol are comparable to emissions offset from the worst case of biomass electricity.

We have also analyzed another case of comparison of bioenergy systems - GHG emissions offset per km of vehicle driven. This case is formulated assuming a special case of biomass electricity use where all of the biomass electricity produced is used to drive electric vehicles and ethanol is used to power Flex Fuel Vehicles (FFVs). As discussed in section 4.5, 145 g CO_2eq/km will be offset if we use ethanol instead of gasoline in Flex Fuel Vehicles (FFVs). In the case of electric vehicles, 110 g CO_2eq/

km is saved if we use biomass electricity instead of the average grid power. Thus, biomass electricity is not a very effective alternative if the end goal of bioenergy policies is to use biomass in transportation sector only. These findings are different from the previous bioenergy comparison studies, which they have estimated the offset of a biomass powered electric vehicle by comparing it to a gasoline powered car only and recommended that biomass electricity has a better environment profile and greater GHG offset potential than cellulosic ethanol in all cases [13].

5.2. Limitation and Future Work

This study addresses some of the main challenges in bioenergy systems LCA. An in-depth study has been conducted to understand uncertainty and variability in the emerging bioenergy agriculture practices, supply chains and conversion technologies. However, some other limitations of a standard average based LCA approach have not been addressed. For example, it is very difficult to understand land use change patterns from national and regional level average estimates. In addition, predicting bioenergy systems supply chain and logistics dynamics is a challenging task. Thus, it is recommended to develop spatially explicit LCA models for such analysis. Using analytical frameworks such as Agent Based Modeling, it is possible to capture farmer's behavior, including what feedstocks will be grown and the types of land expected to be converted to dedicated bioenergy feedstocks.

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Appendix 1 – Conversion /GHG Factors

Conversion factors	
948.452	Btu/MJ
1.055	kJ/Btu
746	W/hp
3,412	Btu/kWh
4	MJ/kWh
239.01	Kcal / MJ
2.471	ac/ha
1.6093	km/mile
0.4536	kg/lb
2,000	lb/short ton
907	kg/short ton
8,766	hr/yr
3.8	L/gal
907.2	kg/ton
5800000	btu/bbl oil eq
3.7	CO2 eq / C

Energy Content			
	Density (kg/L)	*HHV (MJ/kg)*	*LHV (MJ/kg)*
Gasoline	0.74	46.7	42.5
Ethanol	0.78	30	27

Global Warming Potentials	
CO2	1
CH4	23
N2O	296

Source: IPCC Third Assessment Report

GREET 1.8 GHG factors	
Nitrogen production (kg CO2e/kg N)	3.0
Herbicide (average mix for biomass) (kg CO2e/kg)	21.0
Gasoline (g CO2e/MJ)	89.16
Diesel (g/MJ)	96.42
Coal (g CO2e)/MJ)	112.30
NG (g CO2e/MJ)	69.43
g CO2e per kWH of grid electricity	649

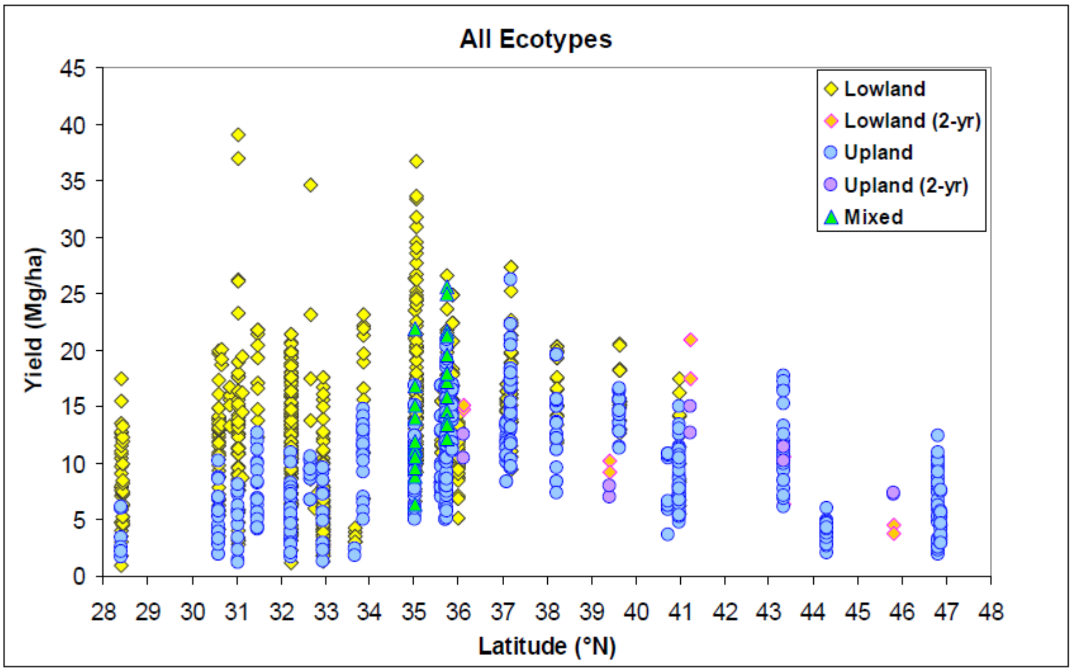
Appendix 2 – Sample MATLAB program for LCA+ Monte Carlo

MATLAB program for simulating life cycle analysis of agriculture subsystem, using Monte Carlo simulation

```
% GHG emissions in Agriculture Production stage of switchgrass
% Switchgrass yeild mean 12 tons/ha , sigma = 5
S_Y = randn(10000,1);
S_Y = ((S_Y*5)+12);
S_Y = min(S_Y,30);
S_Y = max (S_Y,0);

%/Fertilizers
% Nitrogen Application Rate = N_A (kg of N /ha)(mean= 90 ; sigma =
% 15)
N_A = randn(10000,1);
N_A = ((N_A*15)+90);
N_A = min(N_A,180);
N_A = max(N_A,0);
N_A1 = N_A./S_Y;
N_A1 = N_A1*1000;
N_A1 = min(N_A1,22000);
N_A1 = max(N_A1,0);
%N_A1 gm N / ton of switchgrass
GHGEmissionsN = N_A*2.959;
% GHG emissions N (kg CO2e/ha) -> GREET
%GHGEmissionsN = GHGEmissionsN./S_Y;
% GHG emissions N (kg CO2e/ton of switchgrass)
% Fossil Energy N = 50 MJ/ Kg N -> GREET
E_N = N_A*50;
% MJ/ha
%/Herbicides
% Herbicide Application Rate = H_R (kg/ha)mean=
% 1.6 ; sigma = 0.6)
H_R = randn(10000,1);
H_R = ((H_R*0.6)+1.6);
H_R = min(H_R,65);
H_R = max(H_R,0);
GHGEmissionsH = H_R*21.035;
% GHG emissions Herb (kg CO2e/ha)
%GHGEmissionsH = GHGEmissionsH./S_Y;
% GHG emissions Herb (kg CO2e/ton of switchgrass)
% Fossil Energy H = 322 MJ/ Kg H -> GREET
E_H = H_R*322;
% MJ/ha
% Fuel Use in Farming Machines
% F_U mean = 16.4 sigma = 3.3 (l/ha) --> B-KDF / MIT report
F_U = randn(10000,1);
F_U = ((F_U*3.3)+16.4);
GHGEmissionsF = F_U*0.88*43*0.08;
% GHG emissions Diesel(kg CO2e/ha) = F_U (l/ha)*density
(kg/l)*LHV(MJ/kg)*GHGfactor(KgCo2e/MJ)
```

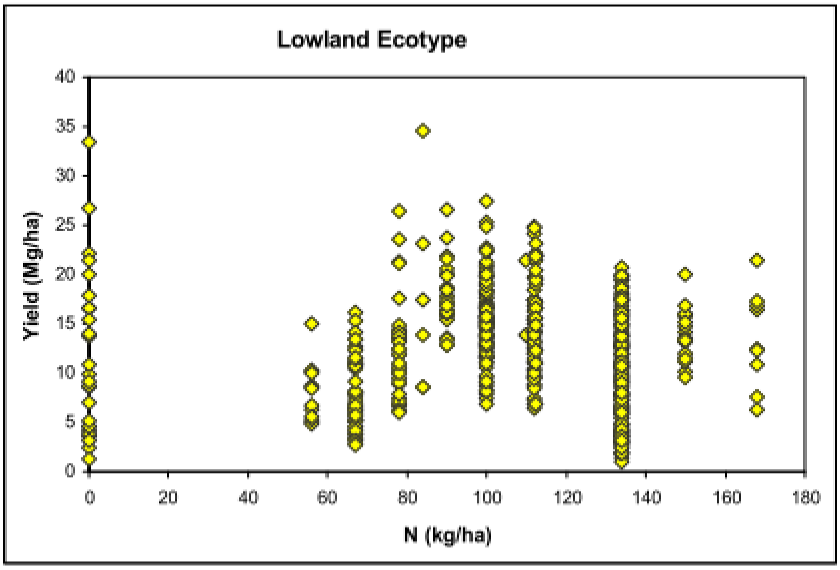
```
%GHGEmissionsF = GHGEmissionsF./S_Y;
% GHG emissions Fuel (kg CO2e/ton of switchgrass)
% Fossil Energy F = 322 MJ/ lt -> GREET
E_F = F_U*0.88*43;
% MJ/ha
% N20 emissions from N fertilizers; triangular plot by GREET
N20_N = trirnd(0.008,0.0115,0.015,10000);
GHGEmissionsN20_N = N20_N*(44/28)*298;
% GHG Emissions N20_N (KgCO2e / Kg of N)
%land use change impacts N2O dynamics - DAYCENT model

GHGEmissionsN20_N1 = GHGEmissionsN20_N.*N_A;
GHGEmissionsN20_N1 = min(GHGEmissionsN20_N1,1000);
% GHG Emissions N20_N (KgCO2e / ha)
%GHGEmissionsN20_N = GHGEmissionsN20_N./S_Y;
% GHG Emissions N20_N (KgCO2e /ton of switchgrass)
GHG_TAg = (GHGEmissionsN + GHGEmissionsH +
GHGEmissionsF+GHGEmissionsN20_N1);
%GHG_TAg (Kg CO2e/ha)
a1= [GHGEmissionsF, GHGEmissionsH, GHGEmissionsN, GHGEmissionsN20_N1,
GHG_TAg];
% (Kg CO2e/ha)
GHG_TAg1= GHG_TAg./S_Y;
%GHG_TAg (Kg CO2e/ton
E_TAg = E_F+E_H+E_N;
% MJ/ha
a2 = [E_F, E_H, E_N, E_TAg];
% MJ/ha
E_TAg1 = E_TAg./S_Y;
% MJ/ ton
```

Appendix 3 – Switchgrass Yield



Switcgrass yield for all ecotypes along different latitudes from 200 field studies (1995-2008)

Source Exploring potential US switchgrass production for lignocellulosic ethanol ORNL/TM-2007/183



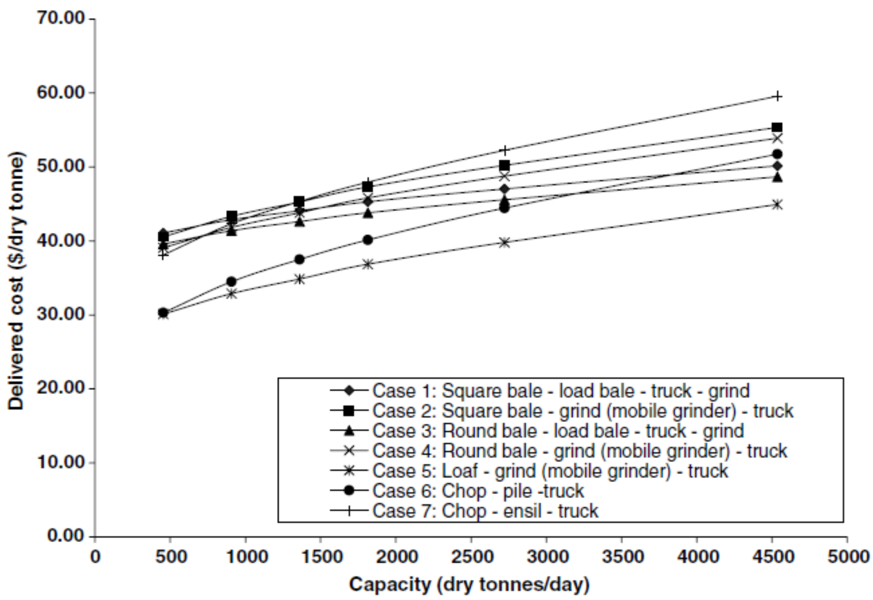
Switcgrass yield variation with N fertilizer use from 200 field studies (1995-2008)

Source Exploring potential US switchgrass production for lignocellulosic ethanol ORNL/TM-2007/183

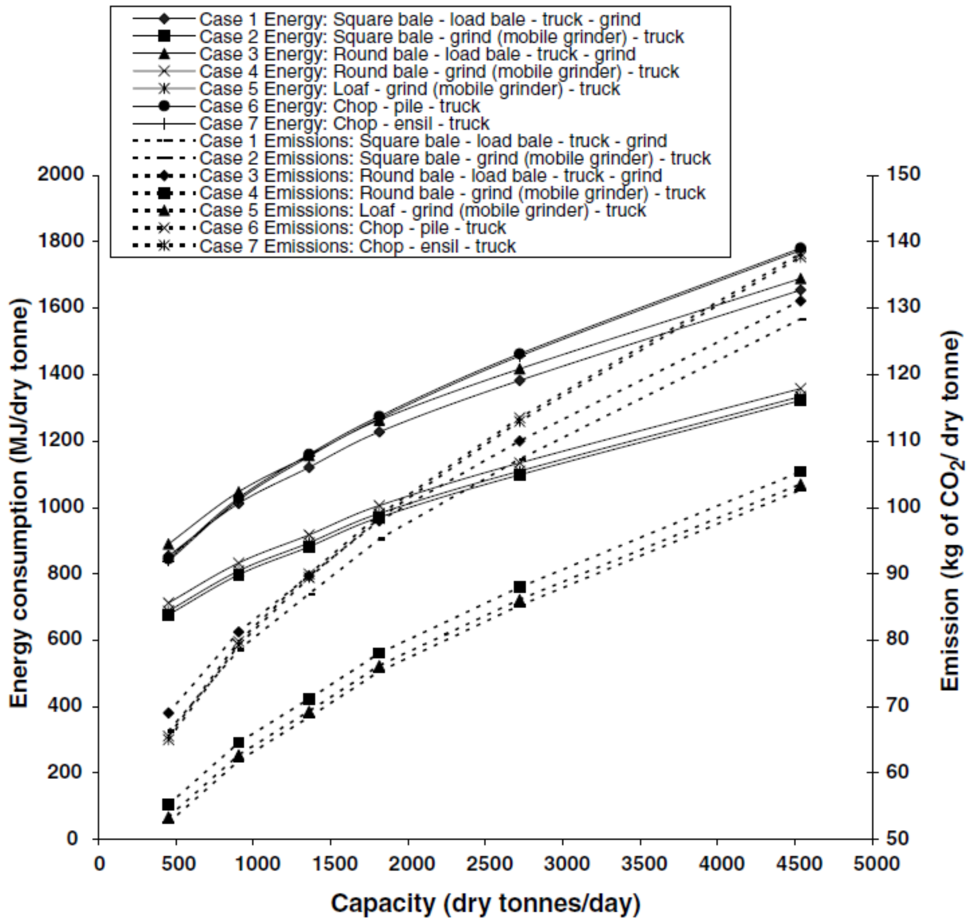
Appendix 4 – Biomass Supply Analysis Model

Integrated Biomass Supply Analysis and Logistics (ISBAL) model for Switchgrass delivery to a biorefinery

IBSAL model simulates the time dependent flow of biomass from field to a bio refinery. It consists of different sub-modules for harvesting, processing (such as, grinding), storage and transportation. Model input data include: local weather data (average daily temperature, humidity and precipitations); average yield of biomass; proportion of land that is cultivated with the crop of interest; crop harvest progress data (including start and end dates of harvest); capacity of the biorefinery; dry matter loss with time in storage; plant moisture content at the time of harvest; operating parameters on different agricultural machinery; and capital and operating costs of different agricultural machinery. The model is built on the EXTEND platform, available from Imaginethat Inc. (Extend Simulation Model, 2005). Main outputs of the model include: delivered cost of biomass to a biorefi nery ($/dry tonne of biomass delivered); GHG emission (kg of CO2/dry tonne of biomass delivered) and energy consumption(MJ/dry tonne of biomass delivered). Cost, energy and emission parameters can be obtained for individual processingsteps. Details of the model can be found in Sokhansanj and Turhollow (2005) and Sokhansanj et al. (2006).

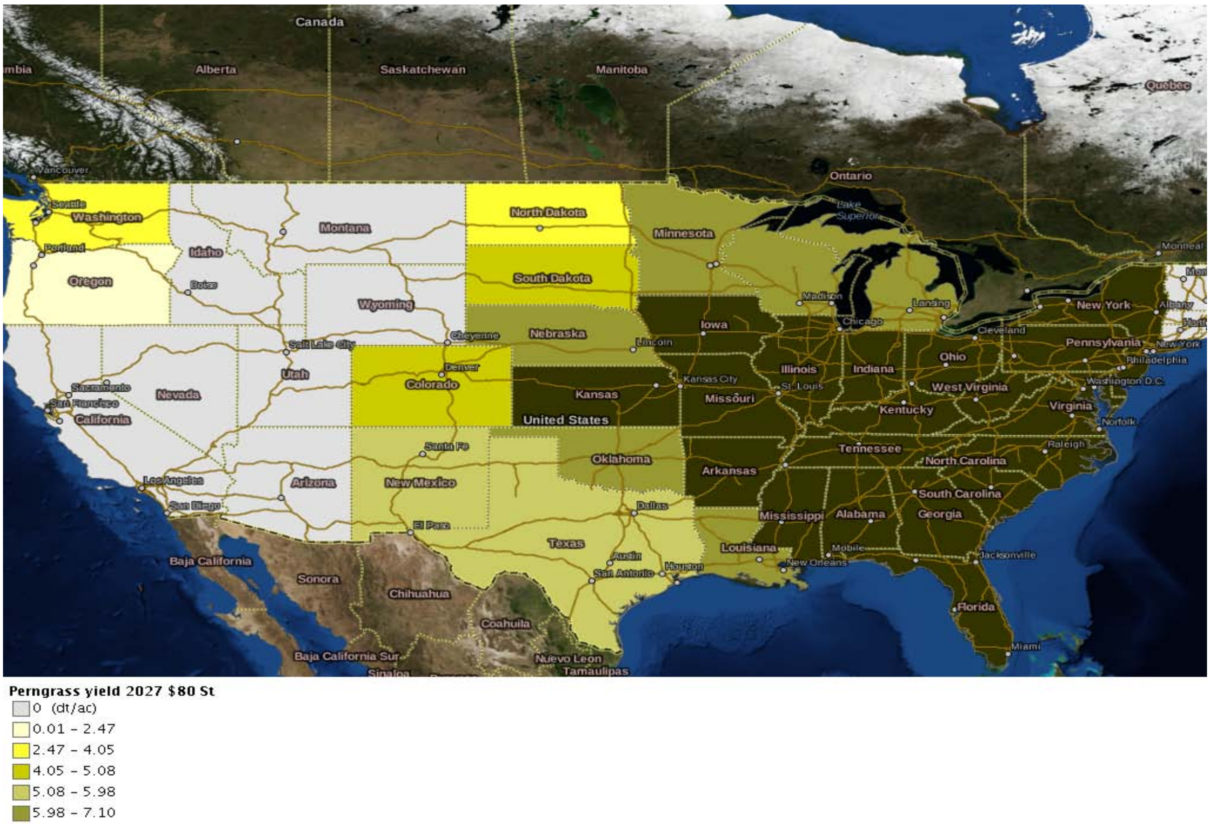


Delivered cost of switchgrass to a biorefinery for different collection, preprocessing, storage and transportation options



Energy consumption and carbon emissions in the different cases

Appendix 5 – Switchgrass Potential



2027 Switch-grass yield @ 80 / ton

Source: Billion Ton study resource map at Bioenergy KDF site (https://www.bioenergykdf.net/biokdf/map)