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Modeling Future Biofuel Supply Chains using Spatially Explicit Infrastructure Optimization

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Modeling Future Biofuel Supply Chains using Spatially Explicit Infrastructure Optimization

by

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Abstract

Policies have been enacted that promote biofuels with the goal of reducing greenhouse gas emissions, reduce dependence on petroleum and to spur rural economic growth. The supply of biofuels that can meet these three goals is limited. The cost of this supply is influenced by the geography of the biomass resource and demand for fuels. Existing studies projecting the future supply have not accounted for the spatial aspects of the biofuel supply in detail.

This dissertation presents a spatially-explicit model of future biofuel supply chains in the United States, with the goal of providing supply curves of biofuels by resource-technology pathway with detailed accounting of the required infrastructure. The model is used to analyze the potential supply of biofuels for meeting the federal Renewable Fuel Standard (RFS2) and analyze biofuels from waste and residue resources in California at high resolution with accounting for air pollutant emissions.

The results of the national case study project that domestic biofuels can achieve the RFS2 mandates for 2022 at fuel prices of between \$3.4 and \$5 per gasoline gallon equivalent. The largest sources of variation are the cost of cellulosic biofuel technologies and the availability of low cost waste resources. Building the 200-250 cellulosic biorefineries needed to achieve the target requires a capital investment greater than \$100 billion but less than \$360 billion depending on technology development and choice of cellulosic technology.

Waste and residue biomass can provide quantities of biofuels that assist with policy goals. Nationally, waste and residue resources are projected to provide between 35 and 64 percent of the RFS2 mandate in both 2018 and 2022. In California, biofuels from waste and residue resources have limited potential for petroleum displacement, but could contribute 40-70% of the LCFS emissions reductions with mixed and uncertain results on air quality.

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1 Introduction

1.1 Motivation

Production of biofuels is increasing worldwide and especially in the United States (OECD-FAO, 2010). This increase is driven by many factors but chief among them are policies mandating or promoting biofuels (see Table 1). These policies promote biofuels as a means to reduce petroleum dependence, reduce greenhouse gases and spur rural economic development. Looking to the future, the policies in place call for transformative change and growth in the biofuels sector. The dominant biofuel technology in the United States, corn ethanol, has little room to grow within the existing federal mandate, while a nascent cellulosic biofuel industry is required to grow from today's demonstration units to commercial production of 16 billion gallons per year (BGY) in 12 years. Where this fuel will come from, at what cost and with what economic, environmental, and land use impacts are questions without satisfactory answers to date. This dissertation presents a spatially explicit model of future biofuel supply chains in the United States, with the goal of providing answers to these key policy questions.

Table 1: Major biofuels related policies

Policy	Jurisdiction	Summary
Renewable Fuels Standard	United States	36 billion gallons of renewable fuels mandated by 2022 in 4 categories
Fuel Quality Directive	European Union	10% of energy used in transport must be from renewable sources by 2020 and a 6% reduction in GHG emissions in transport
Low Carbon Fuel Standard	California	The average carbon intensity of fuels sold must be reduced by 10% by 2020.

Spatial features of energy supplies are generally simplified to national or regional averages in existing assessments future energy supplies. All could be improved with greater detail to the spatial layout of the energy infrastructure with biomass the spatial features are especially important as it has low yield (Btus/acre) compared to other energy sources and costly transport due to low energy density. Furthermore, the generally low economic value per mass of energy feedstock biomass relative to agricultural commodities leads to greater importance of the transportation costs than is generally considered in models of agricultural production (Searcy *et al.*, 2007). For these reasons, existing tools for considering either agricultural production or energy supply are likely to be inadequate for a realistic analysis of biofuel supply.

1.2 Research questions

The focus of this dissertation is the development of a modeling methodology explicitly incorporating the spatial aspects of the biofuel supply chain. Using a spatially explicit framework, I seek to estimate the cost, quantity, direct land use and lifecycle greenhouse gas emissions of biofuels supplied. Since the underlying assumptions regarding biomass feedstock availability, conversion technology costs, and future demand are highly uncertain, a significant portion of this dissertation explores the sensitivity of the model results to alternative assumptions.

The methodology has been developed to be flexible in the policy relevant questions that can be analyzed. However, due to the limited scope of this dissertation not the full breadth of research questions have not been considered. The two case studies presented focus on the following questions for the United States and California in the next decade.

- What will the marginal cost be for producing and delivering biofuels as the quantity demanded changes (i.e., a biofuel supply curve)?
- How much biofuel can be produced relying only on waste and residue resources?
- Where will the industry take root?
- What is the cost and impact – air pollutant emissions and resource consumption – of waste biofuels in the Californian context?

Some of the additional research questions that should be taken into account as policies are developed to promote biofuels that can be asked using the model developed here are listed below.

- Where will the benefits and impacts occur?
- Under what conditions are biofuels the most profitable use of biomass?

- What will be the incremental capital cost of a transition to biofuels (i.e., capital investment required)?
- Are there tradeoffs between the biofuel production cost and environmental or societal benefits?

To be clear, I do not attempt to answer all of these questions in this dissertation.

1.3 Organization

The dissertation is organized as follows. Chapter 2 provides background information important to understanding the research questions. First, the stage is set for biofuel supply assessment by explaining the potential role of biofuels in the fuel sector, and how their production fits into the scheme of energy and agriculture. Previous work describing biofuel supply in both quantities and impacts is reviewed. Past methodological approaches for modeling future biofuel supplies are described. The strengths and weaknesses of each approach are discussed, defining how the methodology developed here contributes to the field.

Chapter 3 lays out the methodology that has been developed. First, the framework of the model and the generic model formulation are given, followed by refinements on the formulation.

Chapter 4 describes the current status of biomass conversion technologies and describes the technology characterizations used in the subsequent case studies. Chapter 5 reviews background literature and describes the data sets used for resource assessments, transportation cost models, and fuel demand.

In Chapters 6 and 7, case studies utilizing the methodology are described. Chapter 6 considers biofuel supply potential in the United States referenced to the year 2018 with a focus on meeting policy goals. Chapter 7 considers near term utilization of waste and residue biomass for biofuels production in California with an emissions accounting framework integrated with the spatial economic model. The two case studies highlight different challenges and benefits in utilizing the methodology. The national scale model uses county-level resource estimates with a spatial fuel demand constraints. The size of this analysis constitutes computational challenges resolved through the coupling of regional scale solutions. The California model demonstrates a high-resolution implementation of the approach with the explicit emissions accounting for the modeled biofuel industry.

Chapter 8 provides a summary of main findings, highlights the strengths, weaknesses and draws relevant conclusions regarding suitability of the modeling approach with recommendations for future enhancements.

2 BACKGROUND

2.1 Biofuel context

In recent government policy in the United States and around the world, biofuels have been suggested as a cure for a number of ills caused by the transportation sector's dependence on petroleum for energy (European Parliament and Council, 2003; U.S. Congress, 2007). The most prominent of these are the reduction of greenhouse gas emissions in the face of global climate change (European Parliament and Council, 2003), enhancement of energy security (U.S. Congress, 2007) and supporting rural economies (European Parliament and Council, 2003; U.S. Congress, 2007). Secondary arguments have been made that the use of some biofuels would have lower air and water quality impacts compared to gasoline and diesel. In particular, ethanol has been used as an oxygenate for reformulated gasoline in order to reduce emissions of smog-forming compounds (Nadim *et al.*, 2001).

From a broad-brush perspective, recent studies suggest that biofuels appear capable of contributing to progress towards those policy goals over the next few decades. An economic model of United States agriculture found that domestic agricultural and forest resources could provide 60 billion gallons of ethanol and 1.6 billion gallons of biodiesel while also significantly increasing farm income and jobs in agriculture and renewable energy (De La Torre Ugarte *et al.*, 2007). A study of the technical potential for "sustainable" cellulosic biomass production in the US was found to be 1.3 billion tons per year, equivalent to approximately 30% of the US petroleum consumption by energy content (Perlack *et al.*, 2005). A study of climate mitigation strategies from the agriculture and forestry sectors found that biofuels provide reductions of approximately 100 million metric tons of carbon equivalent (MMTCE) at a carbon price of $100/MMTCE (McCarl *et al.*, 2001).

However, it is becoming increasingly clear that the attractiveness of biofuels is dependent on the specific pathways used to produce them (Kim *et al.*, 2005; Delucchi, 2006; Farrell *et al.*, 2007; Turner *et al.*, 2007; Unnasch *et al.*, 2007; Zah *et al.*, 2007). Even within corn ethanol production, there is a large range of potential direct greenhouse gas emissions and environmental impacts (Kim *et al.*, 2005; Turner *et al.*, 2007; Unnasch *et al.*, 2007). Zah *et al* (2007) found a large range of both local environmental impacts and greenhouse gas emissions when considering potential biofuel options for Switzerland. Many biofuel pathways demonstrated significantly *worse* environmental performance than the petroleum fuels they would replace (Zah *et al.*, 2007).

Consequently, there is a vigorous debate within the academic community and among government, environmental and industry groups regarding the sustainability of biofuel production – due to both environmental impacts and competition with food production. However, information that relates sustainability to the supply potential is scarce. The definition of "sustainable biofuels" is neither clear nor agreed upon. Generally, the definition of sustainable practice is one that meets current needs without compromising the ability of future generations to meet their needs (WCED, 1987). But the generality of this definition leaves broad room for interpretation in application to the questions surrounding biofuel production (Yeh *et al.*, 2009).

There are many ways in which biofuels can be environmentally *un*sustainable – habitat loss/deforestation, soil degradation, greenhouse gas emissions, pollution of water and air, aquifer depletion, etc. The production of energy crops and the conversion processes of all biofuels require significant water consumption, and many biofuel pathways can lead to reduction in water quality through intensification of agriculture (National Research Council, 2008). The change in life cycle air pollutant emissions using biofuels compared to a baseline petroleum fuel depends on the particular biofuel pathway, with some yielding a net benefit and others a net detriment (Wu *et al.*, 2005). There are also concerns about the soil quality impacts of agricultural residue removal for use in biofuel production (Lal, 2005). And production of biofuels can pose a threat to biodiversity through habitat loss as well as water and soil quality impacts (Cook *et al.*, 1991).

Competition for land between food and energy crops is also cause for caution. The boom in production of corn-based ethanol in response to both federal mandates and gasoline prices played a significant role in the doubling of the price of corn from 2006 to 2008 (Babcock, 2008). Most options to produce biofuels on a significant scale will require the use of large quantities of agricultural land. But productive agricultural land is a limited and valuable resource that provides the basic need of nourishment to a growing global population. The question of whether it is a good idea to incentivize the development of another major use for this scarce resource is becoming important, especially since many agricultural practices have negative environmental impacts.

Furthermore, introducing biofuel production that is competitive with petroleum fuels links the global agricultural and land markets to energy markets. It is not likely to be possible to limit production of biofuels to marginal land; biomass, like traditional crops, will grow better and be more profitable on good agricultural land. A potential danger in linking these markets is that it can give those with higher purchasing power the ability to meet their energy needs by indirectly starving those with lower purchasing power.

Although expanding the quantity of lands in agricultural production can ease the problem of direct food-fuel competition, this expansion often leads to major environmental impacts, including deforestation, habitat loss and resulting loss in biodiversity (Cook *et al.*, 1991), as well as greenhouse gas emissions caused by releasing the carbon stocks of the converted land (Fargione *et al.*, 2008; Searchinger *et al.*, 2008). For many stakeholders in biofuels policy, these impacts more than cancel the gains achieved by the production of biofuels.

Despite these serious issues, however, it is important to note that there is a great deal of variability in the potential impact of biofuel production pathways – on both food production and the environment. Within this variability, the opportunity exists for a limited sustainable biofuel industry. But the viability and extent of such a sustainable biofuels industry depends on the costs of production, primary and co-product market values, and any subsidies for such production influencing overall profits. The policy basis for the latter, in addition to mandates and other government influences, therefore requires extensive information relating to net economic, environmental, and social benefits, if any. The present debate over biofuels in part reflects high levels of uncertainty about these outcomes and the need for more comprehensive information.

The costs and impacts of producing biofuels depend on the geography of the resource to be exploited, the size of the biorefinery and the cost of accessing the fuel market. These factors are not independent. For example, the economically optimal size of a biorefinery will depend on the spatial density of the resource it is exploiting, with dense biomass resources capable of supporting large biorefineries. As biomass resource supply becomes more dispersed, increasing feedstock transportation costs can outpace the scale economies of increasing biorefinery size. High costs to access fuel markets for the sale of biofuel products can also make a low-cost producer less profitable than a producer with higher costs but nearer to the market. Geography is salient for the environmental impacts associated with biofuel production since the transportation of both biomass feedstock and product fuels can be significant for the life cycle impact of biofuel pathways (Wakeley *et al.*, 2008).

A number of studies have considered the basic tradeoff in the design of biofuel supply chains between the size of a biorefinery – taking advantage of economies of scale – and the cost of biomass and biofuel transportation. Transportation of biomass is expensive relative to its value as an energy feedstock due to low energy density (Searcy *et al.*, 2007). Thus in many cases, the additional transportation costs quickly outweigh opportunities for economies of scale in the biorefinery, leading to a clearly defined optimal size of the biorefinery. However, the exact capacity of this optimal size is situation dependent, with the spatial layout of the resource base, the scaling of the technology, purchasing agreements for feedstock (Kaylen *et al.*, 2000) and the product market (Parker *et al.*, 2008) all being relevant factors to consider. The spatial layouts of the resource and product markets in particular are not easily generalizable and vary considerably by locations.

In addition to the spatial aspects, competition for biomass may come from a number of sectors besides transportation fuels. Biomass production and conversion systems resulting in low lifecycle greenhouse gas emissions (low-carbon) are considered attractive for a number of potential products in a carbon-constrained world. Electricity produced from biomass was found by Campbell *et al.* (2009) to be a more efficient use of biomass for the purpose of reducing carbon emissions than biofuels (Campbell *et al.*, 2009). At present, it is unclear which of these products or combination of products will become the most attractive use of biomass. There are viable low or zero carbon alternatives in some sectors – such as wind and solar in the electricity sector – while other sectors that require energy dense liquid fuels – such as aviation and long haul freight – have fewer options and are likely to place the highest value on biomass as a feedstock.

The foregoing narrative illustrates that good policy will require an improved understanding of biofuel systems, including the tradeoffs that exist between the size of the biofuel supply, economics and potential adverse environmental and/or societal impacts. There has been little work done to show the quantity of biofuels that could be brought to bear on the transportation energy system with clear accounting for cost estimation, technology choice, regional variations in supply, systems analysis of the full supply chain, environmental impacts and resource constraints, and the impact of potential regulations. I seek to fill this gap.

2.2 Approaches to modeling biofuel futures

A few different approaches have been taken to project future biofuel supplies. No method provides a satisfactory representation of all the important aspects of the biofuel supply system, but each method can leverage data and knowledge found using the other methods. Consequently, I classify the research to date into three categories. First, there are assessments of biomass and/or biofuels using either technical estimates or economic models of the agriculture sector. Second are transportation fuel or energy sector economic models with limited description of resource supplies. Third are spatial infrastructure optimization models that find the optimal supply system for biomass-based fuels.

Technical estimates of biofuel potential have been performed at a number of scales using a range of limiting factors. Field *et al* (2008) developed a global estimate of biofuel potential using abandoned agricultural land that is not currently forested or urbanized. They found approximately 5% of the world primary energy could be provided by biofuels grown on these marginal lands. Other researchers using similar methods (Tillmann, 2006; Hoogwijk, 2003) found that a range of 2 - 35% of the energy demand could be met. Perlack *et al* (2005) estimated that 1.3 billion tons of biomass could become available in the United States by 2030 under optimistic scenarios of energy crop and agricultural residue production. Williams *et al* (2008) calculated that 32 of 83 million dry tons of the gross biomass produced in the state of California are technically available for energy production. These studies provide quantified resource assessments but do not account for the economics of biomass production and give little if any consideration to the conversion technologies required to produce fuels. They are meant to provide rough estimates of the total sustainably available biomass resource only and do not provide any understanding of whether an economically viable industry is possible.

Economic models of the agriculture and forestry sectors improve upon technical assessments by capturing market effects. Two agricultural sector models have been developed with the purpose of answering questions about biomass as a potential energy and industrial feedstock in the United States and are describe in the following two paragraphs.

De la Torre Ugarte and Ray (2000) developed a dynamic, systems model of United States agriculture that is anchored to an externally provided baseline (such as FAPRI or USDA projections). A value for biomass as an energy feedstock along with estimated cost of production is introduced and the reaction of the agricultural market is simulated. The POLYSYS model has been used to project the impact on agricultural markets of producing 60 billion gallons per year of ethanol by the year 2030 (De La Torre Ugarte *et al.*, 2007).

Khanna *et al* (2010) have developed a "dynamic multi-market equilibrium" model to consider the effects of policies on competition between food and fuel crops. The agricultural sector is modeled in detail with the introduction of switchgrass (*Panicum virgatum*) and miscanthus (*Miscanthus giganteus*) energy crops. Transport of the biomass and conversion to fuels are treated as linear factors that convert biomass to fuel for a single set cost. The fuel market is simulated using elasticities of demand for gasoline and elasticity of substitution between gasoline and ethanol. Also, gasoline price is responsive to changes in demand as ethanol elbows its way into the market. Khanna and her co-authors make use of the detailed data within the model to report endogenously calculated emissions of greenhouse gases.

The Forest and Agricultural Sector Optimization Model – Greenhouse Gas Version (FASOMGHG) is an integrated economic model of the forest and agricultural sectors with a focus on land allocation decisions and subsequent impacts on greenhouse gas emissions (Daigneault *et al.*, 2009). It was used by the EPA in analyzing the RFS2 policy with two main goals (US EPA, 2010). First it provided the economic basis for the allocation of lands to energy crop production. Second it provided the domestic indirect land use change greenhouse gas emission component in analyzing the greenhouse gas impact of the fuel pathways (US EPA, 2010).

The economic models of the agricultural sector treat biomass as having a single value across all locations and types of biomass. This is not an accurate description of biomass for several reasons. Spatial markets will result from the high cost of biomass transportation and discrete locations of large biomass consumers. Biomass producers located near the large consumers of biomass can demand higher prices for their biomass and therefore be more profitable than producers far from the consumers with the same costs of production. Additionally, the term biomass refers to a *heterogeneous* set of materials of recent organic origin. This heterogeneity will be exploited to maximize the benefits of using biomass. The value of biomass generally varies with its end use. A bale of switchgrass has a value to a feedlot based on the nutritional content. The same bale is valued by its cellulose/hemicellulose content by a biochemical ethanol producer and by its heating value (and ash properties) by thermochemical biofuel producers and electricity producers. These three aspects of a biomass feedstock are not proportional and different end users will value different biomass differently. In a simplified world, the end user with the highest value sets the price. Due to these two aspects of biomass it is important to consider both the value of the end use product and the location of the consumers of biomass when projecting supplies of biomass in a competitive market.

Other approaches to economic modeling of biomass and biofuels have focused on the energy market. Two studies to date demonstrate this approach. Alfstad (2008) used the Department of Energy-Energy Technology Perspectives (DOE-ETP) MARKet ALlocation (MARKAL) model to analyze the likely outcome of the RFS2 biofuels mandate in the United States. MARKAL models are dynamic energy sector models with rich supporting information on technologies, resources and markets for energy products. The MARKAL framework uses a least-cost criterion for choosing between energy pathways to meet specified energy demands. In order to focus on biofuels, Alfstad and his collaborators updated the biomass resource assessments and the technology models for biofuels production in the United States and countries most likely to export fuels to the United States and imposed the constraints of the RFS2 policy. The results predict that the mandate will not be met without overcoming significant barriers on the market and infrastructure side of the equation. However, due to the nonspatial nature of these findings, they are more a reflection of assumptions in the model than analysis.

The BioTrans model has been developed to study biofuel transitions in Europe in reaction to policy mandates for biofuels (Lensink and Londo, 2010). It uses a least cost network flow modeling framework to choose biofuel pathways in order to meet mandated production targets. Built with the purpose of analyzing biofuels, it makes several improvements while sacrificing complexity of market interactions in both the agricultural and energy markets. The spatial resolution is country-level for everything except the biomass supply, which is done at a sub national scale. It makes an explicit characterization of marginal lands and the economics of potential energy crop production – yields, cost of production and revenue from an incumbent crop. Multiple technologies compete for resources and fuel market share. Each year is solved successively with installed capacity impacting the conversion cost through learning curves. Despite the focus of dynamics there is no consideration of sunk capital costs and existing capacity. De Wit *et al* (2010) used BioTrans to demonstrate the potential for large market shares for biodiesel in the European market by 2030 and found that technological lock-in is a likely outcome if policies are not designed to diversify the market. The method is limited in that it uses set transportation distances for intra-country deliveries and linear conversion costs.

To address the spatial aspects of biofuels production, a significant literature exists that focuses on understanding the best way to design bioenergy supply chains. A number of studies have focused on optimal biorefinery siting relative to the resource, given a standard biorefinery size (Graham *et al.*, 2000; Zhan *et al.*, 2005). Other studies explore the tradeoff between biorefinery size and feedstock transportation cost (Kaylen *et al.*, 2000; Kumar *et al.*, 2003).

Several recent papers have begun to address the design of a biomass-based industry in a full optimization framework. Freppaz developed a decision support system for the exploitation of forest resources considering multiple energy products and the spatial layout of both the supply and demand (Freppaz *et al.*, 2004). My previous work has included research on the siting and sizing of biomass hydrogen biorefineries exploiting California's rice straw resource (Parker *et al.*, 2008) and biofuels production in the western United Sates (Parker *et al.*, 2010). Schmidt *et al* (2009) developed a spatially explicit supply chain optimization to compare the cost-effectiveness of CO_2 emissions reduction through heat, electricity or fuels production using woody biomass in Austria. The methods used are similar to the methods presented in this dissertation. The main differences are that continuously variable biorefinery sizes are used here while Schmidt *et al* use discrete sizes and the objective is to minimize cost rather than maximize profit. Schmidt and his co-authors use a prescreening method to select potential biorefinery sizes.

These studies have necessarily limited their scopes due to computational and data availability concerns. In order to be used for policy analysis these models need to have an expanded scope that studies large regions such as the United States or the European Union.

The biofuel infrastructure models borrow their analytical formulation from the field of facility location within the field of operations research. For a good background on the facility location problem, see Owen and Daskin (1998). Melo *et al* (2009) provides a recent review of supply chain management studies with facility location. Melo points out that surprisingly few studies of facility location and supply chain management use a profit-maximizing objective despite it being the presumed goal of all industries that are modeled. The profit-maximizing objective described later is a key component to enable policy analysis within the framework.

2.2.1 Summary

The three approaches described above focus on different important traits of the biofuel pathway. The agricultural partial equilibrium models have the strongest representation of the supply of energy crops incorporating the competition for scarce land resources between conventional food crops and energy crops. In general, they either ignore or simplify the infrastructure and conversion technology considerations. The infrastructure models provide the opposite, focusing on the important spatial features and layout of biorefineries while using a simplified resource assessment and considering small regions. The “bottom-up” engineering-economic models bring in the dynamic aspect on the technology side and the full energy market but sacrifice the detailed spatial aspects of resource supply and biofuel system layout. The work presented in this dissertation is a spatially explicit infrastructure model that has been demonstrated at the U.S. national scale. The main advantages of this approach are the following. First, explicit consideration is given to the tradeoff between economies of scale and transportation costs that is constrained by real-world geographic information. This not only improves the estimate but also guarantees that the modeled system is anchored to a realistic supply system. Second, the use of a profit-maximizing framework allows greater flexibility in the types of questions that can be asked. For example, the impact of incentives in the form of subsidies can be analyzed or the impact of spatial variation in fuel prices can be considered. Finally, the data intensive approach based in engineering estimates of costs provides a relatively transparent and flexible model for analyzing the sensitivity of the highly uncertain parameters involved in projecting future fuel supplies.

3 METHODOLOGY

The methodology used here is to build a series of scenarios varying policy, market and technology parameters that influence the design of the biofuel industry. The industry is then modeled using a spatially explicit integrated supply chain model. This model describes the optimal behavior of a biofuel industry given a fuel demand, biofuel selling price, and feedstock supply constraints. If biofuel can be delivered to the fuel terminals for less than the given selling price then it is profitable for the industry to supply that biofuel and the infrastructure is built to reap that profit. If biofuels cannot be delivered for less than the selling price then the fuel demand is met with conventional fuels at the given selling price. In addition, when demand for fuel exceeds the supply of feedstock, the difference is made up with conventional fuels.

The model has been adapted to be responsive to policy and market conditions. This is made possible by (1) flexible spatially explicit resource and technology assessments, (2) a mixed integer-linear supply chain optimization model, (3) spatial models of transportation costs and (4) an environmental accounting model of emissions and resource consumption.

For each scenario, the optimal designs of the biofuel systems are found over a range of prices in order to produce supply curves. The supply curves show the quantity of fuel that would be made available at a given market price for biofuels. In economic terms they are considered long-run marginal cost curves for biofuel production as they account for both capital and operating costs. Along with these optimized supply curves, estimates of greenhouse gas emissions, emissions of criteria air pollutants, water demand, consumption of primary energy sources, land use changes, and types and quantities of biomass consumed can be made subject to data availability at each price point.

To develop optimal biofuel system designs, a number of models are integrated to work together, enabling a systemic view while maintaining computational feasibility. At the center of the integrated model is the supply chain optimization model that sites and sizes biorefineries, allocates the resources to the biorefineries and allocates the fuel produced to the demands. External models provide the input parameters for this optimization model. The resource is spatially characterized using a Geographic Information System (GIS) model that integrates and expands several existing resource assessments. Fuel demand is characterized using a spatial demand assignment model and allocated to fuel distribution terminals. Transportation cost calculations are performed in a GIS network model. The biorefinery cost and performance are described by a spreadsheet engineering model that simplifies the production costs into an integer-linear function of the fuel output and biomass inputs.

3.1.1 Major Strengths and Weaknesses of the Modeling Framework

The proposed approach is an engineering-centric method for developing supply curves. It focuses on the details of engineering costs, environmental impact accounting and spatial modeling. This approach enables meticulous analysis of the variation in environmental impacts, supply and cost of a variety of biofuel pathways with real-world geographies. Capturing the richness of this variation in biofuel pathways will provide insight in the degree to which biofuels can accomplish policy goals. The major weakness of this approach is that agricultural and energy markets are not endogenously considered.

The framework proposed here does not naturally lend itself to the study of economic feedback loops that the industry will create. First, demand for feedstock does not impact the modeled cost of acquiring the feedstock. Since the model maximizes total industry profit, a portion of the profit is expected to flow to the feedstock providers. Second, it is assumed that the modeled biofuels industry does not create any impact on the market price of the co-products. Because the co-product markets are not endogenously considered, sensitivity analysis is required. Finally, it is assumed that the consumption of biomass waste and residue streams does not impact the industries producing the wastes and residue streams. Additionally, biorefineries are developed in a cooperative fashion, which maximizes profit for the industry as a whole, not considering individual market actors. These limitations are due to simplifying assumptions for the model. The simplifications allow the model to focus on spatial aspects – resource and demand layout and infrastructure design – including the secondary market effects would require an iterative approach to finding market clearing prices that would lead to significantly longer computation times.

3.2 Overview

A geographically explicit biomass resource assessment and infrastructure network model is integrated with technoeconomic models of the conversion technologies and an emissions inventory model to provide analysis of potential biofuel supply pathways. The analysis has five main components – 1) geographically-explicit biomass resource assessments, 2) engineering/economic models of the conversion technologies, 3) models for multi-modal transportation of feedstock and fuels based on existing transportation networks, 4) a supply chain optimization model that designs the fuel production system based on inputs from the other models, and 5) an emissions inventory model that calculates the emissions resulting from the designed supply chain. The optimization and emissions inventory models are described below.

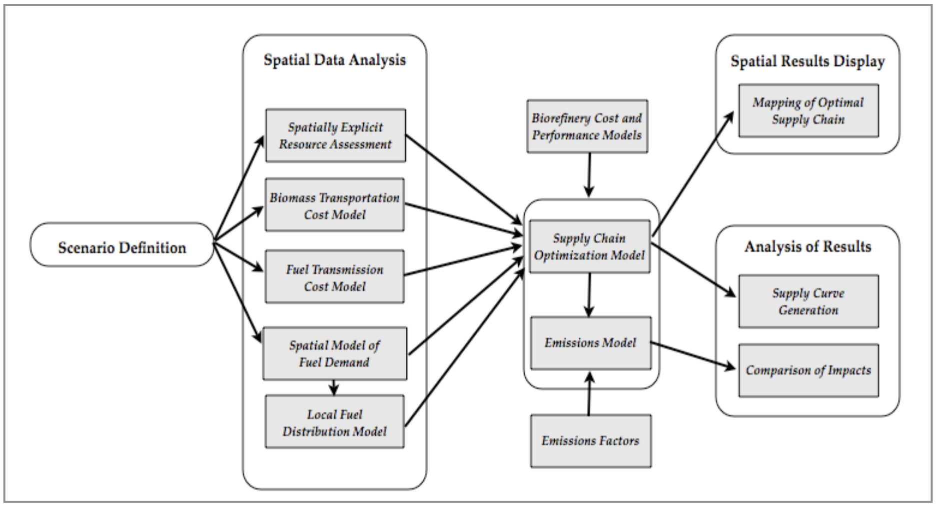

Figure 1: Model organization and interaction of submodels

3.3 Supply chain model formulation

3.3.1 General formulation

The optimization model is formulated as a deterministic, multi-commodity, capacitated facility location problem. A biofuel supply chain optimization model was developed to consider explicit spatial distributions of biomass supply and fuel demands, competition among technologies for resources, and the economies of scale of conversion technologies in finding the best design for biofuel supply chains. The model locates, sizes, and allocates feedstock to biorefineries with the objective of maximizing the profitability of the industry as a whole. The profit considered is the sum of the profits for each individual feedstock supplier and fuel producer over the entire study region. Costs considered are those associated with feedstock procurement, transportation, conversion to fuel, and fuel transmission to distribution terminals. Fuel production and selling price determine industry revenue. The selling prices of the product fuels are input parameters that are varied to create a supply curve.

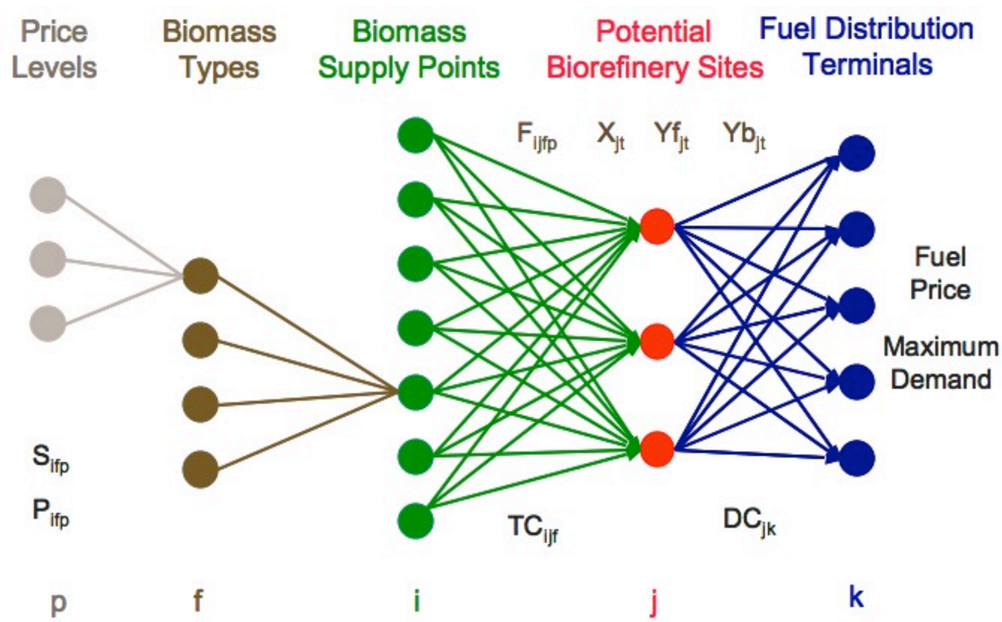

Figure 2: Schematic of optimization model.

The model is formulated as a mixed integer linear program. Decisions integrated into the model are whether to build a biorefinery of a given technology type, 't', at a given site, 'j', (X_{jt}); if built, how many dry tons (US) of feedstock of type, 'f', is consumed per year by the biorefinery (Yf_{jft}), the quantity of fuel product type 'p' produced (Yb_{jpt}) measured in millions of gallons per year (MGY), the fuel distribution terminals to which the fuel is delivered (T_{jkt}), and which feedstock supplies, located at location, 'i' at a particular procurement cost level, 'c', are exploited by the facility (F_{ijfc}) measured in dry tons per year. Feedstock supply curves for each feedstock and supply point are defined at discrete cost levels in the model. These decisions are made for all potential sites simultaneously with no double counting of resources. The objective of the program is to maximize the total annual profit of producing and delivering biofuels to distribution terminals. The profit is defined here as the annual revenue from the sale of biofuels and co-products less the annual cost of producing those biofuels.

Table 2: Model variables and indices

Set Index	Description	Unit
i	supply location	
j	potential biorefinery location	
k	fuel terminal location	
f	feedstock type	
t	conversion technology	
p	product type	
c	procurement cost level	
e	emission (CO, CO2, NOx, etc…)	
Variables		
F_{ijfc}	Feedstock transported	dry tons per year
X_{jt}	Biorefinery built or not	[0,1]
Yf_{jft}	Feedstock consumption	dry tons per year
Yb_{jpt}	Product output	gallons/kWh per year
T_{jkp}	Product deliveries	gallons per year
Ie	Total emissions from modeled industry	tons per year

Table 3: Model parameters

Parameters	Description	Unit
S_{ifc}	Maximum available supply	dry tons per year
D_{kp}	Maximum demand at terminal 'k'	gallons per year
P_{ifc}	Procurement cost	$/dry ton
TC_{ijf}	Feedstock transport cost	$/dry ton
DC_{jkp}	Product transport cost	$/gallon
a_{jt}	Fixed biorefinery annualized cost	$/year
b_{jft}	Feedstock dependent biorefinery cost	$/dry ton
c_{jpt}	Product dependent biorefinery cost	$/gallon or kWh
MP_{kp}	Market price of product	$/gallon or kWh
η_{fpt}	Conversion factor	unit per dry ton
gge_p	Conversion factor for transforming all fuel products from volumetric units to energy units of gge	gge/gallon
M_{jt}	Maximum biorefinery size	dry tons per year
δ	Relaxation parameter for the proportional blend requirement	
ϕ_k	Fraction of national vehicle miles traveled allocated to terminal 'k'	
γ_p	Fraction of LDV fuel demand that can be met by fuel 'p'	
LDV fuel demand	Demand for light duty vehicle fuels in the analysis year	Gallons of gasoline-equivalent per year
CP	Carbon price	$/ton CO2-eq
CI_{pt}	Carbon intensity of fuel product 'p' produced using technology 't' due to conversion process	tons CO2-eq/gallon or kWh
CI_{ft}	Carbon intensity related to the production and consumption of feedstock 'f' using technology 't'	tons CO2-eq/dry ton
FC_{ifc}	Diesel consumed in harvest/ production of biomass	MMBtu/ton
EF_{em}	Emissions factor for emission 'e' per unit of diesel fuel consumed by mode 'm'	grams/MMBtu
EF_{fe}	emissions factor for emission 'e' for feedstock harvest/production from non-diesel inputs	grams/ton feedstock
EF_{te}	Emission factor for emission 'e' from the conversion of biomass to fuel through technology 't'	grams/ton feedstock
FE_m	Fuel economy of transport by mode 'm'	MMBtu/ton-mile
d_{mij}	Miles by mode for each link in the feedstock supply chain	miles
ρ_p	Specific volume of product fuels	gallons/ton
MC_f	Moisture content of feedstock type 'f'	ton H_2O/wet ton feedstock
GWP_e	Global warming potential of emissions species	tons CO2-eq/ton

The revenue is determined by the quantities and selling prices of the products (MP_{kp}). In the model formulation, the energy products are differentiated from other co-products. Non-energy co-products are included in the cost function (as negative variable cost) while energy co-products are part of the revenue. The costs considered are the procurement of feedstock (PC_{ifc}), the transportation of feedstock to the biorefinery (DC_{ijf}), the transportation of the product fuel to the distribution terminals (TC_{jkp}) and the conversion cost. The conversion cost is dependent on the size of the biorefinery. I characterize it here as a binary-linear function with a fixed cost (a_t) if a facility is built and a variable cost (b_t) dependent on the capacity of the biorefinery expressed in terms of feedstock input (Yf_{jft}).

$$Profit = \sum_{jkp} MP_{kp} \cdot T_{jkp} - Cost \tag{1}$$

$$Cost = \sum_{ijfc} [PC_{ifc} + DC_{ijf}] \cdot F_{ijfc} + \sum_{jt} a_{jt} \cdot X_{jt} + \sum_{jt} b_{jft} \cdot Yf_{jft} + \sum_{jpt} c_{jpt} \cdot Yb_{jpt} + \sum_{jkp} TC_{jkp} \cdot T_{jkp}$$

The objective function is combined with a number of constraints representing the physical limitations or restrictions of the biomass industry in the mathematical model. The first set of constraints limit the biomass originating from a source at a price level to be less than the maximum supply of biomass of that type and price level at that source (S_{ifp}) (equation 3).

$$\sum_{j} F_{ijfc} \leqslant S_{ifc} \qquad \forall\, ifc \tag{3}$$

The biofuel produced at a biorefinery is equal to the quantity of biofuel that can be produced from the biomass entering the biorefinery, given the conversion efficiency (η_{ft}) including handling loss (equation 4). I also relate the biorefinery biomass input capacity to the biomass coming into the facility (equation 5) and the product fuels leaving the biorefinery to the production of biofuel at the biorefinery (equation 6).

$$Yb_{jpt} = \sum_f \eta_{fpt} \cdot Yf_{jft} \qquad \forall\ jpt \tag{4}$$

$$\sum_{ic} F_{ijfc} = \sum_t Yf_{jft} \qquad \forall\ jf \tag{5}$$

$$\sum_k T_{jkp} \leqslant \sum_t Yb_{jpt} \qquad \forall\ jp \tag{6}$$

The size of the biorefinery must be zero if the fixed cost has not been paid (binary variable at that site is 0). If the binary variable is 1 then the biorefinery can be no greater than its maximum allowable size for the technology (M_t) (equation 7).

$$\sum_f Yf_{jft} \leqslant M_{jt} \cdot X_{jt} \qquad \forall\ jt \tag{7}$$

Fuel demand is limited at each terminal to represent either technical or policy constraints to the consumption of the fuel at that terminal. Different approaches for this spatial fuel demand constraint are discussed in section 3.3.2.

$$\sum_j T_{jkp} \leqslant D_{kp} \qquad \forall\ kp \tag{8}$$

Non-negativity constraints

All variables representing physical quantities must take on either a zero or positive value (equation 9). The binary variable for the existence of a biorefinery must take on a value of zero or one (equation 10).

$$F_{ijfc}, Yf_{jft}, Yb_{jpt}, T_{jkp} \geqslant 0 \tag{9}$$

$$X_{jt} \in [0,1] \tag{10}$$

Each model run gives results of the industry-wide fuel production for a given price; which biorefinery locations are optimal and how big they are; and which biomass resources are used at each biorefinery. Multiple model runs are performed over a range of fuel prices. Plotting the industry production against fuel price gives the supply curve.

3.3.2 Approaches to spatial fuel demand constraint

Fuel demand at each terminal can be limited in a number of ways. The assumption used in the baseline model is that a proportion of fuel deliveries of a specific fuel type to each terminal must not be greater than δ more than the proportional vehicle fuel demand allocated to the terminal (equation 11). The parameter δ provides the model a small degree of flexibility in fuel deliveries. The choice of this parameter is a tradeoff between computational difficulty and the desired strictness of the constraint. The fuel demand is allocated by the fraction of the national VMT within the terminal's service territory; this value is the parameter ϕ_k. Alternative formulations could include a blend wall (equation 12), where γ_p represents the allowable blend fraction of a given fuel. Modeling E85 infrastructure requires changes to the objective to track the cost of installing E85 fuel pumps and additional constraints to track the quantities of ethanol used in E85 versus E10. I have not modeled in this analysis the required number of E85 stations in a region to accommodate full use of E85 in flex-fueled vehicles.

$$\bar{D}_{kp} = \delta \cdot \phi_k \cdot \sum_{jt} Yb_{jpt} \qquad \forall\, kp \tag{11}$$

$$D_{kp} = \gamma_p \cdot \phi_k \cdot LDV\ fuel\ demand \qquad \forall\, kp \tag{12}$$

3.3.3 Approaches to handling greenhouse gas emissions

In a carbon-constrained world, an economic cost will exist for greenhouse gas emissions that must be accounted for in the profit equation of the biofuel industry. Two options have been explored for incorporating greenhouse gas emissions into the economic model. The first and simplest method uses default carbon intensity values for different classifications of fuels. For example, wet mill corn ethanol facilities can be given a value of 100 g MJ^{-1} of carbon dioxide equivalent emissions while ethanol from corn stover is given a value of 20 g MJ^{-1}. Using this method converts the cost equation to Equation 13. This method requires established emission factors for each biofuel pathway considered, which are not well known in some cases. Furthermore, existing emissions factors may not match the exact pathways being modeled and therefore are not true measures of the modeled biofuel supply.

$$Cost = \sum_{ijfc} [PC_{ifc} + DC_{ijf}] \cdot F_{ijfc} + \sum_{jt} a_{jt} \cdot X_{jt} + \sum_{jt} b_{jft} \cdot Yf_{jft} + \sum_{jpt} c_{jpt} \cdot Yb_{jpt} + \sum_{jkp} TC_{jkp} \cdot T_{jkp} + CP \cdot [\sum_{jpt} CI_{fpt} \cdot Yb_{jpt} + \sum_{jft} CI_{ft} \cdot Yf_{jft}] \quad (13)$$

Alternatively, emissions for the biofuel pathways modeled can be tracked within the model to provide accurate estimates of the specific pathways modeled down to the transportation distances and modes. This method presents its own difficulties in data requirements and ensuring consistency. It is also not used in the current regulatory environment. The California Air Resources Board, the US EPA and UK Renewable Transport Fuel Obligation all use a default and opt-in framework for determining the carbon intensity of a specific batch of fuel. The emissions tracking model is described by Equation 14.

$$I_e = \sum_{ijfc} [FC_{ifc} \cdot EF_e^{tractor} + EF_{fe}] \cdot F_{ijfc} + \sum_{ijfcm} d_{ij}^m \cdot FE^m \cdot EF_e^m \cdot F_{ijfc} / (1 - MC_f) + \sum_{jft} EF_{te} \cdot Yf_{jft} + \sum_{jkpm} d_{jk}^m \cdot FE^m \cdot EF_e^m \cdot T_{jkp} / \rho_p \quad (14)$$

$$Cost = \sum_{ijfc} [PC_{ifc} + DC_{ijf}] \cdot F_{ijfc} + \sum_{jt} a_{jt} \cdot X_{jt} + \sum_{jt} b_{jft} \cdot Yf_{jft} + \sum_{jpt} c_{jpt} \cdot Yb_{jpt} + \sum_{jkp} TC_{jkp} \cdot T_{jkp} + \sum_{e} CP \cdot GWP_e \cdot I_e \quad (15)$$

The emission factor formulation (equation 13) is appropriate for analysis of the industry response to policies with default values for different pathways. It can also give a better representation of the carbon impacts in some cases. For example, the best value for the carbon intensity of a bushel of corn may not be the carbon intensity for the particular bushel used but rather the marginal bushel on the world market.

3.3.4 Alternative cost minimization model

The modeling approach taken here is to develop a profit-maximizing model. In many cases, a profit-maximizing model yields the same results as a cost minimization model. However, a profit maximizing model has several characteristics that make it more advantageous than cost minimization for this particular application.

The first advantage of profit maximization is the flexibility of constraints it allows. In cost minimization, some constraints must be predetermined that are not necessary for profit maximization. For example one must minimize cost subject to the full utilization of the resource or satisfying a predetermined demand. These constraints are necessary to prevent the model from always producing a null answer. The constraints have the disadvantage of reducing the model's flexibility. In choosing the optimal design, fractional levels of resource use and demand satisfaction may be the best option. This is especially true for modeling the biofuel industry which will account for a fraction of the fuel market into which the biofuels are sold. A profit maximizing approach avoids these issues by allowing the model to choose which resources to use and which demands to serve based on balancing the costs of production of a good with the price of the good.

The second advantage is in the interpretation of the results. A profit maximizing approach seeks to resolve the question about how much fuel can be produced from a resource while recognizing the importance of market prices for answering the question.

A third advantage is that with mixed integer-linear models the marginal values are not reliably obtained. Economic theory tells us that the marginal cost is the interesting metric for evaluating cost of meeting a production target for any good. The profit maximizing model – as the dual problem to cost minimization – provides this information in a straightforward manner.

The last advantage of the profit maximizing method is that it allows for infrastructure design to respond to price differentials between demand centers. This feature can be used to replicate the disparate fuel prices currently seen across space or to evaluate regional policies that may attract biofuels to a region such as California's Low Carbon Fuel Standard. The model can be used to evaluate the prices that California would need to pay in order to attract enough low carbon biofuels to meet the standard.

Despite the advantages of the profit-maximizing model, some research questions are better suited to a cost minimization approach of the model. Conversion from the profit-maximizing framework to a cost minimization is straightforward. The objective is replaced by an objective to minimize the cost and a binding constraint must be introduced.

Depending on the research question, either the supply or the demand can be binding constraints. In the case of a mandated volume of fuel, an interesting question is: what is the least cost system for meeting the mandate? The total demand becomes the binding constraint, as seen in Equation 16. In some cases, the research may be interested in the least cost system for utilizing a certain resource. For example, the results of an agricultural-economic model may give the production of biomass at $40/ton at the roadside. This assessment depends on all farmers being able to get that price and so all the resource must be used for a consistent biofuel supply assessment. In these cases, Equation 17 replaces the supply constraint (Equation 3) in the generic formulation.

$$\sum_{jkp} \bar{T}_{jkp} = Demand \tag{16}$$

$$\sum_{j} F_{ijfc} = Supply_{ifc} \qquad \forall\, ifc \tag{17}$$

Greenhouse gas emissions may also provide a binding constraint for a cost minimization model. Either as an absolute reduction against the baseline gasoline or by expanding the system boundaries to include petroleum fuels production. As a reduction against the baseline the constraint can be formulated as Equation 18.

$$\sum_{p} CI^{gasoline} \cdot gge_{p} \cdot T_{jkp} - \sum_{e} GWP_{e} \cdot I_{e} \geqslant GHG^{target} \tag{18}$$

3.3.5 Competition with other biomass consuming industries

Competition for biomass feedstock between industries is an expected outcome of the combination of policy, market, and technology developments that seek to move away from fossil feedstocks for many sectors including electricity, fuels, plastics, and chemicals. These new and increased uses for biomass will impact the cost of providing biofuels by providing a competing use for biomass. Each sector has its own characteristics of quantities, technologies, yields and prices that influence the competitiveness of each for limited biomass resource. The generic model can easily accommodate these uses of biomass, provided availability of the needed data. The nonfuel markets would be added as additional products from biorefineries with the conversion technology models updated to include the technologies to produce the alternative biomass-based products. An example of this considering competition between electricity and biofuel sectors can be found in Tittmann, *et al* (2010).

3.3.6 Linking to results from agricultural economic models

Agricultural economic models are arguably the preferred method for a resource assessment for agricultural biomass. The predominant method for performing a resource assessment with agricultural economic models is to set a farm gate price for biomass as a perturbation of the existing agricultural system and find out how the introduction of this new commodity impacts the system. For the purposes of the proposed modeling framework this is problematic. To remain consistent with results of agricultural economic models, only biomass corresponding to a single farm gate price can be used and all of the biomass available at a single farm gate price must be consumed if any of it is consumed. This type of resource assessment does not fit neatly into the modeling framework.

To address this shortcoming two approaches can be taken. The first is to employ the cost minimization version of the model for each farm gate price. The second is to loop the profit maximizing analysis to find the price point where all or almost all of the biomass available at a farm-gate price is consumed. The second approach allows for the integration of other resource assessments with the agricultural resource assessment and for the model to exclude a small fraction of resources that are unattractive mostly due to high transportations costs associated with remote locations or feedstocks with especially low conversion efficiencies. I prefer the second approach.

3.4 Submodels

3.4.1 Conversion technology characterization

A central component of the supply chain optimization model is the characterization of the cost and performance of each biorefinery. Spreadsheet engineering/economic models of the conversion technologies are developed based on literature. These models standardize the accounting framework and allow for key parameters to be analyzed. The model outputs an integer-linear function for production costs, yields over a range of feedstock types, and environmental performance. The integer-linear functional form is used because it allows for the inclusion of economies of scale in a model that is computationally feasible.

The costs of production consider capital, operating and maintenance and non-feedstock input costs. The capital costs are annualized based on a given discount rate and economic lifetime for the biorefinery. The annualized costs of production for the biorefinery are calculated for the size range considered valid for the technology characterization. To convert the polynomial functions into linear functions, a linear regression is performed on the annualized costs to give the parameters a_t, and b_t used in the annual cost equation (equation 2). If there is a strong dependence on the product capacity as opposed to the feedstock capacity, then the parameter c_t is estimated. Similarly if there is a compelling reason to consider each feedstock differently then a set b_{ft} can be found. The parameter M_t is the upper limit for the biorefinery size in terms of feedstock capacity, which is taken from the technology characterization.

The technology characterization models are designed to flexibly react to changes in assumptions, automatically updating the parameters for the optimization model. When existing biorefineries are considered, the capital costs are either set to zero – as a sunk cost – or depreciated based on the age of the existing facility.

It is important to note that the linear regression of the economies of scale for the biorefineries can change the nature of the production function. Linearizing the annualized cost of production converts any constant economy-of-scale production function to a decreasing economy-of-scale production function with implications for any resulting conclusions on optimal facility size. The linearized model will generally predict smaller optimal facility sizes than a model would using the functional form presented in the literature. Conversion to integer-linear production functions is required in order to avoid cost equations with terms X^{α}, where $0 < \alpha < 1$. These types of functions perform poorly using existing optimization algorithms when X can equal zero.

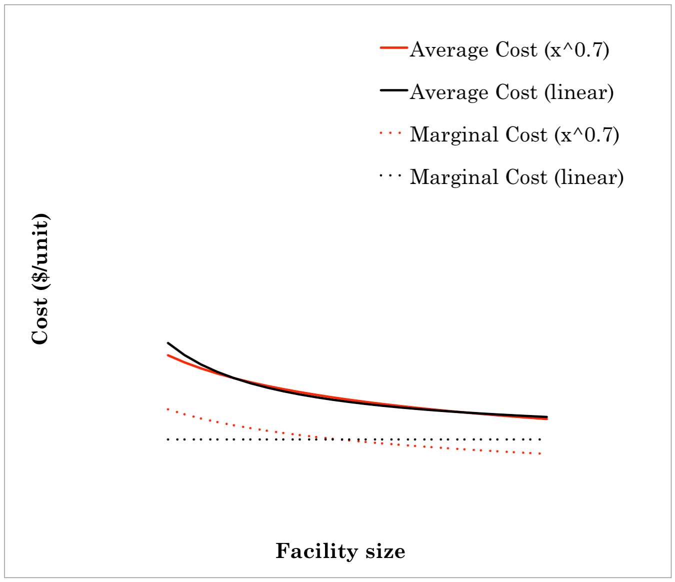

Figure 3: Impact of linearizing the conversion cost models on average and marginal costs – axis intentionally left blank

3.4.2 Resource assessments

The resource assessments can come from a variety of sources and methodologies. More detail on the resource assessment methodologies is provided in the section 4.2. The assessments need to be standardized for use in the model. The resources need to be located and made to conform to the discrete supply curve framework of the model.

The resources are given a geographic identifier matched to a point layer in the GIS. County resolution data are mapped to the county centroid. Municipal data are resolved to the city center. These point sources for the resources are connected to the transportation network by a shortest path algorithm so that their transportation costs can be calculated.

All discrete procurement costs (costs at the roadside of the supply location) provided in the assessment become unique identifiers of the set of procurement cost levels (the index 'c' in the formulation). Marginal additions of biomass supply are denoted for each feedstock type, location and procurement cost level. Some resource assessments are reported in cumulative quantities and are converted to marginal quantities. When available, emission factors for the biomass supplies are recorded to the database using the same identifiers.

3.4.3 Potential biorefinery locations

Selecting a set of potential biorefinery locations can be done in a number of ways. The goal in selecting potential locations is to include all locations that may be optimal while limiting the total number of potential locations to ease computational effort. One method is to use all supply locations as potential locations. In most cases this provides more locations than are needed. Potential locations that are close together can be effectively redundant but cause significant issues with the computational effort of deciding between two nearly identical outcomes.

An alternative approach that is taken here is to limit the potential locations based on logical constraints and then reduce the number by removing redundant locations. Logical constraints include the following:

adequate population to provide workforce, access to transportation infrastructure (major highways and rail lines) or the existence of a similar facility such as a pulp mill or biomass power plant. The criteria used here are taken from Tittmann, *et al* (2010) and can be described as follows.

Potential locations are a subset of cities in the region. Cities are included if they have existing petroleum refineries, existing or proposed biomass conversion facility or existing industrial facility with similar requirements. Cities without existing facilities but with connectivity to infrastructure are considered if their population is greater than 10,000. Infrastructure connectivity is defined as maximum distance to a railroad less than 5 km or maximum distance to a marine terminal less than 15 km. Removing facilities that are less than 50 km apart further reduces these potential locations. In this case, the largest city of the cluster is chosen to be the representative potential location.

Using the largest city in the cluster results in all large population centers being chosen as potential locations. The exact locations used in the model are not likely good candidates in these cases. However, the transportation costs to the location is representative of the area within 50 km of the location. In most cases, there will be an appropriate site within that distance. The emphasis of this analysis is solving a national scale implementation for policy analysis which requires ignoring some details in the local geography.

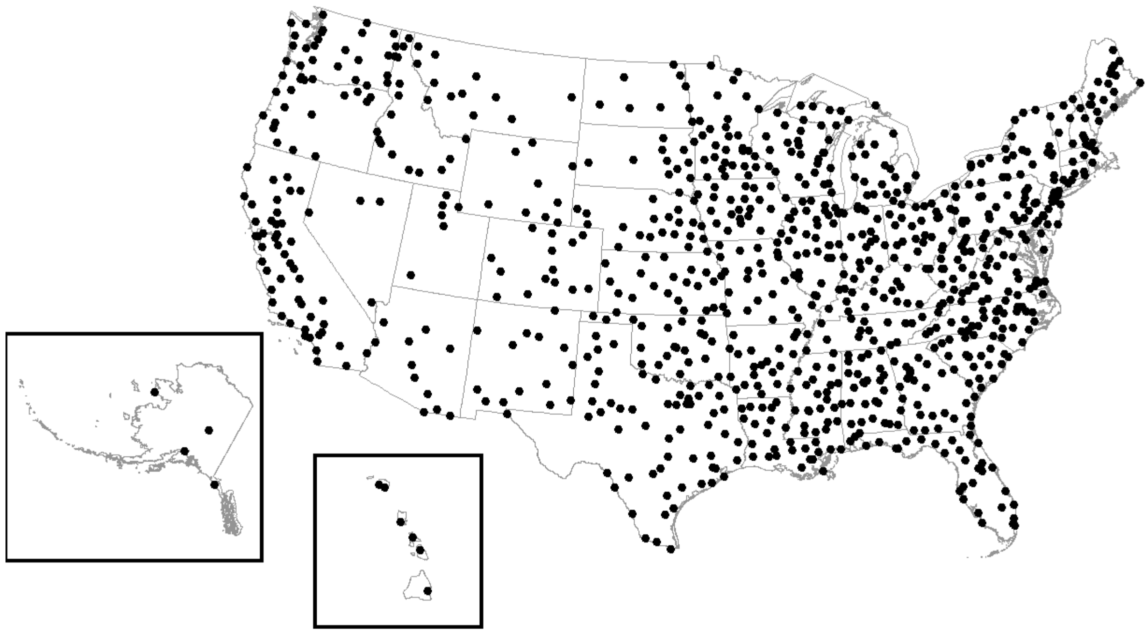

Figure 4: Potential locations for biorefineries

3.4.4 Transportation network model

The transportation costs are modeled using the Network Analyst feature in ArcGIS (McCoy, 2005). The unit costs for all potential links – cost of transporting one ton of biomass or one gallon of fuel between each source and biorefinery or each biorefinery and fuel distribution terminal – are calculated over the transportation network and passed to the supply chain optimization model. This includes loading and unloading costs in addition to the distance dependent costs. The transportation network consists of a GIS network of the road, rail, and marine routes available for transporting feedstock and fuel along with a set of engineering economic models for the cost and performance of the transportation modes for each feedstock and fuel type.

In addition to the unit cost of transportation on a given link, the route distance by mode and fuel use is calculated for the chosen routes. These can be used to provide emissions accounting data and to adjust the cost of transportation to quickly reflect sensitivities to the fuel price. Full accounting for fuel price changes would require re-optimizing the routes as route choice and mode switching may occur. The benefit of performing the re-optimization of routes would be small compared to the effort required and therefore it is not performed.

The optimal route choice for any given origin and destination pair and its cost are not impacted by the design of the biofuel industry. The additional congestion caused by the biorefinery is not modeled in the work to date. Accounting for the congestion costs would require an iterative process of solving the optimization model, updating the cost function, resolving the network analyst, then resolving the optimization model and repeat until convergence.

3.5 Defining the appropriate spatial resolution for analysis

The main advantage of the approach developed in this dissertation compared with previous approaches is the explicit consideration of space. The choice of spatial resolution for the analysis presents a tradeoff between improving model fidelity and increasing computational effort. At the extremes, low resolution can aggregate resources to greater than the biorefinery maximum size – negating the value of the optimization model – and high resolution can lead to a computationally intractable model. An additional consideration in this tradeoff is the resolution of credible and consistent resource data for the scope of the analysis.

There are three aspects of spatial resolution. First is the resolution of the resource assessment. In most cases, the resource assessments spatial resolution is going to be limited by the available underlying data. The second aspect is the resolution of the potential biorefinery locations. As discussed earlier, the resolution of the set of potential locations can be limited by aggregating qualifying locations that are redundant for the purposes of modeling. Finally the resolution of the fuel demand needs to be considered. I have chosen to aggregate fuel demand to fuel distribution terminals. Extending the analysis to refueling stations would require an increase in the number of fuel delivery variables for each refueling station in the region of analysis.

4 Conversion Technologies

In this chapter, I provide the background on the literature of biofuel conversion technologies that are used in the following case studies. Costs and performance are described for a range of current and future conversion technologies. The data used in the national case study is described and set in the context of the existing literature.

The technologies to produce biofuels are in various stages of development. Some, corn ethanol and FAME biodiesel, are currently operating commercially. These technologies have well known current costs and informed projections of how they will develop in the future. Other technologies are in early demonstration phase. The best available estimates for these technologies are from detailed techno-economic modeling and evaluations. The diversity of uncertainty between the different technologies needs to be recognized in evaluating the relative costs.

Table 4: Summary of Conversion Technology Status and Cost Models Used

	Corn Ethanol	FAME	Cellulosic Ethanol	F-T Diesel
CURRENT TECH. STATUS	Commercial	Commercial	Demo	Demo
COST MODEL				
Current tech	X[1]	X[2]		
Future tech c. 2018 (nth plant)			X [3]	X [4]

[1] (Antares, 2009; Shapouri and Gallagher, 2005)
[2] (Antares, 2009)
[3] (Antares, 2009; Laser *et al.*, 2009; Hamelinck, 2006)
[4] (Antares, 2009; Hamelinck, 2006)

The Antares Group, LLC as part of a collaborative project (Antares, 2009), developed many of the conversion technology models used here. I have departed from these models in the cases of cellulosic ethanol where the rest of the literature points to a more conservative view of the technologies for the 2017-2022 timeframe and for biomass-based Fischer-Tropsch diesel where a significant fraction of the literature is more optimistic. In both cases, optimistic and pessimistic technology models are presented.

The cost data are presented in year 2008 constant dollars with 2018 energy prices taken from the Annual Energy Outlook 2010 (EIA, 2010) unless otherwise noted. The data from the referenced papers have been modified to be consistent using a simple levelized cost of production found using equation 19 with an after tax real internal rate of return of 10% and a 20 year lifetime, unless otherwise noted. The capital and maintenance costs were adjusted from each study to year 2008$ using the Chemical Plant Engineering Index (2010) which accounts for escalation in the cost of building chemical plants over time. The operating and non-energy variable costs were adjusted using the Producer Price Index for basic chemical manufacturing (Bureau of Labor Statistics, 2010).

$$LCC_{fuel} = \frac{CRF \cdot C_b \cdot \left(\frac{S_x}{S_b}\right)^{\alpha} + Cost_{FOM} + Cost_V \cdot S_x - MP_{coproduct} \cdot Y_{coproduct}}{Y_{fuel}}$$

$$where \quad CRF = \frac{i \cdot (1+i)^n}{(1+i)^n - 1} \tag{19}$$

Table 5: Parameter definition for levelized cost equation

Term	Definition	Commonized Value
i	internal rate of return	10%
n	economic lifetime	20 years
C_b	Capital cost at base scale	varies by study
S_b	Reference or base scale	varies by study
S_x	Modeled scale	varies by technology
$Cost_{FOM}$	Fixed annual operation and maintenance cost	varies by study
$Cost_v$	Variable cost as a linear function of scale	varies by study
$MP_{coproduct}$	Market price received for co-product	see Table 6
$Y_{coproduct}$	Annual production of co-product	varies by study

Table 6: Standardized assumptions for comparing technologies

Energy Inputs/co-products			**Source**
Natural gas	6.51	$/MMBtu	AEO2010
Electricity	0.050	$/kWh	AEO2010
Gasoline	3.07	$/gal	AEO2010
Diesel	3.12	$/gal	AEO2010
Propane	23.86	$/MMBtu	EPA (2010)
Hydrogen	1,590	$/ton	EPA (2010)
Feedstock Costs			
Corn	3.60	$/bu	FAPRI (2009)
Soy oil	0.498	$/lb	FAPRI (2009)
Yellow grease	0.255	$/lb	USDA Market News (2009)
Corn Stover	50	$/ton -dry	assumed
Wood Chips	50	$/ton -dry	assumed
Switchgrass	50	$/ton -dry	assumed
Non-energy co-products			
Distillers Dry Grains	123	$/ton	FAPRI (2009)
Glycerin	0.058	$/lb	Antares (2009)

Three recent comprehensive studies project the cost of many of the conversion technologies that provide a consistent context for the rest of the literature. The EPA studied the cost of biofuel production as part of an impact analysis of the EISA 2007 (EPA, 2010). A European project (de Wit *et al.*, 2010) modeled the current cost of biofuel technologies with progress ratios and scale economies to simulate growth of the industry. Future technology costs were not calculated from this study and only current technology costs are shown. Tao and Aden (2009) provide a review and comparison of techno-economic models of biofuel technologies developed by the National Renewable Energy Laboratory and USDA for policy analysis. The authors revised the models to compare the technologies at the same capacity of 45 million gallons per year of fuel output.

4.1 Corn ethanol

Ethanol produced from corn is the dominant biofuel pathway in the United States. There are two types of technologies – wet mill and dry mill. Wet mill technologies separate the germ, fiber, gluten and starch components of the corn kernel through steeping, screens, cyclones and presses. The starch fraction can then be converted to ethanol. It is the more capital and energy intensive process with lower ethanol yields but higher value co-products. Dry mill processes first grind the corn, sending the full kernel through the saccharification and fermentation process before separating ethanol from the co-product distiller's grains (which is typically dried) - the rest of the corn plus yeast bodies (dried distillers grains or DDG). Dry mill ethanol facilities produce more than 86% of the current ethanol production (Mueller, 2010).

The Antares model for dry mill ethanol is based primarily on the USDA's 2002 Ethanol Cost of Production Survey (Shapouri and Gallagher, 2005) with capital costs taken from (Gallagher *et al.*, 2005). Building on these earlier studies, the Antares study updated the yield of ethanol to 2.8 gallons per bushel, the electricity costs to $0.057/kWh and updated the capital and other operating costs to year 2008 dollars using appropriate inflation indices. Process energy fuel (mostly natural gas) is a significant cost that has increased at a rate greater than the production cost index. The main process energy fuel price was not indexed directly to a current fuel price because the process fuel is reported only as a cost and the surveyed plants used a variety of process fuels. Average process heat energy input is reported as 34,800 Btu per gallon. Assuming natural gas fuel for process heat and 85% efficient boilers the natural gas demand is 40,941 Btu per gallon of ethanol. An updated cost curve is shown in Figure 5 with AEO2010 projected energy prices for 2017 (natural gas, electricity and gasoline) and 2017 DDGs price from agricultural projections by Food and Agricultural Policy Research Institute (FAPRI) at the University of Missouri (FAPRI, 2009) for the co-product credit.

The Antares model gives one estimate of current ethanol technology. Tao and Aden (2009) provide another using a techno-economic model developed by USDA (Kwiatkowski *et al.*, 2006). Tao and Aden estimate higher costs of production than the Antares study due to significantly higher capital costs. Offsetting a fraction of the assumed higher capital costs are assumed lower energy use and labor costs compared with the Antares study.

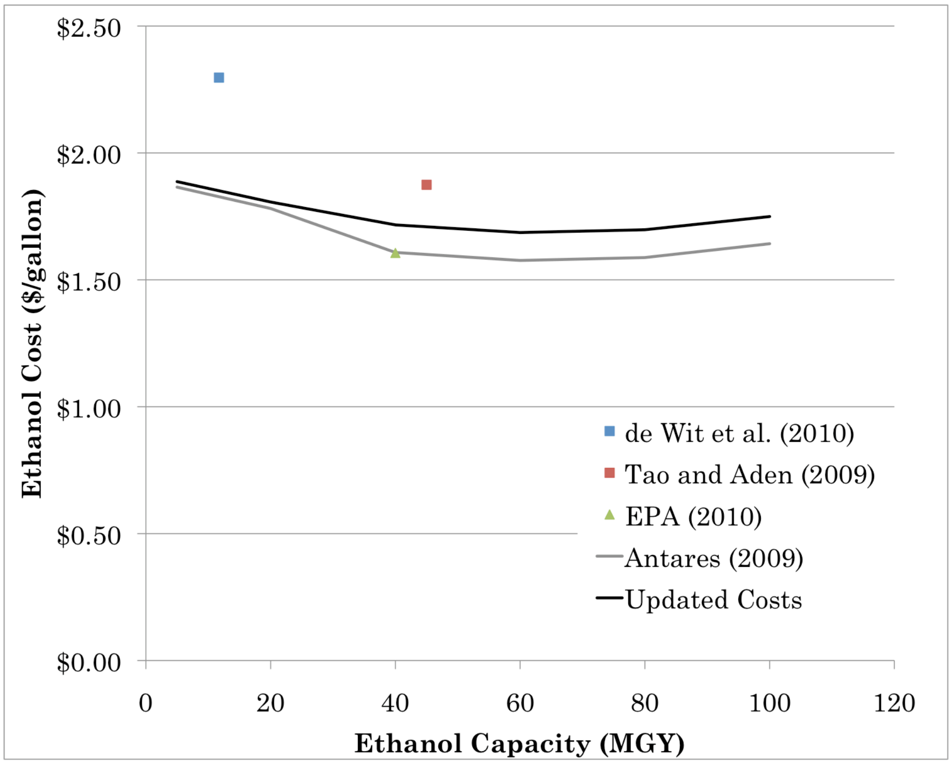

Figure 5: Comparison of estimated levelized costs of production for corn ethanol - Near term technology assessments are represented by squares and mid term technology (7-15 years ahead) are triangles

For analysis of the RFS2 regulation, the US EPA developed a technology projection for 2022 for most biofuel technologies (EPA, 2010). The corn ethanol technology modifies the same USDA techno-economic model used in Tao and Aden with lower energy use. Further potential improvements to the technology are given as reductions in the levelized cost of production from the baseline, the largest of which was -$0.093/gallon for corn fractionation where corn oil is separated as an additional co-product. Revising the Antares model with EPA's assumed energy use brings it into agreement with EPA's cost estimate.

The Antares model was used for two reasons. First, it provides costs of production over a range of biorefinery scales, allowing the modeling of existing facilities that have a distribution of capacities. Second, the existing corn ethanol industry will provide the majority of the 15 billion gallons of corn ethanol that is eligible for credit under the RFS2. While improvements to the corn ethanol industry will continue to be made, refinements on the corn ethanol model are a low priority for this research.

Table 7: Economic parameters for dry mill corn ethanol technology

	<40 MGY	>40 MGY
Base Study	Antares (2009)	Antares (2009)
Capital Cost* ($)	$S_x*(3.263*S_x-0.0565*S_x^2+0.00044*S_x^3)*10^6$	
Fixed O&M ($/gal)	$0.218	$0.198
Natural Gas Consumption (Btu/gal)	40941	40941
Electricity Consumption (kWh/gal)	1.19	1.19
Other variable costs	$0.177	$0.166
Ethanol Yield (gal/bushel)	2.8	2.8
DDG Yield (lb/bushel)	18.8	18.8

*S_x = ethanol production capacity in million gallons of ethanol per year

4.2 Fatty Acid Methyl Ester (FAME) biodiesel and "Renewable" diesel – hydrotreatment of lipids

Conversion of lipids to diesel replacement fuels is currently performed using a transesterfication process to create fatty acid methyl esters (FAME) or conventional biodiesel. Emerging technologies seek to create a hydrocarbon fuel that can be freely blended with diesel through a hydrotreatment process. These two technologies are modeled as competitors for the lipid feedstocks.

FAME biodiesel is made by transesterfication, a catalyzed chemical conversion of oils or fats and an alcohol (typically methanol) to biodiesel and significant quantities of glycerol co-product. FAME can be produced from virgin seed oils, waste greases or animal fats though the process design is optimized differently for the different resources. The dominant production process in the US uses alkali catalyst with virgin soy oil feedstock accounting for approximately 78% of biodiesel production in 2008 (U.S. Census Bureau, 2009). This process is described in Haas *et al.* (2006) and Zhang *et al.* (2003). Zhang *eta al.* (2003) finds that an acid catalyzed process is most economic for waste cooking oil. The dominant cost in producing biodiesel is the feedstock, especially true for virgin seed oils.

The Antares models for FAME production are based on Haas *et al.* (2006) for virgin seed oils and Zhang *et al.* (2003) for yellow grease. Adjustments were made to update costs to 2008 dollars. Specifically, Antares adjusted labor costs upward based on experience and the value of the co-product glycerol downward to $0.05/lb due to market saturation. The glycerol value of $0.15/lb is used in most studies but the price of glycerol has dropped to $0.05/lb during periods of high biodiesel production as the additional supply of glycerol resulting from biodiesel production greatly outpaced demand growth. With a billion gallon per year mandate for biodiesel, Antares expects the price of glycerol to remain low.

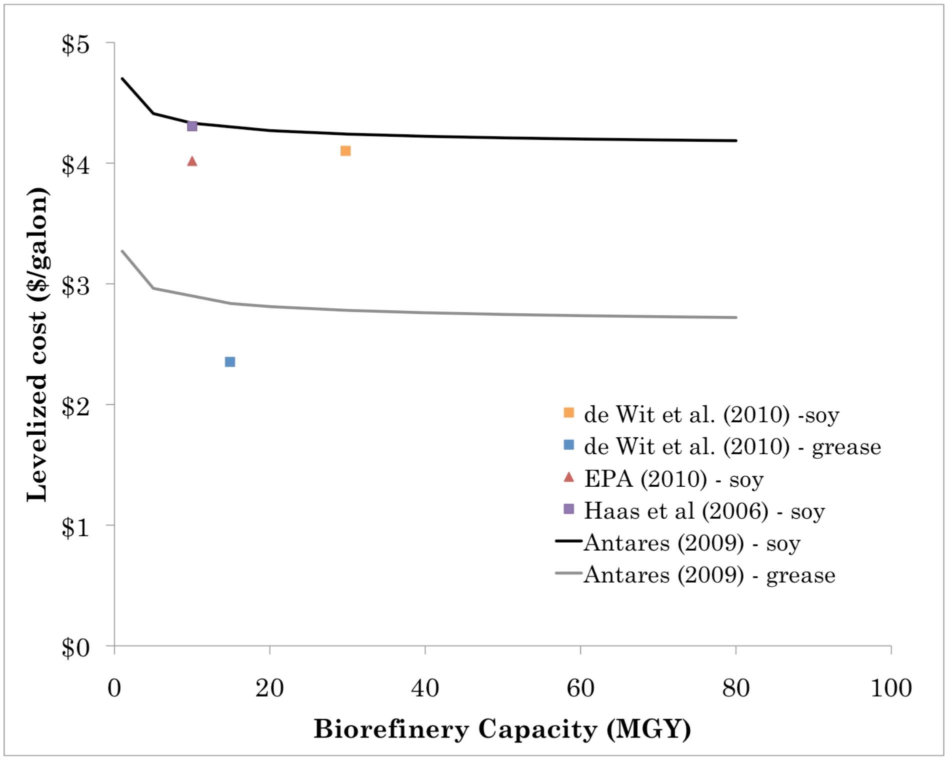

Figure 6: Comparison of estimated levelized cost of production for FAME biodiesel - Near term technology assessments are represented by squares and mid term technology (7-15 years ahead) are triangles

The EPA projects a lower cost for biodiesel production in 2022. The expected improvements are from reduced operation and maintenance with labor and chemicals making up the majority of the reduction. The difference is not large as the feedstock cost dominates (EPA, 2010). de Wit *et al* (2010) also project similar but lower costs of production for seed oil-based biodiesel.

The acid catalyzed process for waste greases has higher operating cost but making use of a low cost feedstock makes it less expensive than FAME from soy oil. The de Wit *et al.* (2010) study has a much lower capital cost, lower O&M and slightly higher yields for waste grease-based biodiesel leading to a $0.43/gallon difference in the levelized cost.

Techno-economic analyses of the hydrotreatment process are based on the UOP/Eni process (Holmgren *et al.*, 2007). In the process, the lipids and hydrogen pass through a hydroprocessing unit where the oxygen is stripped from the lipids through decarboxylation and hydrodeoxygenation reactions. The resulting products are a combination of "green diesel" and lighter hydrocarbons (naphtha and/or propane) with byproducts of water and carbon oxides (CO and CO_2). The green diesel fuel is reported to have a number of desirable properties – high cetane number (70-90), energy density equivalent to ultra low sulfur diesel, sulfur content of less than 1 ppm (USLD < 10 ppm sulfur) and good stability. Holmgren *et al* (2007) identify the potential to use green diesel as a premium blendstock allowing for the use of lower valued light-cycle oil as part of a diesel blend.

The Antares model considers two configurations for the hydrotreatment process; one as a stand-alone unit within a petroleum refinery and one as co-processing within the same hydroprocessing units as petroleum products. The stand-alone units have higher capital costs but lower hydrogen demand and higher green diesel yields. The coprocessing design has higher hydrogen requirements because the hydroprocessing units for crude oil operate in conditions that favor the hydrodeoxygenation reactions over the decarboxylation reactions, which consume 3.75 times the hydrogen per oxygen removed (Antares, 2009).

The EPA's estimate of the cost of hydrotreament-based diesel is slightly higher than the Antares model. The EPA model is based on the stand-alone design but assumes higher hydrogen consumption (.224 lb/gal compared to 0.117 lb/gal) (EPA, 2010). The higher hydrogen cost is offset somewhat by an assumed lower capital and operating expenses besides hydrogen.

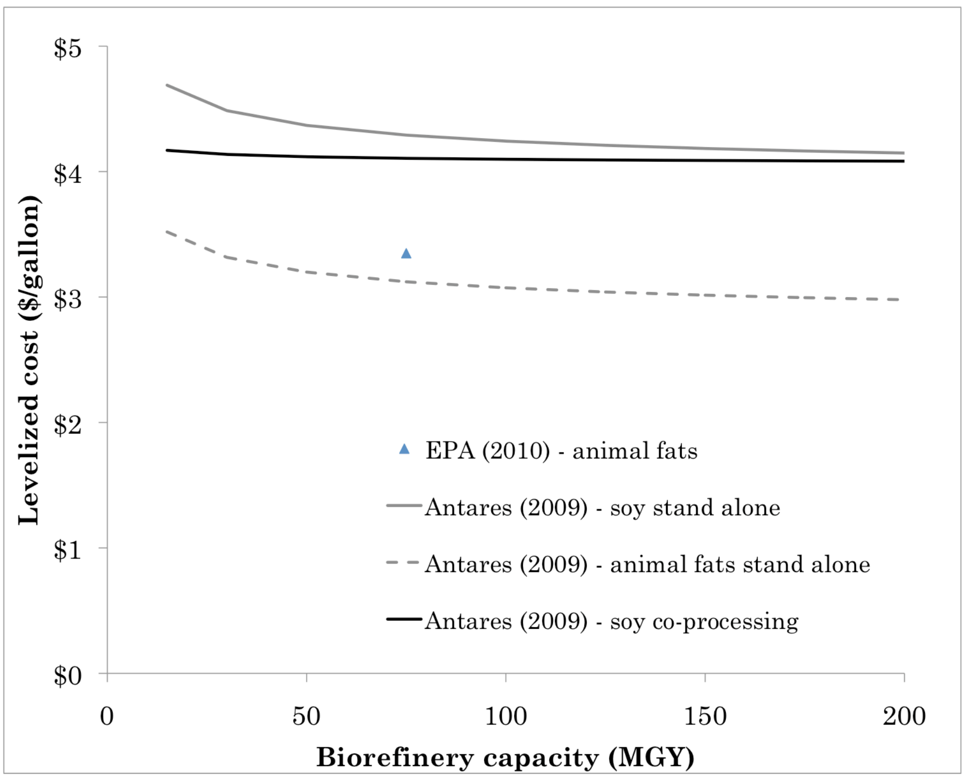

Figure 7: Comparison of estimated levelized cost of production for hydrotreatment of lipids to diesel – all estimates are for mid term technologies (7 – 15 years ahead)

Table 8: Economic parameters for lipids to diesel conversion technologies

	FAME - virgin oils	FAME - waste fats and greases	Hydrotreatment
Base Study	Antares (2009)	Antares (2009)	Antares (2009)
Capital Cost @ 20 MGY (million$)	$19.813	$19.813	86.603
Scaling factor	0.6	0.6	0.6
Fixed O&M (% of Capital)	0.021	0.021	0.055
Natural Gas Consumption (Btu/gal)	6424	16417	-
Electricity Consumption (kWh/gal)	0.1008	0.1512	-
Other variable costs ($/gal)	$0.205	$0.470	$0.094
Biodiesel Yield (gal/ton)	258.2	266.3/249.1	255.4
Glycerin Yield (lb/gal)	0.8	0.8	-
Propane Yield (gal/ton)	-	-	22.4

4.3 Cellulosic ethanol

Ethanol production from cellulosic biomass is not currently a commercially viable technology. Estimates for the cost of production rely on a number of engineering studies with process-level modeling of the biorefinery. The majority of studies of cellulosic ethanol consider the biochemical pathway where the cellulose and hemicellulose are converted to sugars through enzymatic hydrolysis and saccharification then fermented to make ethanol. Tao and Aden considered the thermochemical pathway via gasification and synthesis and found the cost and performance to be similar to the biochemical pathway at the scale of 45 million gallons of ethanol per year (Tao and Aden, 2009). The biochemical route is taken to be the model cellulosic ethanol technology due to the larger base of supporting literature. The thermochemical pathway may prove to be the technology better suited in certain cases but given the overall uncertainty in the technology costs and performance the performance of the thermochemical pathway is likely to fall in the range studied.

The biochemical pathway begins with feedstock pretreatment to make the cellulose available to the enzymes. There are a number of techniques under research and development for this pretreatment including dilute acid hydrolysis, ammonia fiber explosion, liquid hot water, and steam explosion. In the process of exposing the cellulose the hemicellulose is broken into its component sugars (xylose, arabinose, etc.). The exposed cellulose is then converted to glucose with cellulase enzymes. Glucose is fermented to ethanol and the 5-carbon sugars are fermented to ethanol either in a combined reactor using recombinant *Zymomonas mobilis* or in separate reactors using yeast for the C6 sugars and *Z. mobilis* for the C5 sugars. In the advanced designs of Laser *et al.* (2010) and Hamelinck *et al.* (2005) a consolidated bioprocessing (CBP) approach is taken where all biological conversions (enzyme production, enzymatic hydrolysis and fermentation) occur in the same reactor. This design is attractive but the catalyst to make it possible has yet to be identified. In most designs, the lignin is separated from the beer, dried and combusted to produce steam and electricity for the biorefinery with some net export of electricity.

There is a large range of projected costs using "current" technology. There are three main sources of variation in the costs estimates. First is the expected yield of ethanol from cellulosic material. Estimates range from 52.4 gallons per ton to 76.4 gallons of ethanol per dry ton of switchgrass or corn stover. This variation is due to difference in the performance of the pretreatment, cellulase enzymes and fermentation organisms each study assumes. Dutta *et al.* (2010) and Kazi *et al.* (2010) use experimentally verified performance measures and result in the highest production costs. Second is the capital investment required. This is due to the variety of configurations studied as well as the yield differences. Within the same study capital costs varied by 42% due to different configurations of pretreatment, hydrolysis, fermentation, and distillation (Kazi *et al.*, 2010). The third factor is the variable operating cost – mainly the cost of cellulase enzymes. For example, Aden (2008) projects cellulase enzymes available at $0.32/gal of ethanol where Kazi *et al.* (2010) puts the cost at $1.05/gal. Also of interest is that the estimate for year 2000 technology in Wooley *et al.* (1999) falls below the more recent estimates of current costs, demonstrating that as more is learned about these technologies limitations are identified that lead to additional costs.

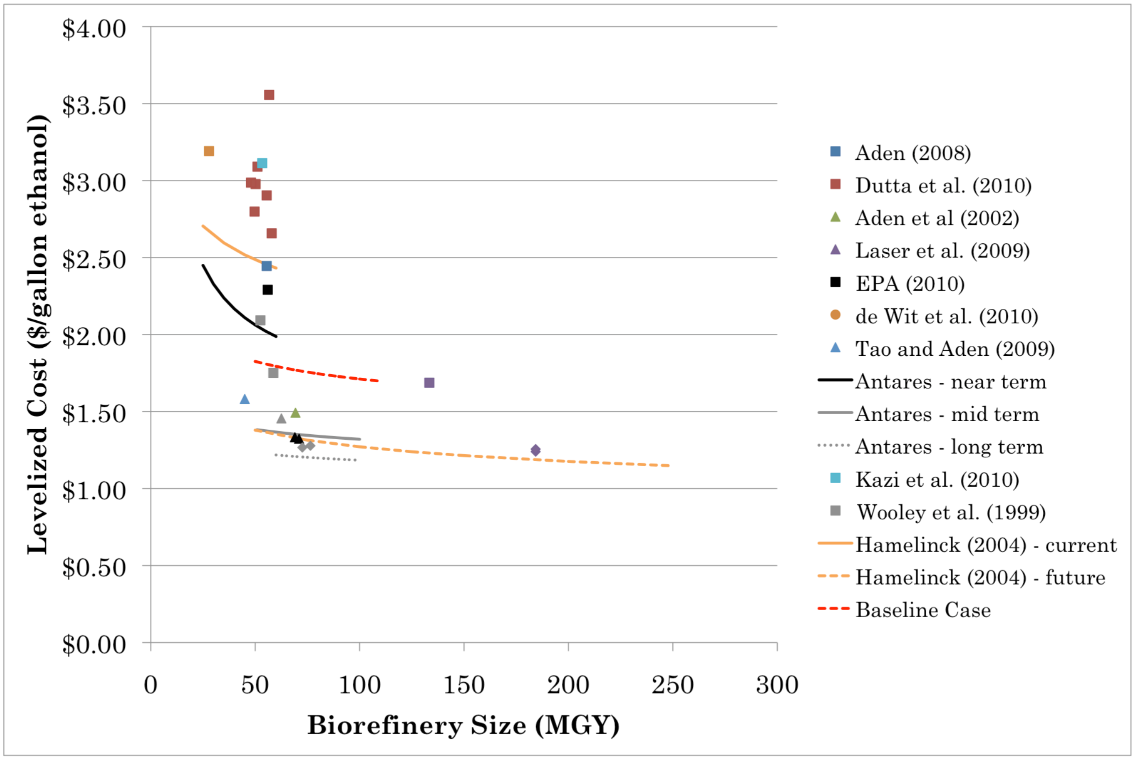

Figure 8: Comparison of estimated levelized cost of production for cellulosic ethanol - Near term technology assessments are represented by squares, mid term technology (7-15 years ahead) are triangles; long-term projections are shown as diamonds.

For this dissertation, I have chosen to use three potential technology outcomes for the timeframe of 2017-2022. The pessimistic case is represented by the current technology estimate by Hamelinck *et al.* (2005). The middle case is represented by the base case characterization of Laser *et al.* (2009) which is also the best-in-class design for 2000 in Wooley *et al.* (1999). Scaling of capital costs for the optimistic case uses the same 0.84 scaling factor as in Hamelinck *et al.* Finally an optimistic case is based on the Antares model for "mid-term" technology (Antares, 2009).

Table 9: Economic parameters for cellulosic ethanol conversion technologies

	Baseline	Pessimistic	Optimistic
Base Study	Laser (2009)	Hamelinck (2005)	Antares (2009)
Base scale (tonnes of dry biomass per day)	2,000	2,000	2,000
Ethanol output (million gallons per year)	53.1	50.7	50.9
Capital Cost @ base scale	$349.60	$458.17	$211.09
Scaling Factor	0.84	0.84	0.8
Fixed O&M (% of Capital)	0.03	0.017	-
Variable Costs ($/gal)	$0.35	-	$0.35
Cellulase enzymes ($/gal)	-	$1.00	-
Cellulose to ethanol (% theoretical)[5]	0.720	0.7	.799
Hemicellulose to ethanol (% theoretical)	0.765	0.714	0.765
Electricity efficiency (LHV)	0.035	0.05	0.034

The pessimistic and baseline characterizations are for nth of a kind facilities using what the authors consider near-term technologies. There are two reasons why these current technology characterization are used rather than future technology characterization for the timeframe. First, all future technology cases have costs of production for enzymes around $0.10 per gallon of ethanol. The current state of technology based on press releases and industry presentations has enzyme costs of at least $0.50 per gallon of ethanol up to $1.00 per gallon of ethanol (Novozymes, 2009). Given that the baseline scenario here is based on technology that was projected to be available in 2000 and has yet to be achieved by 2010, assuming quick

[5] Biological conversion of ethanol achieves maximum yield when all sugars present in the biomass are converted to ethanol. The maximum yield is dependent on the type and quantity of sugars in the biomass. The efficiency of the conversion technologies is described here relative the maximum yield based on the composition of the biomass.

progress to $0.10/gallon is an optimistic outlook. Second, I take the approach that cost reductions to the nth of a kind plant from the 1st of a kind plant will require a number of biorefinery construction cycles estimated to be 3 to 4 years by the technoeconomic studies making current nth of a kind projections appropriate for commercial cost in the medium term (<12 years).

4.4 Fischer-Tropsch diesel

Thermochemical conversion of biomass to fuels can take many routes. The Fischer-Tropsch synthesis process is among the most studied and furthest developed. Commercial facilities exist or have existed in the past for production of F-T fuels from both coal and natural gas. The biomass gasifier and the optimizing of gas clean up and the F-T synthesis process for biomass-based synthesis gas are the required advancements. There are a number of biomass gasifier configurations that have been studied, the details of which can be found in Hamelinck *et al.* (2004), Larson *et al.* (2009) and Swanson *et al.* (2010).

There is a large range in the projected cost for current technology F-T diesel production. This represents some disagreement on what technologies are current and which are unproven as well as difference in design. The Swanson study states that hot gas clean up (tar cracking) is not yet commercial while all other studies use it. The Antares study uses an indirectly fired atmospheric gasifier while most others use pressurized oxygen blown directly fired gasifiers. In projecting future technology versus current technology, Hamelinck *et al.* (2004) foresees no changes in the design but projects reductions in capital and operating costs due to incremental improvements and increases in scale. Larson *et al.* (2009) present a case with mature technology where a once through configuration is designed for greater electricity production than the other studies. The EPA projection is significantly lower compared to other studies at similar scale and timeframe (EPA, 2010). Little information was provided to support this estimate.

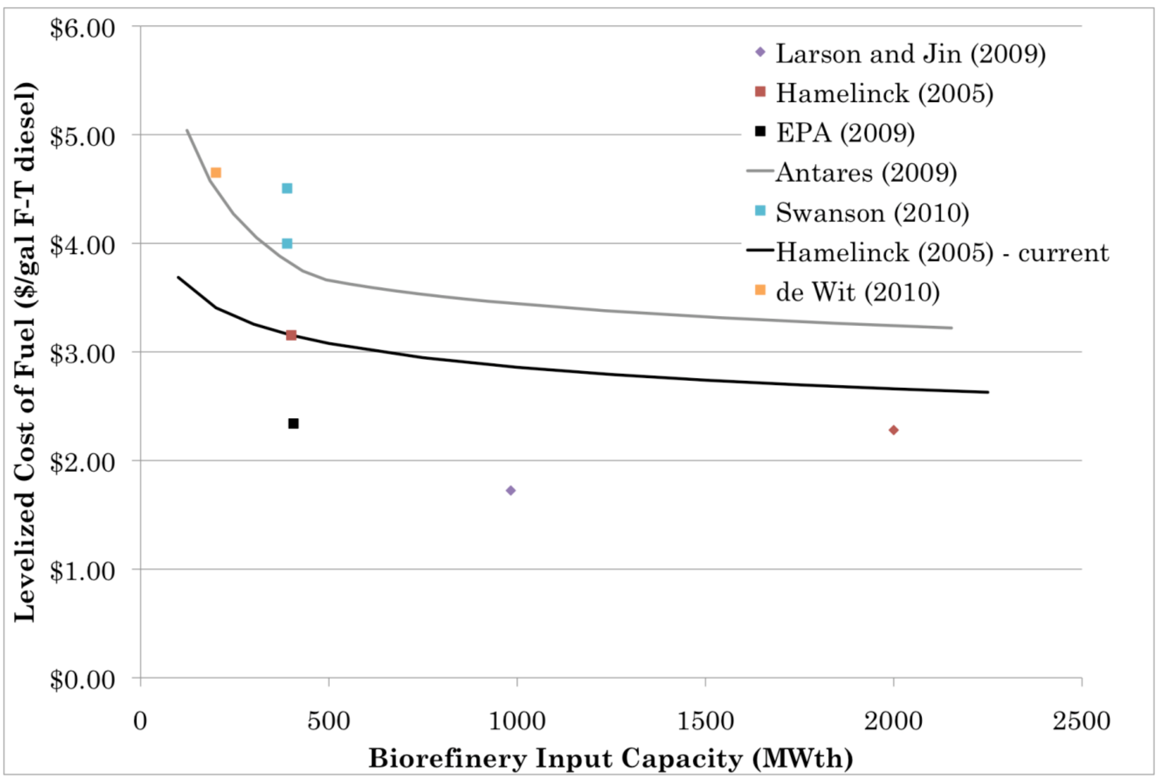

Figure 9: Comparison of estimated levelized cost of production for F-T diesel technologies - Near term technology assessments are represented by squares, mid term technology (7-15 years ahead) are triangles; long-term projections are shown as diamonds.

Baseline and pessimistic technology models were developed from the Antares (2009) and the Hamelinck *et al.* (2005) studies respectively. There are three main differences in the cost and performance of F-T diesel for the purposes of this study. First is the Antares technology characterization has significantly higher capital costs. Second, the Antares technology characterization has stronger economies of scale up to 750,000 tons per day capacity and weaker economies of scale beyond that size. Third, the Hamelinck technology produces more fuel products and less electricity. The Antares technology has a higher overall efficiency (including electricity) but at significantly higher cost.

Table 10: Economic parameters for Fischer-Tropsch diesel conversion technologies

	Baseline	Pessimistic
Base Study	Hamelinck (2005)	Antares (2009)
Base scale (tonnes dry biomass per day)	2,000	2,000
F-t Diesel output (million gallons per year)	31.7	27.3
Capital Cost @ base scale (million $)	$459.59	$765.69
Scaling Factor	0.85	0.74/0.9*
O&M (% of Capital)	0.044	0.042
Diesel efficiency (LHV)	0.370	0.304
Naphtha efficiency (LHV)	0.069	0.12
Electricity efficiency (LHV)	0.035	0.157

*Scaling factor is 0.74 below 680,000 dry tonnes of biomass input per year and 0.9 above.

4.5 Comparison of cellulosic technologies

The two technologies for cellulosic biomass produce different fuel products, have yield advantages with certain feedstocks, have different assumed maximum and minimum capacities and the F-T diesel technology relies more heavily on income from co-products. A comparison of the levelized cost for the modeled technologies is given in Figure 10. Under the assumptions of the analysis, the optimistic and pessimistic scenarios for F-T technologies have lower levelized cost than the cellulosic ethanol technologies with similar levels of optimism. This does not mean cellulosic ethanol will not be the technology of choice. Its lower capital cost – the pessimistic ethanol technology has lower capital costs than the optimistic F-T diesel technology – translates into lower risk in investment in the initial small scale biorefineries that will lead to learning. Given limited capital availability, path dependencies develop when one technology is more aggressively pursued impacting the relative cost in the future. For this reason, scenarios are developed in the national modeling analysis with all combinations of technology optimism.

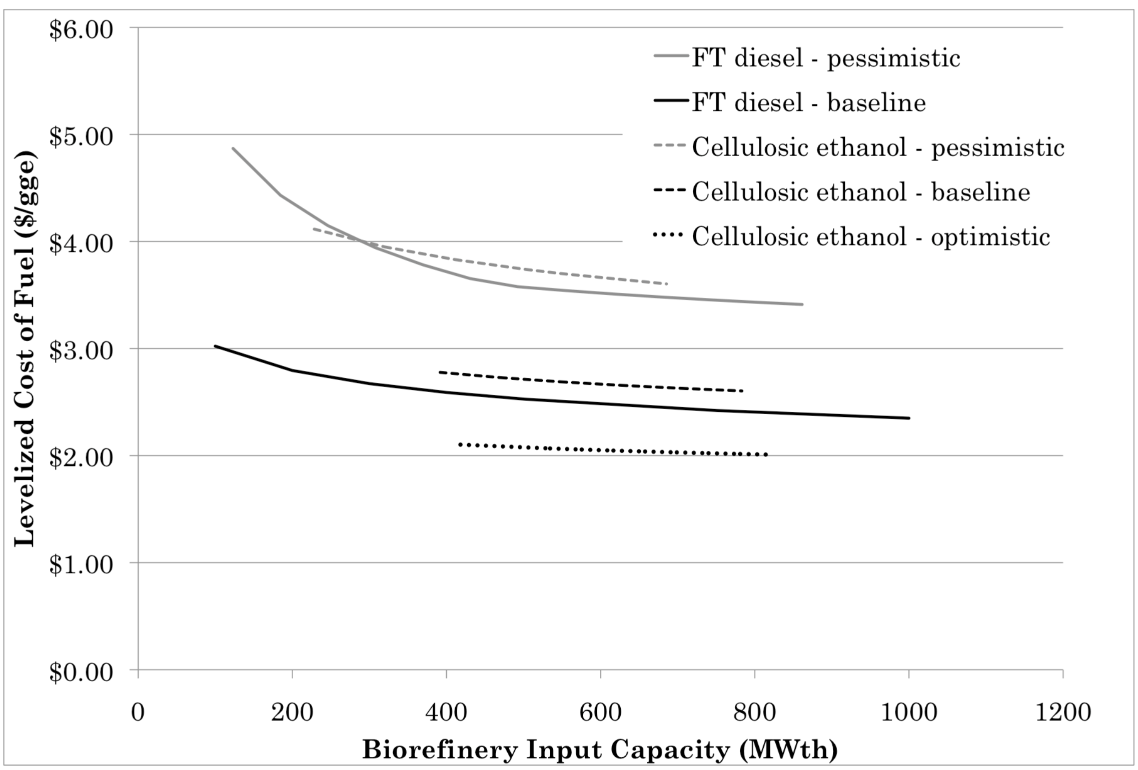

Figure 10: Comparison of modeled cellulosic biofuel technologies using switchgrass as feedstock

4.6 Conversion technology model parameters

The detailed technoeconomic models are simplified into integer-linear annualized cost functions for use in the optimization model. Using the detailed models, the annualized cost of production for each technology is plotted as a function of the input capacity of the biorefinery in units of tons of feedstock per year. A linear fit is found for the plot. The intercept (a_t) and slope (b_t) are parameters used for the cost function in the optimization model. The cost estimates are only valid over the analyzed range of facility capacities. The sizing the biorefineries below the minimum biorefinery size is avoided by the model due to the high average cost of production. Sizes above the maximum size are prevented by a constraint in the model using the parameter M_t giving the maximum size for a biorefinery of technology 't'. The model parameters used in the national case study are given in Table 11.

Table 11: Model parameterization for conversion facilities

	Annualized Cost of Production[a]		Maximum Capacity (tons input /year)
	Fixed (million $)	Capacity Dependent ($/ton)	
Model Parameter	a_t	b_t	M_t
Grains to Ethanol:			
Dry Mill	$1.79	$32	1 million tons
Wet Mill	$15.35	-$64[b]	3.37 million tons
Cellulosic Ethanol:			
Baseline	$13.76	$77	1.31 million tons
Pessimistic	$15.96	$99	1.15 million tons
Optimistic	$7.35	$53	1.36 million tons
Fischer-Tropsch Diesel:			
Baseline	$12.76	$89	1.72 million tons
Pessimistic	$30.16	$154	1.36 million tons
Fatty Acids Methyl Esters:			
Yellow Grease	$0.93	$170	320,000 tons
Virgin oil/Tallow	$1.81	$60	320,000 tons

[a] Includes capital and operating cost and value of non-energy co-products
[b] The value of the co-products is more than the operating cost of the wet mill facility

4.6.1 Existing Facilities

Existing biorefineries have fundamentally different cost structures compared with new biorefineries. The capital investment has already been made and has limited bearing on whether or not the facility produces. For these facilities the operating costs determine their profitability. The distinction is made for existing corn ethanol facilities, whose costs were modeled using the same conversion cost models as new facilities with two modifications. First, the sizes of the facilities were fixed at their current size. Second, the capital costs are not charged because they are assumed to have already been spent. The existing biodiesel facilities were not considered separately from new biodiesel facilities in the work shown here.

5 DATA

The framework described in Chapter 3 is sufficiently general to consider a wide range of the problems requiring spatial supply chain modeling. In this chapter, I provide the background on the literature of the resource assessment, harvest and transportation costs, and spatial fuel demand that are used in the following case studies. The data used in the national case study is described and set in the context of the existing literature. The existence of these data sources has influenced the development and implementation of the model to date. However, deviations on and improvements to these data sources can be accommodated within the framework.

5.1 Resource assessments

One of the advantages of the modeling framework developed in this dissertation is the ability to bring in diverse resources for consideration. However, this requires consistency across the resource assessments used. Each resource type is unique in terms of the data available and appropriate methodology for an assessment. For waste and residue resources, one must first answer how much is produced and then must consider how much can be technically and/or sustainably collected and at what cost. For energy crops, the potential production must be determined and then an estimation of the economically viable quantities determined including the cost of production and competition for land.

5.1.1 Agricultural residues

Agricultural residues are straws, stovers and other plant components remaining in the field after harvest of the crop. They play a role in maintaining soil health and preventing erosion (Lal, 2009; Wilhelm *et al.,* 2007). Limited removal of the residues has been proposed as a source of biomass. This depends on there being excess residues beyond their soil maintenance function or an economic alternative to provide the soil maintenance functions. The quantity of residues per acre that can be sustainably removed (Q_s) can be described by the simple difference between the gross production of residues per acre (Q_g) and the residue retention requirement for soil maintenance (Q_r) (equation 20).

$$Q_s = Q_g - Q_r \tag{20}$$

Gross residue production is estimated based on grain production statistics using equation 21. HI_c is the harvest index of the crop defined as the grain fraction of the total above ground biomass (by weight). The residues are the remainder of the above ground biomass.

Since agricultural statistics track grain yields only and do not track residues or total biomass, estimates of residues are based on the harvest index and grain yield. This makes estimates of total residue production highly dependent on the harvest index. However, the harvest index is not measured on a regular basis and may change over time or across space. There is an incentive to increase the harvest index to shift the effort of the crop towards the production of grains. If the harvest index increases, the production of residues will drop if total biomass does not also increase.

The harvest index values used in many current assessments (Graham *et al.*, 2007; NAS, 2009; Banowetz *et al.,* 2008) trace back to Gupta *et al.* (1979). The underlying assumption in these studies is that yield growth has not and will not come from increasing the harvest index but from increasing the total biomass per unit area. According to Johnson *et al.* (2006), this is not the case. Between 1940 and 200 grain yield increase far outstripped residue yield increases (see Table 12).

$$Q_g = Y_c \cdot \left(\frac{1}{HI_c} - 1\right) \tag{21}$$

Table 12: Grain and residue yield growth from 1940 to 2000

	Grain yield kg ha-1		Harvest index		Residue Yield kg ha-1		Grain increase	Residue increase
Crop	1940	2000	1940	2000	1940	2000		
Barley	1280	3860	0.27	0.5	3460	3860	201.6%	11.6%
Corn	1890	8400	0.35	0.53	3510	7450	344.4%	112.3%
Oat	1150	2210	0.33	0.44	2340	2810	92.2%	20.1%
Sorghum	930	3980	0.34	0.47	1800	4490	328.0%	149.4%
Soybean	1260	2560	0.3	0.46	2940	3000	103.2%	2.0%
Wheat	1050	2800	0.28	0.45	2700	3420	166.7%	26.7%

Source: Johnson *et al.,* (2006)

Residues also play an important and not completely understood role in maintaining soil health. Metrics of soil health that have been identified and studied for residue requirements are erosion prevention (Nelson, 2002; Graham *et al.*, 2007; Banowetz *et al,* 2008) and soil organic carbon (Wilhelm *et al.*, 2007; Johnson *et al.*, 2006). In contrast, Lal argues that no removal is the only sustainable practice due to potential issues with soil health, specifically cultivation of beneficial soil organisms (Lal, 2009). The existing studies show that the required residue retention rates are dependent on the soil type, slope, climate, crop rotation and tillage practices. The residue retention is determined by the maximum required for each of three metrics, water erosion, wind erosion and soil organic carbon. Wilhelm *et al.* (2007) demonstrate that for corn stover the binding soil health constraint is soil organic carbon.

The accepted methodology for estimating required residue retention rates due to soil erosion concerns was developed by Nelson *et al* (2002). The minimum residue retention rate in this work is the quantity of residues that are required to prevent soil loss due to erosion from exceeding the tolerable soil loss level T. T is the maximum amount (tons/acre-year) of soil erosion that will not lead to prolonged loss of productivity as defined by the United States Department of Agriculture's Natural Resource Conservation Service (USDA-NRCS, 1999). T-values are established based on soil type, soil depth and local climate/geology. Although T-values vary across the landscape, they generally range from 1 to 5 tons per acre per year.

The Revised Universal Soil Loss Equation 2 (RUSLE2) model [citation] is used to simulate rainfall erosion for a given crop rotation on a given soil type and given climate. RUSLE2 has been developed by the USDA – Agricultural Research Service, National Resource Conservation Service and the University of Tennessee to aid farmers in making informed choices in cultivation practices with respect to soil erosion (USDA –ARS, 2008). The model finds the soil loss due to water erosion for a given soil under a given cultivation practice in a given location. The model is run over multiple values for crop yields in order to develop a curve describing soil loss as a function of residue cover. The curve is then used to find the residue cover corresponding to a soil loss of T for the major soil types in every county (Nelson, 2002). Residues required to prevent wind erosion are found in a similar fashion using the Wind Erosion Equation (WEQ) (Woodruff and Siddoway, 1965).

Nelson is expanding the above methodology to include consideration of soil carbon (Nelson, 2010). The soil carbon constraint is modeled using the Soil Conditioning Index (SCI) in the RUSLE2 model. If a rotation with residue removal yields a negative SCI, that rotation is disallowed. By batching multiple rotations with different levels of residue removal, the maximum potential residue removal rate for each soil type can be determined. A realistic set of crop rotations were developed in consultation with regional experts from NRCS and then allocated to soil types within the counties based on NASS statistics of current production (Nelson, 2010). The maximum of the three retention rates (wind erosion, rain erosion, and SCI) is reported as the minimum sustainable residue retention (Q_r) and the available residue is found using equation 20. This is the approach used for the national case study.

There are several points where varying the assumptions made in the analysis can lead to significantly different results. Decisions must be made to estimate crop yields and harvest indices in the future. Two approaches have been taken in the work shown here for estimating crop yields. The first and more conservative approach is to estimate residue production based on historical yields and planted areas. Average yields and planted acres for the past ten years are used. The second approach uses projections of future county-level yields based on current yields (average of 2006-2009[6]) (USDA-NASS, 2010) and the projected national yield increase over time from the USDA's Long-term Projection (2009). Each county is assumed to experience the same percentage increase in yields. This provides a more optimistic estimate of available residues.

In both cases, the harvest index remains the same. This may lead to an overestimate of available residues as small differences in harvest index can have large impacts on the calculated residue that can be sustainably removed. For corn, the harvest index of 0.5 reported as used in Graham *et al* (2007) predicts 12% more gross residue produced and 43% more residue that can be sustainably removed[7] compared with the 0.53 harvest index reported in Johnson *et al* (2006). Despite this potential for overestimation, the data set used is the best that is currently available.

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[6] Averages taken only for years when the crop was planted in a given county.
[7] Calculated using 3,860 kg ha^{-1} corn grain yield and a residue retention requirement of 5.25 Mg ha^{-1} reported by Wilhelm *et al.* (2007) for continuous corn rotations with no or conservation till cultivation.

The second important set of assumptions is the allocation of rotations and tillage practices to specific soil types. Data are not available at this fine a scale so assumptions are unavoidable and introduce a level of uncertainty in the total quantity of residue that is sustainably available. National and county level data are available on the tillage practices used for the major crops (CTIC, 2008). Conservation or no till agriculture result in significantly lower residue retention rates compared to conventional till. Projecting how the shares of these cultivation practices will change over time has a large impact on total residue quantities. In the work presented here, the current shares are used in the conservative case (historical averages) and all conservation tillage is used in the optimistic case (projected yield case).

The costs of harvesting these residues were generated using standard engineering and economic parameters for machinery that might typically be used to harvest and/or field process, bale, and transport corn stover or small-grain straw to the field edge (INL, 2008). The agricultural feedstock harvest and logistics model is described in Appendix A. An additional limiting factor on residue removal comes from the efficiency of the harvest equipment – the ability of the equipment to harvest the residues on the field (1 = total removal of biomass). The harvest model used here assumes a 38% harvest efficiency (INL, 2008) using a two pass harvest system with a combination shredder/windrower and baling. Others report as much as 70% harvest efficiency using a three pass system (shred, windrow and bale) (Brechbill and

Tyner, 2008). In the base case, the 38% harvest efficiency is used. As a sensitivity, the optimistic case is run with 70% harvest efficiency and the same cost as the base case. Using the 70% harvest efficiency increases the total residue available by 70%.

In the data set obtained from Nelson using projected yields, land area and 100% conservation or no till cultivation, 75% of gross corn stover production is on fields where at least 70% of the stover can be sustainably removed. 92% of the gross stover production is on fields where ate least 38% of the stover can be removed. In these cases the majority of the stover is limited by the assumed harvesting constraints. For wheat straw this is also the case.

Additionally, the value of the nutrients removed from the field is included in the cost of residues. It is assumed that all of the macronutrients (nitrogen, phosphorous, and potassium) that are removed with the residue must be replaced with commercial fertilizers above the application that would take place if the residues remained in place. Assumptions on nutrient content of the residue biomass are given in Table 13 along with the assumed price for fertilizer replacement. The 2018 prices for nutrients were found by taking the 2008 prices reported in (USDA-NASS, 2009) and adjusting them using the prices paid indices for fertilizers in (FAPRI, 2009). The yields and cost were aggregated into county-level supply curves expressed in terms of total dry tons available at the field edge at a given cost of production for each county in the region.

Table 13: Nutrient replacement for agricultural residues (lb nutrient/dry ton residue removed)

Residue	Nitrogen	Phosphorus	Potassium	Source
Corn Stover	15.9	5.9	30	Brechbill and Tyner (2008)
Wheat Straw	11	3	15	Mullen and Lentz (2007)
Barley Straw	12.8	1.6	33	Tarkalson *et al.* (2009)
Sorghum Stover	8.5	2.4	33.9	Powell *et al.* (1991)
Fertilizer Price 2008 ∣ 2018 ($/lb nutrient)	0.35 ∣ 0.33	0.89 ∣ 0.98	0.46 ∣ 0.51	USDA-NASS (2009) ∣FAPRI (2009)

Residues (trimmings, dead wood, etc.) are also generated from the growth, cultivation, and removal or replacement of orchard and vineyard crops. Production statistics (land area and yields) by crop were obtained from the 2007 Census of Agriculture (USDA-NASS, 2009). Average annual quantity of residue produced from cultivation of each crop was obtained from an analysis performed in California (Williams, 2008). The cost of residue pick-up and transport to the field edge is assumed for purposes here to be \$30 dry ton^{-1} based on Jenkins *et al.* (1984).

Three scenarios for agricultural residues are used in the national case study. In the baseline and high residue cases, the quantity of residue that is sustainably available was obtained using 2018 projected yields and crop land allocations. The baseline is further reduced by a 38% harvest efficiency limit. The high residue case uses a 70% harvest efficiency limit. The third scenario uses historical yields and crop land allocations in determining the sustainably available residue quantities.

The residues available in the high and historical residue scenarios are mapped in Figure 11 at $50, $100 and $150 per dry ton. The baseline case follows the same spatial distribution as the high case but with lower quantities and higher costs. The resource is concentrated in the corn producing regions of the country. The harvest cost is dependent on the yield making the low cost and high producing regions co-located.

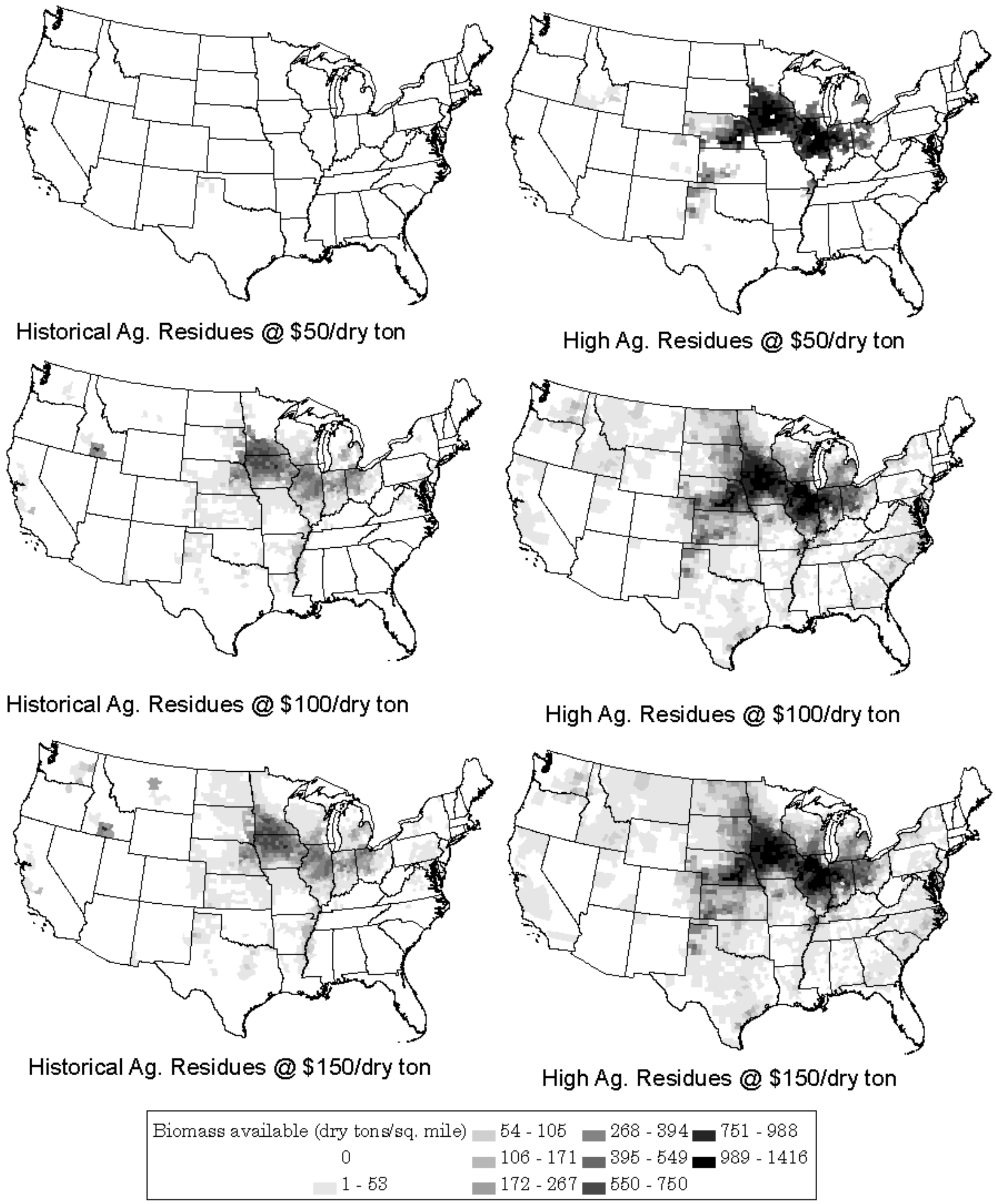

Figure 11: Maps of agricultural residues in the historical and high cases

5.1.2 Forest residues

Forest residues can come from three sources – integrated harvesting operations, "other forest removals" and mill residues. For the national case study, data developed by Skog (2008) are used. Their methods are described below and in (BRDi, 2008) .

Two estimates were made for residues from the integrating harvesting of lumber, pulpwood and wood biomass. The first is to take a fraction of recent logging residues from timber harvest. Data on the 2007 timber harvest was used with 50 and 65% of gross logging residues assumed to be available. The second method is to simulate thinning operations on all timberland where stand density is greater than 30% of the maximum stand density index for a given forest type. The simulated uneven aged thinnings produce woody biomass from the tops and branches for trees greater than 5 inches in diameter at breast height (dbh) and from whole trees 1 to 5 inches dbh. Costs for this woody biomass are estimated based on the cost of roadsiding and chipping as well as a stumpage price ranging from $4 per dry ton when no residues are used to 90% of pulpwood stumpage when all residues are used. The Fuel Reduction Cost Simulator (FRCS) model is used to find the costs of roadsiding and chipping (Fight *et al.*, 2006). An average of these two estimates is used for the national model analysis. The integrated harvesting operations that would yield the biomass estimated here are not conventional practice currently and would represent a shift in harvest methods.

Residues are also available from “other forest removals” including urban land clearing and cultural operations. The quantity of this resource is taken from an estimate of 2007 removals (USFS, 2008). The estimate makes no projection for how this resource may change over time. Skog *et al* assume that 50% of the resource is technically available with 34% of the technically available resource available at a cost of $20 per dry ton and the remainder available at $30 per dry ton.

Some residues produced in from primary wood products mills are not currently used and others could be available if the price paid is above the value of their current use. 2007 production of mill residues is used as the estimate of future residue production. The unused fraction – 1.3 of 86.7 million dry tons – is assumed to be available at $10/odt. No attempt was made to characterize the prices at which the residue currently used would become available and therefore they are excluded from the analysis.

Two scenarios were considered for forest residues. The first excludes forest on federal lands while the second includes these lands. The reason for this distinction is that the federal Renewable Fuel Standard (RFS2) disallows forest residues from these lands for the production of fuels that meet the mandate (USEPA, 2010).

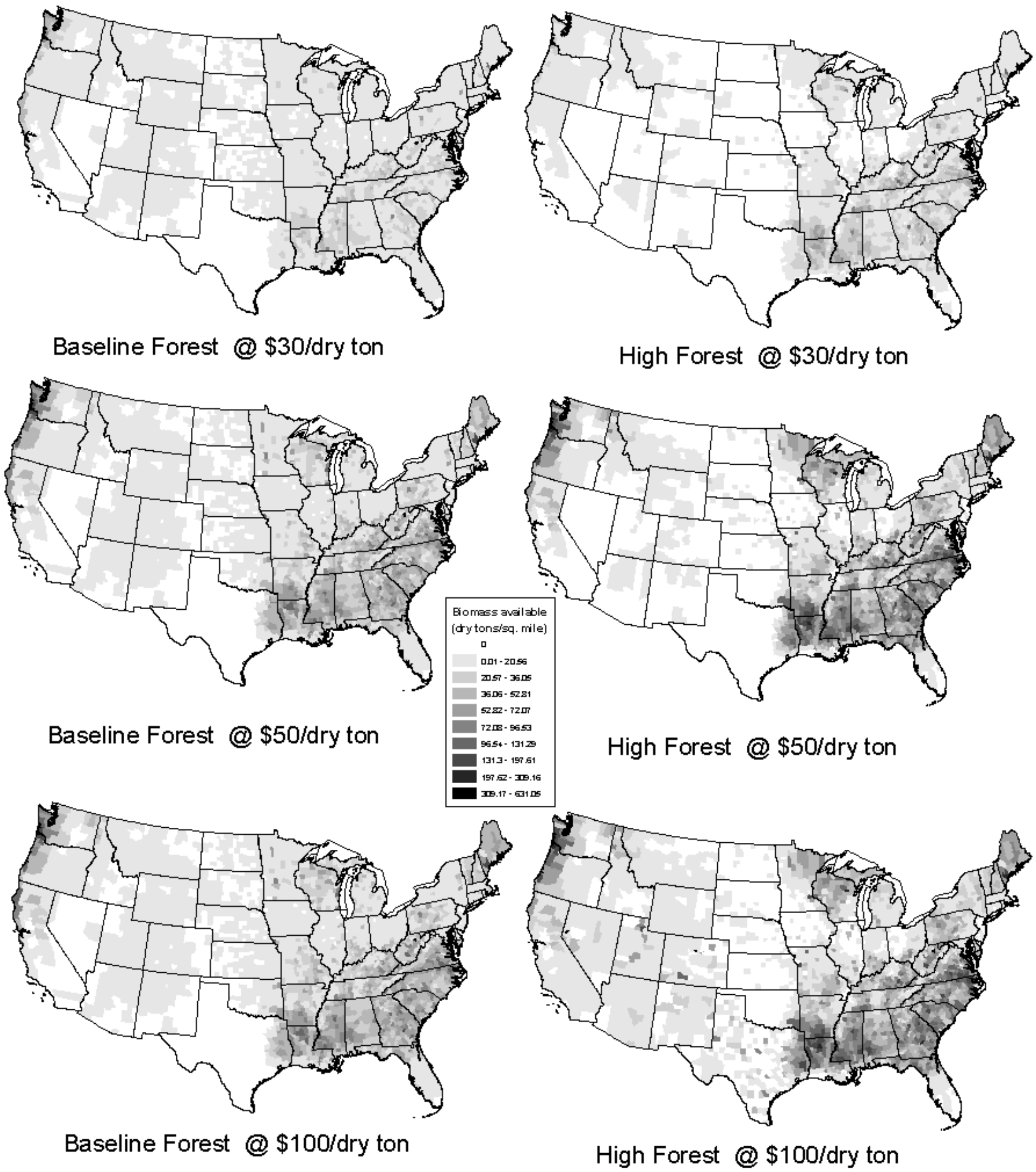

Figure 12: Map of forest residue resources

5.1.3 Pulpwood

In the case where biorefineries demand biomass at a high price, they would compete directly with pulp mills for pulpwood. Skog *et al* (2010) have estimated pulpwood supplies using an econometric approach. The quantity of pulpwood that would become available at higher prices from both increases in supplies and decreases in demand from pulp mills in response to the price shift were found using estimates of the elasticity of pulpwood supply. At a county level, increases in pulpwood supply are limited to not exceed annual timber growth. Displacement of current pulpwood uses is also limited to below 20% of 2007 use due to uncertainties in the elasticity estimates especially the range over which they are valid.

The pulpwood supply for 2017 is shown in Figure 13. The resource is concentrated in the south east and the states around the Great Lakes.

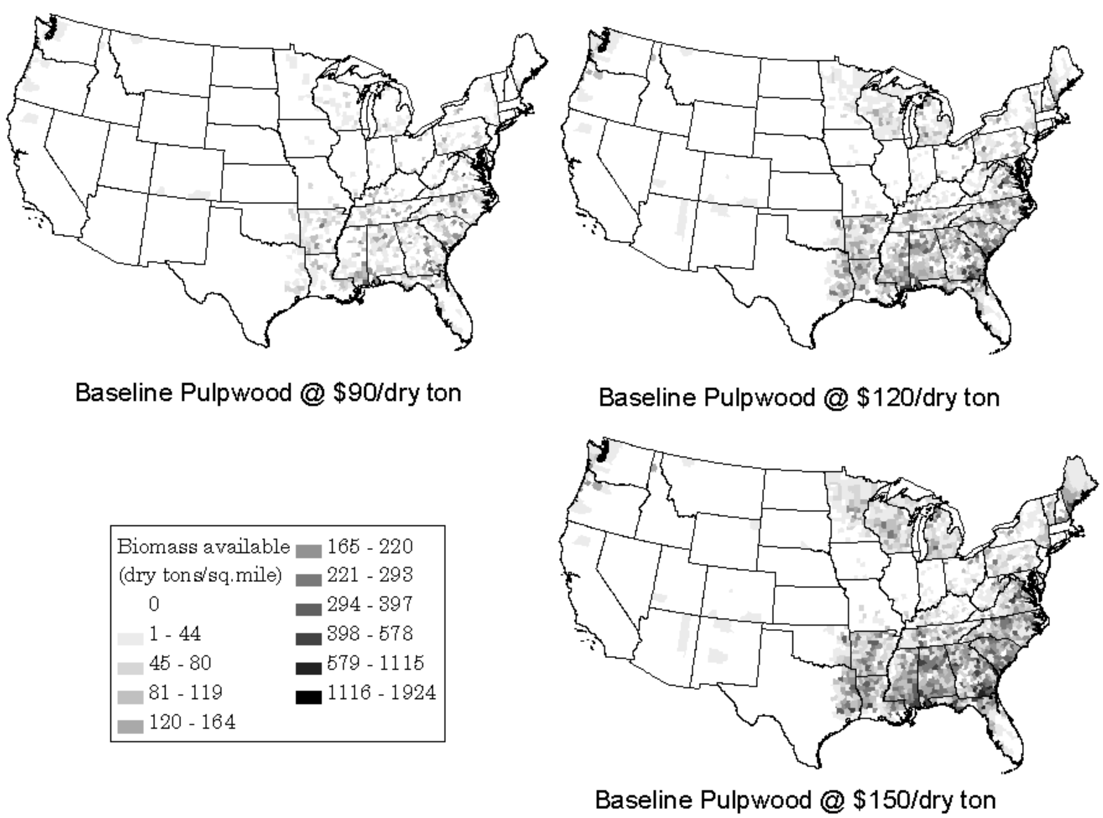

Figure 13: Map of pulpwood supply

Sensitivity to the base pulpwood supply was performed by varying the prices by +/- 20%. The case of a 20% reduction in the prices represent a depressed market for pulpwood in other industries and is used in the high feedstock scenario. The case of a 20% increase in the prices represents an increase in pulpwood demand for conventional uses and is used in the low feedstock scenario.

5.1.4 Municipal solid wastes

Current municipal waste production in the United States is estimated by two sources – the EPA (USEPA, 2009) and the biannual "State of Garbage" report (Arsova *et al.*, 2008). These two sources have significantly different estimates. For 2006, EPA estimates 169.55 million wet tons of biomass were landfilled while the State of Garbage study puts that number at 266.4 million tons. The two studies use significantly different approaches. The EPA study uses a "materials flow methodology" using data on the production/consumption of products in the U.S., average data on use and their expected lifetimes supplemented with waste characterizations and surveys to estimate the annual generation and recovery of wastes. The approach bypasses the need for consistent data collection of the waste which varies by state and locality (USEPA, 2008). The State of Garbage study attempts to standardize the data collected by states using a survey. A characterization of the waste stream is not attempted; only the mass of waste that is recycled, combusted or landfilled is estimated (Simmons *et al.*, 2006;

Arsova *et al.,* 2008]. In the national model shown in Chapter 5, state-specific waste generation rates (tons per capita) from the State of Garbage report are used along with the characterization from the EPA method.

The total quantity of biomass of several categories available from municipal wastes are calculated at the city level based on population (P_i), state specific generation estimates (WG_i), the fraction of total MSW generated that is currently landfilled of a given category (f_f), the fraction recoverable (R_f) and the moisture content (MC_f) using equation 22. The fraction of a resource that is recoverable is unknown and will vary with the price the market is willing to pay for it. The assumptions used here were developed from consultation with experts (Antares, 2008). These estimates represent an optimistic scenario where 45% of all wastes currently landfilled are diverted for fuel production. As a base case, the quantity available is assumed to be half of this. In a pessimistic case, only the woody construction and demolition debris is considered available.

$$S_{if} = P_i * WG_i * f_f * R_f * (1 - MC_f) \qquad (22)$$

Table 14: Summary of MSW landfilled

MSW Category	Fraction of Total MSW (wet weight basis) - f_f	Recoverable Fraction - R_f	Moisture Content - MC_f
Food Waste	18.6%	50%	70%
Paper/Cardboard	20.7%	50%	10%
Wood	8.9%	75%	12%
Yard trimmings	7%	75%	46.5%
Mixed waste*	18.4%	75%	18.6%

*Mixed waste includes the unrecoverable fraction of the other categories plus inorganics. It is 51.7% biogenic by weight and 40.8% biogenic by energy content

Both of these estimates do not include construction and demolition debris, biosolids or industrial process wastes that may also be landfilled. McKeever (2004) estimates that 11.6 tons of woody construction wastes and 69.3 of demolition wastes were generated in 2002. 40% of the demolition wastes were woody with 11.7 million tons economically recoverable. The demolition generation rates are based on an EPA study for 1996. The construction wastes are calculated using 10% and 20% waste factors for wood used in construction and renovation respectively. This resource is highly dependent on the housing market and can be expected to fluctuate over time. As a conservative estimate, construction and demolition wastes are assumed to remain the same as the 2002 estimate. Demolition wastes may contain lead and other heavy metal contaminants which make this resource unattractive for some applications, for example, biomass power plants.

Biomass is culled from the MSW stream at materials recovery facilities. These facilities accept MSW for a charge (tipping fee), sort out saleable fractions and send the rest to the landfill where they must pay a tipping fee. Materials recovery for biomass is a relatively new and undocumented operation for cost estimates. Antares, LLC reported an estimated $25 to $30 per ton cost for sorting feedstock quality biomass out of the MSW stream (Antares, 2008). In a review of studies on materials recovery facilities, Porter reported in 2002 that costs range from $30 to $80 per ton of recycled material (Porter, 2002). A cost of $30 per dry ton of feedstock quality biomass is used here. Tipping fees are not considered in the analysis and the $30 per dry ton cost is meant as a net cost including tipping fees received and paid by the materials recovery facility.

Individual states may have better data for their particular waste streams. California, for example, provides detailed reporting of wastes landfilled in the Solid Waste Information System (SWIS). Williams *et al* (2008) use information provided to estimate biomass potential from municipal wastes. The SWIS data are used for the California case study.

Furthermore, projections of future municipal waste production are speculative. The EPA data suggest that while waste generation has increased slightly below the rate of population growth between 1990 and 2008, increases in waste recovery has kept the discards constant (USEPA, 2009). There is good reason to believe this trend will continue as virgin materials become scarcer and the global demands for materials increases in line with population increases and increasing global affluence. Even if the total quantity stays the same, the composition of the waste stream will change over time. Between 1990 and 2008, paper and yard trimming discards decreased by 18 and 19.2 million tons per year, respectively, due to recovery while food scrap discards increased 10 million tons. Projections of available wastes are highly uncertain and the ones used here are likely optimistic considering historical trends.

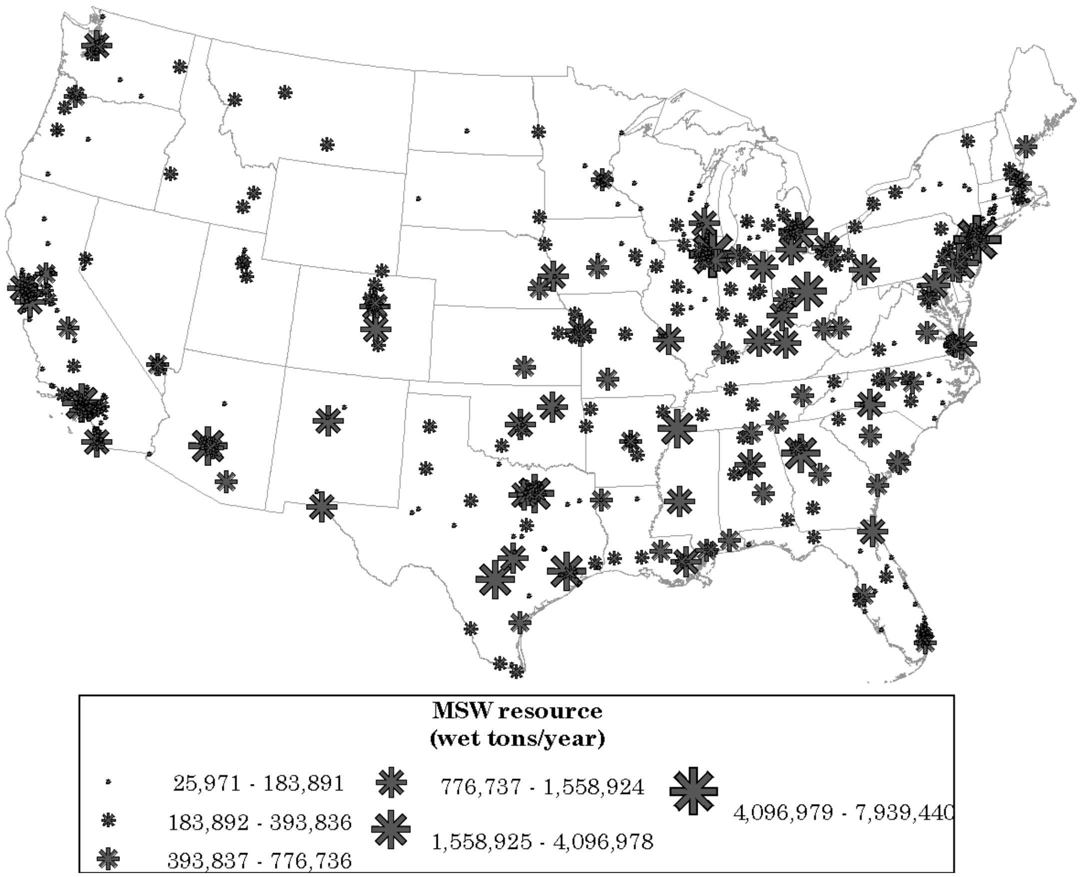

Figure 14: Distribution of estimated MSW production

5.1.5 Energy Crops

A number of crops are being considered for cultivation for the purpose of energy production. Chief among these are perennial grasses and short rotation woody crops.

Any estimate of production of energy crops relies on basic agronomic data for the yields and costs of production for the energy crop. As these crops are not currently grown in wide-scale agricultural systems, these data are not available across space. Projecting yields is therefore done using either models of growth based on the limited available data (Clifton-Brown *et al.*, 2004; Jain *et al.*, 2010; Thomson *et al.*, 2009; Wullschleger *et al.*, 2010) or by simply using average yields from available data and limiting the areas to regions with similar conditions as the existing trials. Alternatively yields and costs for similar crops such as hay for perennial grasses or pulpwood for woody crops can be used as proxies. Assumptions about yield growth over time can greatly impact total quantities and the economic viability of the resource.

Models have been developed for switchgrass and miscanthus production in the United States using average precipitation, temperatures, solar radiation and soil moisture data at sub-county scale and averaged to county level yields (Khanna *et al.*, 2008;Wullschleger *et al.*, 2010; Thomson *et al.*, 2009). The estimates of productivity vary by study and are difficult to compare without the full spatial data set. Reported averages are not a good reflection of the different distributions of yield for economically viable crops. The averages consider all lands not selecting locations that are likely to be put into production, which are likely to be some of the higher yielding locations. The model of miscanthus production in Illinois projects yields that are as much as 3.5 times higher than switchgrass leading to lower costs of production (Khanna *et al.*, 2008). Additionally the locations of greatest yield for miscanthus were in different regions of the state than the greatest yields for the incumbent crop rotation (corn/soy bean) suggesting that there may be locations where energy crops have a competitive advantage over conventional crops depending on market prices. For the national case study, the switchgrass yields developed by Wullschleger *et al* (2010) were used. The switchgrass cultivars are classified into two categories; upland and lowland varieties. In general, upland varieties are adapted to poor quality lands while lowland varieties are native to river bottom soils and have higher yields.

Next, the land base for energy crop production needs to be estimated. This can be done by including the energy crops in an agricultural sector economic model as done in de la Torre Ugarte and Ray (2000) and Khanna *et al* (2008) and explained in section 2.2. An alternative method is to assign production on lands that are logical candidates. Examples include lands that are currently underutilized such as idled cropland and cropland put into pasture (West *et al.,* 2009) or Conservation Reserve Program (CRP) lands that may have harvests of perennial grasses with minimal impact on the conservation goals (Perlack *et al.*, 20005).

The approach taken in the national case study is to assign energy crop production to currently underutilized lands. Land use data from the Census of Agriculture (USDA-NASS, 2009) on a county level were used. Lands classified as cropland but that were either idled or used as pasture during the 2007 growing season were considered to be underutilized. Idle cropland is land on farms that does not require improvements for crop production but was not reported as harvested, summer fallow, pastured or having crop failure. Idle cropland includes lands set aside through the Conservation Reserve Program (CRP), which provide an environmental benefit by keeping marginal lands out of intensive agricultural production. Cropland that is pastured is generally the marginal lands that shift into and out of crop production depending on the market. For example, in 2007 there were 35.8 million acres of cropland pasture while in 2002 when crop prices were lower there were 60.5 million acres in cropland pasture. Scenarios were considered with 25 and 50% of these lands put into energy crop production. Additional lands were considered for the conversion of pastureland to energy crop production.

While this method is arbitrary, it provides similar land type conversions as found using economic modeling methods. Khanna *et al.* (2010), found that the majority (75-98%) of land converted to energy crop production as predicted by their model is from cropland-idle and cropland-pasture. Only in the case where CRP lands are disallowed and farm-gate prices for biomass is high ($90/dry ton) is a significant fraction of energy crops grown replacing conventional crops.

The cost of production for energy crops depends on the cultivation practices, including fertilizer and pesticide use, seeding rates, and equipment operations (tilling, harvesting, etc.), which in turn depend on and impact the yield of energy crops. The cost of the inputs – labor, fertilizers and fuel –

vary across space and will impact the relative competitiveness of regions. In addition, the opportunity cost for the use of the land must be taken into account. This can be done through integrated economic models that determine the land value endogenously or through exogenous evaluations using either land rent surveys or the value of the land for production of the dominant crop in the county.

In the national case study, variable production cost (all cost excluding land rent) were estimated based on the study of switchgrass production for the Iowan context (Duffy, 2008). This assumes an eleven year crop rotation. The first year is establishment only with no harvest. In the second year, 25% of the area is expected to need to be replanting. The yields of the crop are assumed to be the average yield for the county from year 2 through year 11. Nitrogen fertilizer is applied at a rate of 100 pounds per acre every year. Phosphorous and potassium fertilizers are applied at replacement rate based on the yield of switchgrass. Land rent is taken from the 2008 National Agricultural Statistics Service survey (USDA-NASS, 2010), using non-irrigated cropland at the county level where available and the state average where county level land rents were not reported.

Three scenarios were explored for energy crop production in 2018 for the national case study. In the baseline and low cases, switchgrass can potentially be grown on 50% and 25% respectively of the cropland classified as idled or pastured in the 2007 US Census of Agriculture. The quantity and costs for this potential switchgrass production are found using upland switchgrass yields and the production cost model discussed above. The upland yields were chosen to represent yields on the marginal lands assumed to be available. This resource is provided to the optimization as potential feedstock. However, if they are not profitable to be consumed, they are not produced and the land is idled or put into pasture. For the high energy crop scenario, the land available is expanded from the baseline by adding 5% of current pastureland and production is increased by assuming higher yielding lowland switchgrass on all lands.

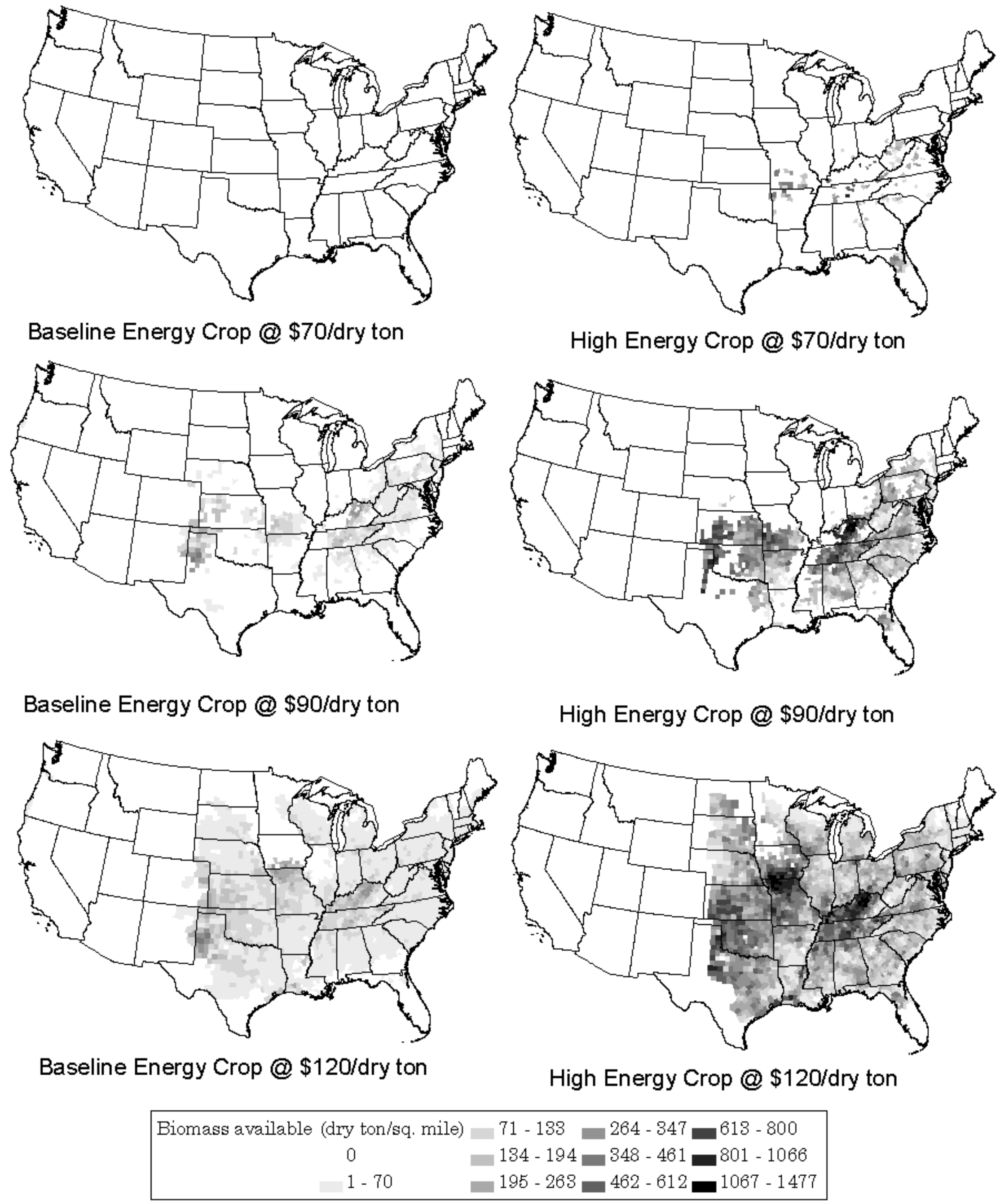

Figure 15: Maps of potential energy crop supplies under the baseline and high energy crop scenarios

5.1.6 Commodity Crops

Projections of production and prices for corn, soybeans, and canola in 2018 by county was estimated using national projections from the USDA's

Baseline Agricultural analysis (USDA, 2009) and county-level production statistics for the 2007/2008 crop year as reported by USDA's National Agricultural Statistics Service (USDA-NASS, 2010). Similar statistics exist from the Food and Agricultural Policy Research Institute (FAPRI) (2009). For each crop, FAPRI and the baseline analysis provide annual estimates of potential commodity crop yields and area planted for the crop years of 2008/2009 through 2018/2019. Projected production (total volumes or weights) forecasts for each county in the study area in which corn, soybeans, and/or canola were produced were estimated by multiplying the percentage change in yield and planted area on a national basis for each of the three crops between the 2008/2009 crop year and the average of the 2017/2018 and 2018/2019 crop years. The crop years of 2017/2018 and 2018/2019 were used instead of one single year as decisions concerning 2018 plantings could be made in an earlier year. Increases in yield and area were projected to be 16.2% and 6.0% for corn; 8.2% and 2.8% for soybeans; and 10.1% and 16.3% for canola and these were applied to 2008/2009 crop year statistics. Prices were taken from the FAPRI projections and were applied as a single national price point.

The projections could be used to develop estimates for national supply curves, but they would be at an extremely aggregated resolution and only valid for a single year due to potential changes in exports, agriculture and energy legislation, and alternative fuel demand. County-level supply curves for individual grain crops are also subject to these factors, but especially local grain/oilseed prices, which are not accurately known. Therefore, due to these reasons, supply curves were not developed. Instead, the quantity of corn and soy oil provided to biofuel production is specifically limited through constraints on the maximum national consumption in the model. The fraction of soy oil going to biodiesel is limited to not increase more than 50% above the FAPRI projection. At this maximum use, 38% of all soy oil is consumed for biofuel as opposed to 25% in the original projection. A constraint is introduced to the model to limit corn ethanol to 15 billion gallons per year in accordance with receiving credit within the federal RFS2. This level of corn consumption for ethanol is identical to the projected corn use for ethanol in the agricultural projections used. Both the soy oil and corn consumption constraints are maximum limits. The model is free to choose lower values of commodity crop consumption.

Projections of agricultural commodities such as these are tenuous at best as agricultural, energy, and/or environmental legislation, market forces, and the world petroleum situation concerning supply and demand strongly influence the agricultural markets and are highly uncertain.

5.1.7 Animal fats and waste greases

Edible and inedible tallow, lard and choice white grease, byproducts of the meat processing/slaughter industry, are potential feedstocks for biodiesel production. Each has distinct characteristics and price structures. Statistics derived from two independent sources (Kay, 2009; Jacobsen, 2009) give an average generation of edible and inedible tallow of about 5.8 billion pounds from approximately 70 separate locations across the United States, primarily in Kansas, Nebraska, Texas, and Colorado which if utilized for biodiesel production would equate to almost 800 million gallons. Over 1.8 billion pounds of both pork lard and choice white grease are generated in approximately 70 separate locations that could potentially supply up to 255 million gallons of biodiesel. Prices for edible and inedible tallow and pork lard and choice white grease obtained from a national source have varied considerably between 2003 and mid-2009 ($0.11 to $0.48 per pound) (Jacobsen, 2009). A price of $0.25 per pound ($500/ton) is assumed for the analysis.

Waste grease feedstocks (e.g. restaurant greases) are a secondary but accessible source of biodiesel feedstock. Estimates of this resource were made based on methodology developed by (Wiltsee, 1998) using urban population statistics. Municipalities with populations greater than 100,000 according to the 2000 U.S. Census were included in this analysis. Population expansions were estimated for each city in 2017 using data for state population growth derived from data provided by the U.S. Census Bureau (U.S. Census Bureau, 2005).

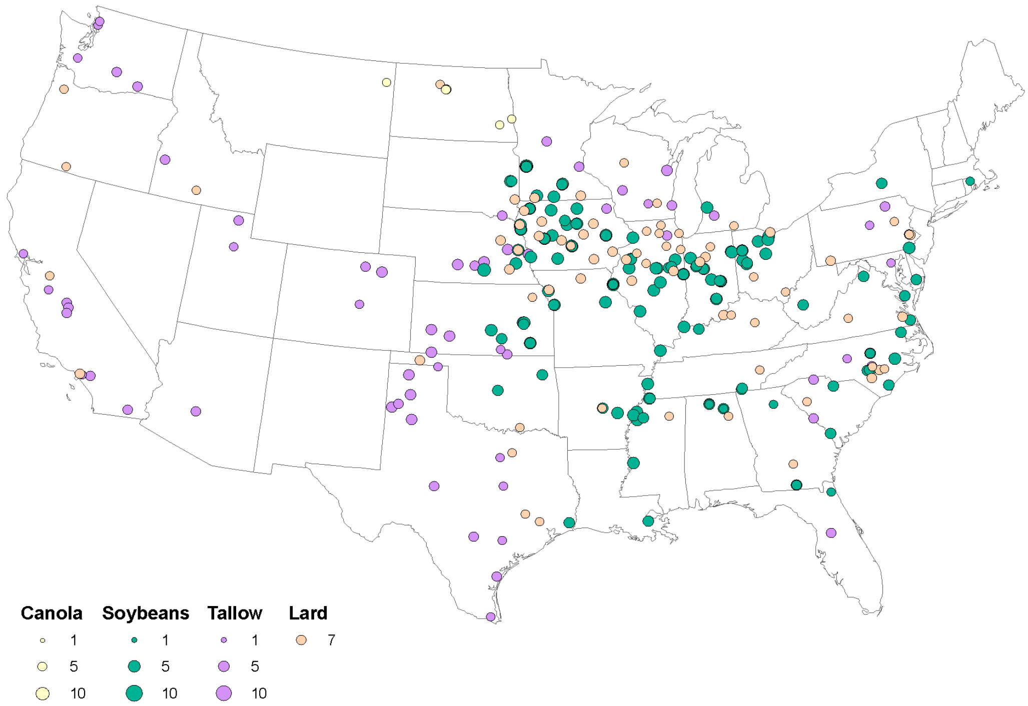

Figure 16: Lipid resources including canola and soy crushing plants and animal fats from rendering facilities (thousand tons per year).

5.1.8 Summary of national resource data set

The resources considered in this study are all assumed to be available at a given procurement cost (at the roadside) without feedback from the biomass demanded. A summary of the costs and quantities is given in Table 15 for resources that have a single cost without spatial variation. For the commodity crops, the total projected production is given in Table 15. In the model, the total quantity of these resources that can be consumed is constrained nationally but not at the county level of resolution. The costs and quantities for cellulosic resources, which have spatial distribution of cost, are aggregated and shown in Figure 17 for the baseline scenario, Figure 18 for the high scenario and Figure 19 for the low scenario.

Table 15: Roadside cost of grain and lipid resources

Resource	Procurement cost	Available Quantity (tons)
Corn	$130/ton ($3.64/bushel)	386,397,000
Soy oil	$690/ton ($0.35/lb)	16,174,000
Canola oil	$794/ton ($0.40/lb)	459,000
Animal Fats (Choice white grease, tallow and lard)	$500/ton ($0.25/lb)	3,866,000
Yellow grease	$320/ton ($0.16/lb)	652,000

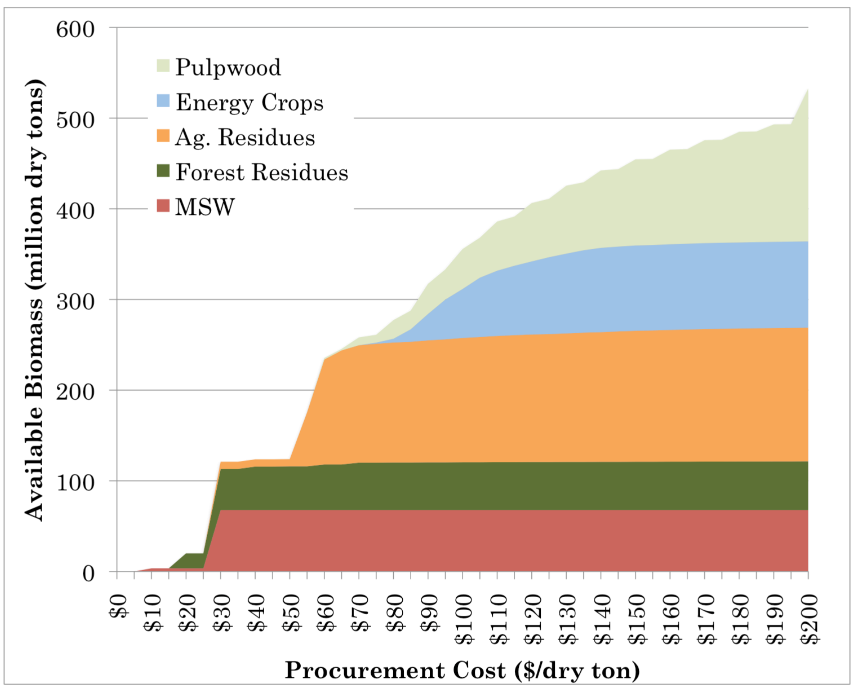

Figure 17: Baseline supply of cellulosic biomass resources.

In total, this study considers a baseline scenario where 533 million dry tons of cellulosic biomass are available at a maximum roadside cost of $200/dry ton. There are very few cellulosic resources available below $20/dry ton in the resource assessment. Below this point only unused mill residues and source-separated yard wastes are available. The majority of the forest residue biomass becomes available at roadside costs of $20 to $30 per dry ton. At $30/dry ton a significant amount of MSW resource is made available. This is a result of assumptions about MSW sorting costs and is an area where further study could improve the estimate. At roadside costs between $55 and $70 per dry ton, the majority of agricultural residues become available. The majority of energy crops are estimated to cost between $80 and $120 per dry ton depending on the county of production. The pulpwood supply for biomass grows constantly starting at $70 per dry ton.

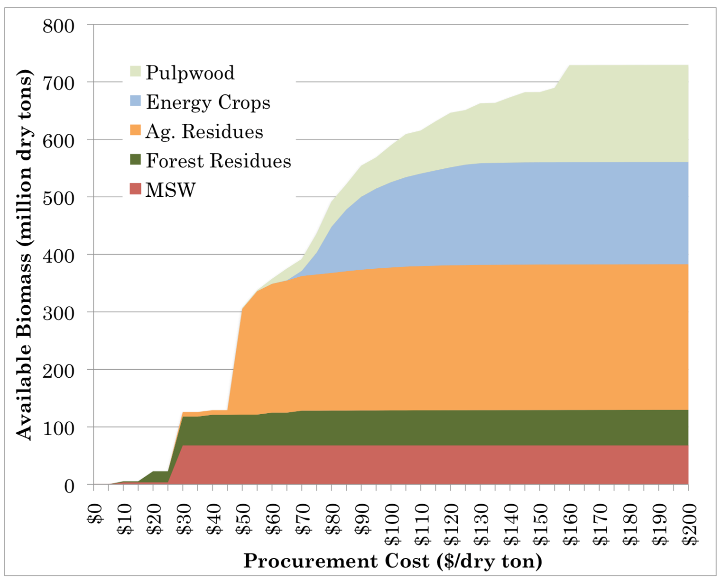

Figure 18: Cellulosic biomass supply in high scenario

In the high scenario for cellulosic biomass, a maximum supply of 797 million dry tons of biomass are projected to be available at a procurement cost of $200 per dry ton. In the high scenario, the largest increase from the baseline comes from agricultural residues. The resource increases by more than 100 million dry tons and the range of procurement costs is reduced with the majority of the resource becoming available between $45 and $50 per dry ton. The second large increase comes from energy crops where approximately 80 million dry tons of additional resource is projected. The supply of municipal wastes is doubled, increasing the supply by 67 million dry tons. The pulpwood supply curve is shifted down by 20%, making the supply available starting at $60/dry ton. Only minor additions are made to the forest residues due to including federal lands.

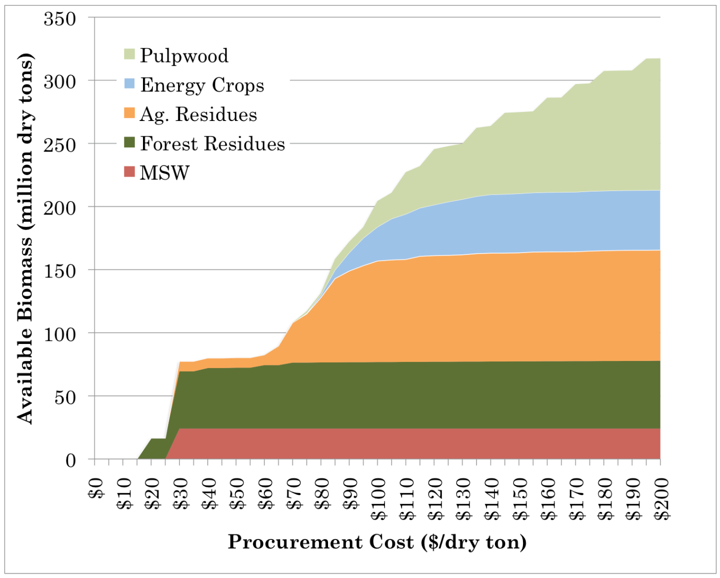

Figure 19: Cellulosic biomass supply in low scenario

In the low scenario for cellulosic biomass, a maximum supply of 317 million dry tons of biomass are projected to be available at a procurement cost of $200 per dry ton. Energy crops are reduced to half the baseline. Limiting MSW to woody resources, reduces the supply of MSW biomass to 36% of the baseline estimate. The agricultural residue resource is significantly reduced and the distribution of costs are spread over a greater range. The forest residues are unchanged and make up a greater percentage of the total resource.

Table 16: Summary of projected biomass resources in 2018 (million dry tons)

	This Study (<$50/dry ton | <$75/dry ton | <$100/dry ton)		
	Low Estimate	Middle Estimate	High Estimate
Agricultural Residues	0 | 30.2 | 71.2	0 | 122.7 | 128.2	159.2 | 227.5 | 238.8
Orchard & Vine. Wastes	8.0 | 8.0 | 8.0	8.0 | 8.0 | 8.0	8.0 | 8.0 | 8.0
Forest Residues	47.9 | 52.3 | 52.5	47.9 | 52.3 | 52.5	53.4 | 60.5 | 60.9
Pulpwood	0 | 1.6 | 26.0	0 | 8.7 | 33.2	1.6 | 33.2 | 64.4
Energy Crops	0 | 0.4 | 26.0	0 | 0.4 | 52.1	0 | 60.4 | 293.8
MSW - Total	24.2	67.55	135.2
C & D Wood	15.8	15.8	31.5
Urban Wood	8.5	8.5	16.9
Paper and Cardboard	0.0	13.3	26.6
Food Wastes	0.0	3.9	7.8
Yard/Green Wastes	0.0	3.3	6.7
Mixed Organics	0.0	22.9	45.7
Total	80.1 | 116.7 | 207.9	123.5 | 259.7 | 341.6	357.4 | 524.8 | 801.1

A summary of the resource assessments from three other studies is shown in

Table 17. The studies all found significant quantities of cellulosic biomass available with the lowest value of 410 million dry tons for the National Academies current assessment. The assessment used in this analysis is roughly in agreement with these studies.

Table 17: Summary of other resource assessments (million dry tons unless otherwise noted)

	Liquid Transportation Fuels from Coal and Biomass (NAS, 2009)			Billion Ton Study (2005)	U.S. EPA RFS2 Impact Analysis (2010)	
	Current	2020	Estimated delivered cost ($/dry ton)		Possible[8]	Used in 2022[8]
Agricultural Residues	91	130	$55 - $140	250 - 425	642 (wet)	61.8
Orchard & Vineyard Wastes	N/A	N/A	N/A	N/A	N/A	N/A
Forest Residues	110	124	$72 - $104	109 - 186	40 – 118	1
Pulpwood	N/A	N/A	N/A		N/A	N/A
Energy Crops	119	182	$101 - $199	156 - 377	321	85.6
Municipal Solid Wastes - Total	90	100	N/A		44.5	26
C & D Wood				28 – 39	8	
Urban Wood					5.3	
Paper and Cardboard					23.8	
Food Wastes					6.5	
Yard/Green Wastes					0.9	
Mixed Organics						
Animal Manure	6	12	N/A	N/A	N/A	N/A
Agricultural Processing Wastes	N/A	N/A	N/A	75	N/A	N/A

5.2 Transportation cost model

Transportation costs for all modes have two components; a fixed cost for loading and unloading of the material and a variable cost of transportation. The fixed cost depends on the format of the material (liquid, bale, or chip) and the resulting equipment operations required. The variable costs depend on the distance and time of the route along with local labor, fuel rates, truck capital cost and the effective size of the load. The format, density and

[8] The EPA document provides a rough estimate of possibly available resources and a projection for the biomass used in 2022 to meet the RFS mandate as determined using economic modeling.

moisture content of the material transported determine the effective load size.

The transportation cost model must account for the loading and unloading costs separate from the variable cost. Not doing so changes the functional form of the transportation costs and leads to an overestimate of the marginal cost of longer delivery distances. This would result in erroneous optimal sizing of biorefineries at smaller scales than the actual costs.

5.2.1 Biomass transportation costs

The model of biomass transportation via truck used here is based on the feedstock logistics model developed by Idaho National Laboratory, which includes labor and fuel estimates that vary based on year and state (INL, 2010). Separate cost models were developed for transportation of baled material and bulk material.

For transport of baled material, bales are loaded onto a flat bed trailer with a capacity of 26 bales or 17 tons. Loading is performed by a loader with the truck driver waiting and strapping down the load. The total load time is 33 minutes. The truck travels to the biorefinery where it is weighed in and unloaded using a loader again with a total time at the biorefinery of 35 minutes. The return trip is assumed to be empty, requiring the biomass to assume the entire roundtrip cost. The truck is assumed to have a fuel economy of 6 miles per gallon.

Bulk material is loaded via conveyor or directly from the chipper. The load time is 13 minutes for a 19.9 ton load. Emptying the truck using a truck tipper takes 12 minutes.

A fixed price of diesel that varies by state corresponding to a $3.55 per gallon national average is used. It is feasible for the price of diesel to instead be linked to the fuel price used for each point on the supply curve for consistency but this approach was not pursued at this time. The cost of labor also varies by state and corresponds to a national average of $20.24/hr for truck drivers and $14.70/hr for loader operators.

Rail costs used in this study are based upon a study of published ethanol transport rate schedules (Hughes, 2009). The costs are fitted to a linear model. Previous analysis of rail rates found no significant difference between agricultural products (similar to biomass) and ethanol on a per rail car basis. The ethanol rail rates are converted to biomass rates using an assumed 100 tons per rail car. I have also included a loading and unloading cost (INL, 2010).

Marine transportation costs are based on a published rate schedule for river barge (Tidewater, 2007). The rates were fitted to a linear function of distance similar to the rail rates above.

Searcy *et al.* (2007) provides an alternative model of biomass transport in the Canadian context. A comparison between the models used here and Searcy *et al.* is shown in Figure 20. The largest difference is in the fixed cost for rail transport. Searcy *et al.* uses an engineering basis to calculate the cost of a rail transport. This includes the rail spur and time/equipment/labor for loading and unloading the biomass onto a unit train for the biomass supplier and the cost of transporting the unit train for the railroad.

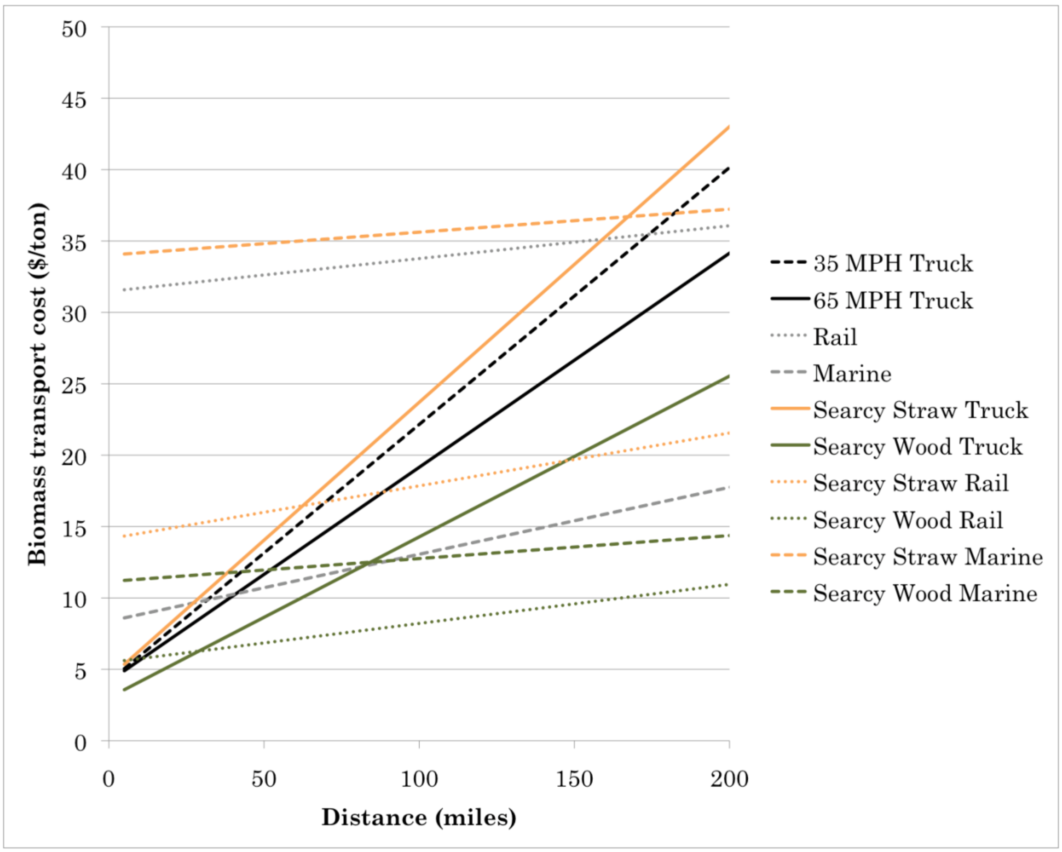

Figure 20: Transportation cost as a function of distance by mode

5.2.2 Liquid fuel transportation costs

Costs for transportation of liquid feedstocks and fuels for rail and marine transport are assumed to be the same as biomass on a per rail car or barge basis. The rail cars have 30,000 gallon liquid capacity and the barges have 1,260,000 gallon capacity.

For truck transport, the cost of the tanker trailers replaces the cost of the bulk transport trailers in the biomass transport cost equations. Additional insurance is applied for the transport of hazardous material.

5.2.3 Network Data Set

To accurately calculate the costs of transporting feedstock and fuels along the supply chain. The transportation network includes existing highways, rail lines, and marine transport routes, as well as inter-modal facilities. The inclusion of inter-modal facilities allows for the calculation of loading and unloading costs associated with the transfer of feedstock or fuel from one mode of transport to another. For road transportation, the network was built to enable the calculation of both time and cost of travel between two locations. Thus, each segment of the network is attributed with a mode and speed of travel. Data from a variety of sources was compiled to build the geographic and cost components of the transportation network. The Bureau of Transportation Statistics has recently released a new version of the road and rail network. The data include estimates of the actual speeds on each road. These are incorporated into the transportation model (BTS, 2009).

The railway network model contains mainline and secondary lines (spurs). Connections of a refinery to the railway only occur on secondary lines to identify the most likely locations for rail service. Figure 4 shows an overview of the national transportation model.

Many of the resources are reported at the county level and need an additional transportation cost added to account for the travel within the county. The intra-county transportation cost is calculated using the average "city-block" distance from any point in the county to the centroid. This geometric measure uses the perimeter of the county to estimate average travel distance. Additionally, it is assumed that the average travel speed along this route is 35 mph. These intra-county costs are then combined with the county centroid-based network transportation model.

These data were incorporated into a geodatabase in the ArcGIS software environment. Once the network was built the Network Analyst extension was used to create an origin-destination cost matrix from all source origins to all potential biorefinery locations. Similarly, network analysis was used to calculate the least cost paths from all potential biorefinery locations to all petroleum distribution terminals.

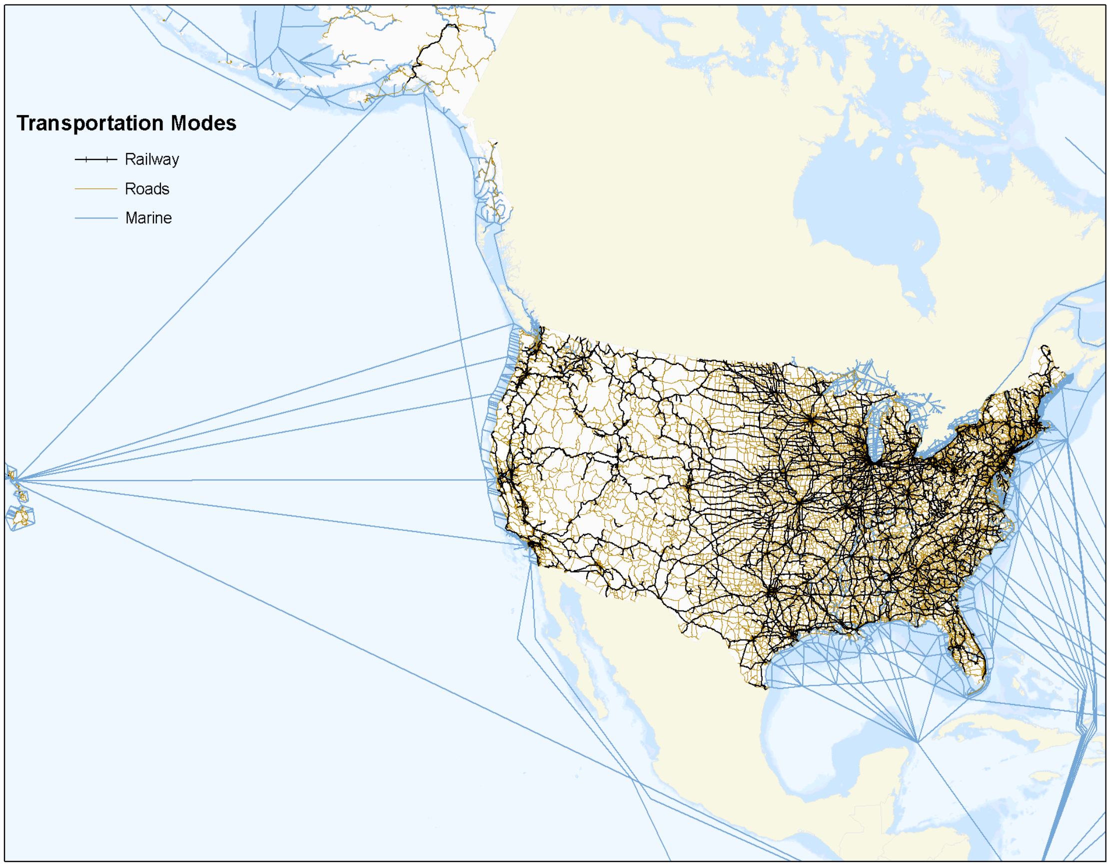

Figure 21: National transportation network.

5.3 Terminal costs

At the fuel distribution terminals, investments will be needed to accommodate the use of biofuels. These investments include new storage tanks, blending equipment, rail or barge receiving facilities and upgrades to the vapor recovery equipment if handling ethanol blends for the first time. The storage tanks are sized for 8.2% of average annual throughput (30 days). New storage tanks cost $40/bbl for ethanol, $35/bbl for the F-T diesel or diesel via hydrotreatment of lipids and $70/bbl for biodiesel (USEPA, 2010). Blending equipment capable of blending each fuel were estimated at

$310,000 (USEPA, 2010). The cost of rail facilities were estimated by the EPA to be $500,000 for manifest deliveries (individual rail cars), $10,000,000 and $25,000,000 for unit train facilities with capacities of 229 million gallons per year and 613 million gallons per year. The terminals are assumed to use a unit train facility when annual capacity reaches 9 million gallons per year. The cost of unit train facilities were linearly extrapolated from the two points given in the EPA analysis.

5.4 Spatial fuel demand

While this work does not find an equilibrium between supply and demand, two aspects of demand are important in determining the cost of supplying biofuels. First is the total consumption limit for each fuel (ethanol, F-T diesel, or biodiesel). Second is the spatial distribution of the demand, which impacts the cost of delivering biofuels to the market. This spatial distribution of demand is a constraint in the model limiting the quantity of each type of biofuel that may be sold from each fuel distribution terminal.

The fuel demand is based on a projection of vehicle miles traveled (VMT) by census tract for the year 2015 obtained from Oak Ridge National Laboratory (Hu, 2010). This data set is based on the National Household Transportation Survey from 2001 (Hu *et al.*, 2007) and county-level projections of population. A regression analysis was used to find the determinants of VMT from the survey data. Then the VMT by census tract was calculated based on statistics for each census tract and the parameters from the regression analysis. In performing the analysis, the Hu *et al* eliminated Manhattan because it was an outlier with less VMT per capita. I added Manhattan to the data set provided by using the 2005 county level VMT data from the EPA (Codd and Mullen, 2007) and a population correction to project to 2015. No attempt was made in this analysis to adjust the projections from 2015 to 2018.

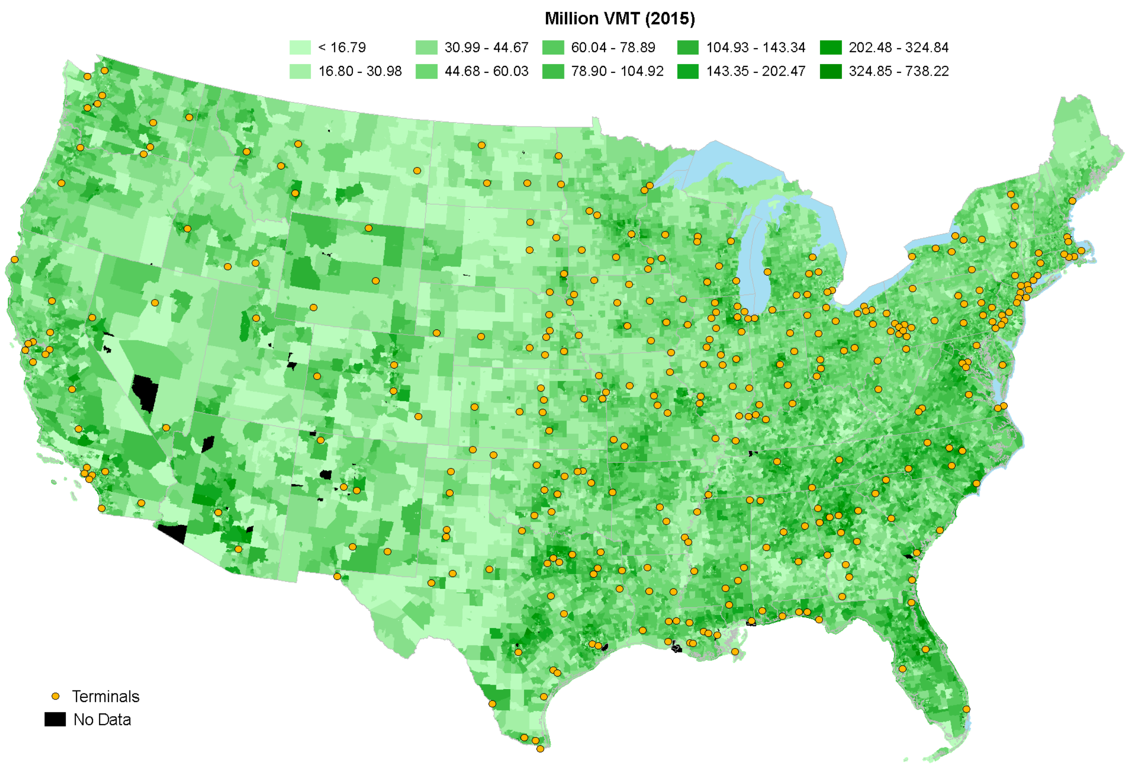

Figure 22: Distribution of fuel terminals and projected 2015 VMT by census tract

VMT for each census tract is assigned to the nearest fuel distribution terminal. The set of distribution terminals was limited by merging terminals within 20 km of each other with the terminal in the largest population city being retained in the set. Fuel demand is calculated by multiplying the fraction of the national VMT that is supplied by a given terminal and national projections for fuel demand. The demand provides a limit on biofuel consumption based on blend limits and/or the market share of vehicles capable of consuming higher blends (for example, FFVs) as described in section 3.3.2.

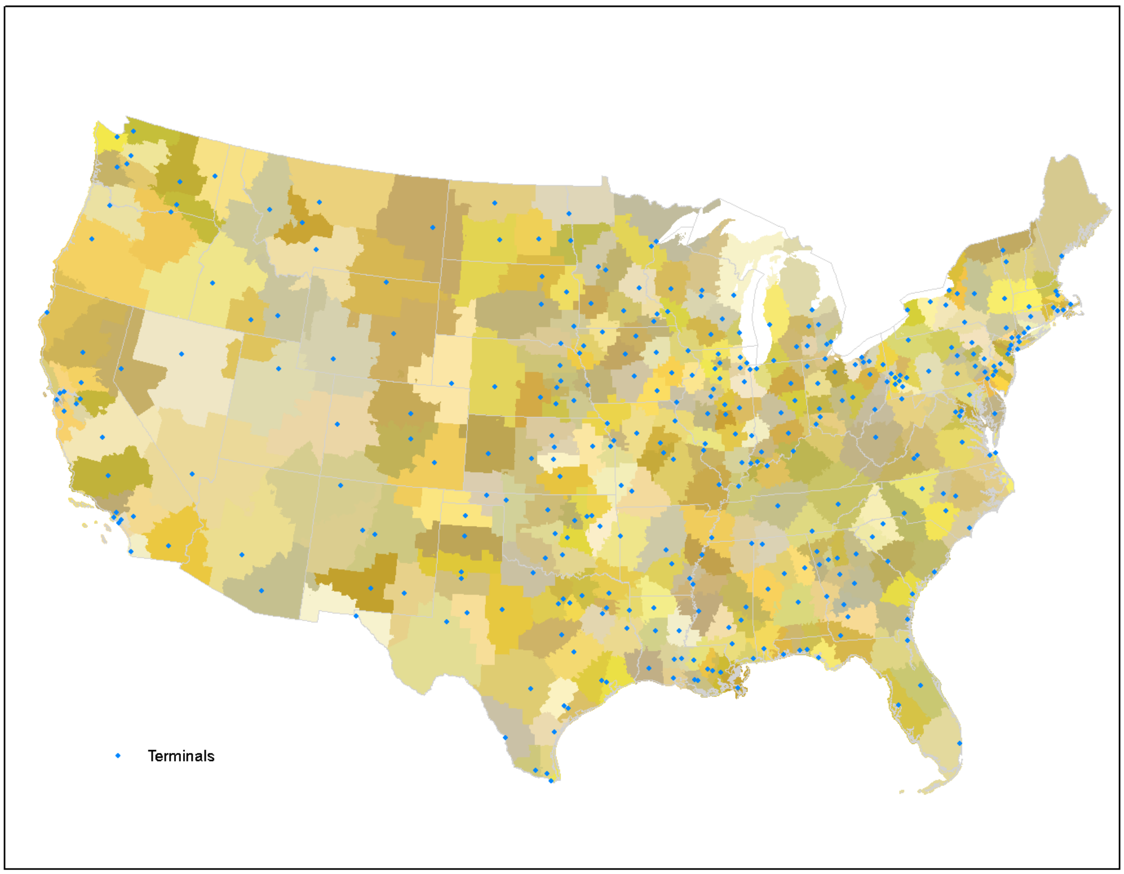

Figure 23: Modeled service areas for each fuel distribution terminal

Improvements to this basic method can be made if there is knowledge about the spatial variation in the fleet of vehicles. Two main refinements are possible. First is to correct for relative fuel economy of the fleet mix in different regions. Second would be to use knowledge about the spatial deployment of the fleet of FFVs to improve upon case studies considering spatially targeted deployment of E85 stations.

6 CASE STUDY 1: NATIONAL MODEL

6.1 Introduction to the Case Study

The revised Renewable Fuel Standard (RFS2) in the United States mandates significant growth in the biofuels industry through 2022. Biofuels equal to the 36 billion gallons of ethanol (on energy basis) or 23.6 billion gge are required to be consumed. The mandate represents an increase of 25.4 billion gallons of ethanol-equivalent from 2009 production levels. Volumes of biofuels are mandated for each year from 2009 to 2022. This case study employs the methodology and data sets described above to analyze the potential for biofuels to meet this target. The analysis focuses on the 2018 mandate because it is the last year provided in the agricultural projections that were used to develop the agricultural residues and commodity crop resource assessments (USDA, 2009). I will discuss the implications for achieving the 2022 mandate as well.

The RFS2 creates four embedded categories of biofuels (See Table 18). The categories are designated by their lifecycle greenhouse gas intensity and the feedstocks used to create them. To qualify as a renewable fuel, the lifecycle greenhouse gas emissions of the fuel must be 20% less than gasoline and be derived from “renewable biomass”; existing biorefineries are given an exemption for this requirement. Advanced biofuels are a subset of renewable fuels with greenhouse gas emissions 50% less than gasoline and not ethanol derived from corn starch. Cellulosic biofuels are a subset of advanced biofuels with greenhouse gas emission 60% less than gasoline and that are derived from cellulose, hemicellulose or lignin. Biomass-based diesel is a second subset of advanced biofuels with the added restriction that it must be a diesel fuel (the 50% greenhouse gas reduction applies). The mandate is uses an energy basis, which gives a gallon of renewable diesel a credit of 1.6 gallons of ethanol-equivalent.

Table 18: RFS2 mandated quantity of biofuels (billion gallons of ethanol equivalent) (USEPA, 2010)

Year	Renewable Fuel	Advanced Biofuel	Cellulosic Biofuel	Biomass-based Diesel	RFS2 Corn ethanol limit
2006	4				4
2007	4.7				4.7
2008	9				9
2009	11.1	0.6		0.5	10.5
2010	12.95	0.95	0.1	0.65	12
2011	13.95	1.35	0.25	0.8	12.6
2012	15.2	2	0.5	1	13.2
2013	16.55	2.75	1	1	13.8
2014	18.15	3.75	1.75	1	14.4
2015	20.5	5.5	3	1	15
2016	22.25	7.25	4.25	1	15
2017	24	9	5.5	1	15
2018	26	11	7	1	15
2019	28	13	8.5	1	15
2020	30	15	10.5	1	15
2021	33	18	13.5	1	15
2022	36	21	16	1	15

The study uses a 2018 target for technology costs and feedstock availability, which is presumed to allow sufficient time for the development and initial deployment of second-generation biofuel production technologies. As a first approximation, a scenario is examined for a coordinated refinery infrastructure built in 2018 based on a representative year for resource and cost estimation. Sensitivity scenarios were developed around uncertainties in conversion technology performance, resource availability and limits to the demand for ethanol fuels. More detailed information on conversion technologies and feedstock supply data is given in the preceding two chapters.

6.2 Model Formulation

The general model formulation is given in Chapter 3. However, several refinements were made for this case study. First, corn ethanol production is limited to 15 billion gallons per year. Second, soy oil consumption for biodiesel is limited to increase by no more than 150% of the projected soy oil used for biodiesel in the FAPRI projection for 2018 as described in section 5.1.6 (FAPRI, 2009). This is equal to 30% of all soy oil projected to be produced in the United States in 2018. The reason for this constraint is that there is no explicit price response in the model and biodiesel production would consume all soy oil at high fuel prices without a limitation. Third, a supply of imported sugarcane ethanol is introduced to the model at coastal ports.

To model imported sugarcane ethanol, a stepwise supply for imported sugarcane ethanol was developed based on the work of Babcock *et al* (2010) that analyzed the ethanol prices and supplies under combinations of the ethanol policies with a stochastic model of gasoline prices and corn yields in 2011 and 2014. I fitted a linear curve to the price and imported ethanol quantities derived under the no policy scenario in Babcock *et al*. I used the slope of this curve for the elasticity for imported ethanol however the quantity does match the projected imports at the price in AEO2010 so I shifted the intercept of the supply curve to match the price and quantity predicted in AEO 2010 for 2018 for consistency with the AEO2010 (EIA, 2010).

The cellulosic conversion technologies were differentiated by the category of resource that they can consume. Both cellulosic ethanol and F-T diesel technologies were assumed to be capable of using all cellulosic materials but any single biorefinery is limited to a single category of feedstock (herbaceous material, woody material or other waste materials). These categories represent resources that with similar pretreatment processes at the biorefinery. A potential biorefinery is considered for each of the categories at each location. The result is that there are three potential cellulosic ethanol and three potential F-T diesel biorefineries at any given site all of which could be chosen in the optimal solution.

The energy co-products of electricity and naphtha are credited at the biorefinery. In the general formulation, the co-products have spatially explicit demand nodes. Incorporating the spatial demand for co-products requires additional data collection effort, which has not been undertaken. Electricity is valued at $0.05/kWh. Naphtha is valued at 90% of the fuel price for a given model run. There is a possibility that the naphtha could be upgraded to be mixed with gasoline and would then count as part of the renewable fuel production. However, in their analysis of the RFS2 mandate, the EPA stated that naphtha from biomass F-T production is not a good candidate for upgrading to gasoline unlike petroleum naphtha (USEPA, 2010). I have followed this convention of not including naphtha for defining the volumes of biofuels produced.

6.3 Scaling up the model

The biorefinery siting optimization model is solved using the MIP solving algorithm in CPLEX optimization software from ILOG using the GAMS model language (ILOG, 2009; McCarl, 2004). The computational difficulty of the model depends on the number of variables with the number of binary variables being most important. The full national model proved too large for commercial MIP solvers to solve in reasonable time. Attempts to solve the full model did not progress past building the model. The attempts were aborted after 15 hours with more than 25 GB of memory required. To speed the process, the optimization is performed in two steps where the results of first stage models were used to define the feasible set for a simplified national model. The first stage models optimize the biofuel production without consideration of the fuel deliveries. The first stage models were split out of the national model based on resource type and region; regional models for the woody and herbaceous resources, and national models for grain, lipid and municipal solid waste resources. Several first stage models were run for each region to span the likely set of outcomes including all lignocellulosic resources going to F-T diesel production in the case of limited ethanol demand. The production models were run for all scenarios (given below) at $3 and $6 per gge with both cellulosic biofuel technologies and each biofuel technology separately.

In a previous study of the western United States, cellulosic resources were rarely economical to delivered more than 100 miles to the refineries (Parker *et al.,* 2010). This trait allows the fuel production and resource allocation portion of the model (leaving fuel deliveries out) to be solved regionally without loss of the optimal solution. I divided the country into 9 regions. In order to avoid unusual solutions at the region boundaries, the regions are expanded to include all resources with transportation costs to the potential locations in the region below $45 per wet ton. This way the regions are overlapping. Through this approach the majority of variables that do not add value to the model but just computational difficulty are removed from consideration for the national model.

To take advantage of the two stage models the 21 sets of screening models need to solve quickly. Each model requires computer hardware with at least 12 GB of memory and multiple fast processors. Solving the models for this case study sequentially on one server would require 4 weeks to provide a feasible set for the reduced national model, then an additional 3 to 6 days to develop supply curves for each scenario. This process would need to be repeated as errors are found or changes in the parameters were desired. To speed the process without the prohibitively expensive purchase of multiple servers, the screening models were solved simultaneously using cloud computing. Solving the 21 screening models simultaneously reduced the time from 4 weeks to 3 days. This allows for analysis to be completed in a weeks time instead of 2 months at much lower cost.

The results of the screening models were combined to form the feasible set for the national model. Then the national models for each scenario were run to develop supply curves simultaneously. Finally, the national models were revised to find the price point where the 2018 RFS2 mandate is achieved. The fuel price is adjusted using a while loop starting at the nearest point on the supply curve that is below the mandated volume then adding $0.01/gge and solving until the mandated volume is reached.

6.4 Scenarios

Scenarios were developed around technology performances and feedstock availability for cellulosic biofuels and fuel demand limits. The baseline scenario uses the best estimates for technology performance and resource availability. All other scenarios present deviations from the baseline. Across all scenarios, the lipid and corn technologies remain the same and the lipid resource supplies are unchanged. They are described in Chapters 4 and 5 respectively.

The cellulosic biomass resource base for the baseline uses the middle case resource datasets that were described in Chapter 5. The technologies employed are the baseline technologies described in Chapter 4. The demand for ethanol fuel is limited to the blend limit of E10 for all gasoline vehicles. The demand for F-T diesel is limited at 95% of all diesel demand and biodiesel is limited to 5% of diesel fuel. To simulate this, a limit on ethanol demand was given for each terminal equal to providing all gasoline energy as E10. Due to the lower energy density of E10 versus gasoline, the volumes are adjusted to reflect an equal quantity of energy. The ethanol limit is calculated from the projected gasoline-like fuel demand in 2018. The EIA projects 17.3 Quads (1 Quad = 10^{15} Btu) of energy will be consumed by the transportation sector in the form of gasoline-like fuels. If all of this fuel is provided as E10 that translates into a limit of 153 billion gallons of E10 or 15.3 billion gallons of ethanol. 50.9 billion gallons of diesel fuel are projected to be consumed in the transportation sector for 2018 by the EIA (2010).

There are three sets of scenarios developed off the baseline (See Table 19). The first concerns the conversion technologies for cellulosic biofuels. An optimistic scenario uses the optimistic parameterization for cellulosic ethanol along with the baseline F-T diesel technology. An optimistic characterization was developed for the cellulosic ethanol technology but not F-T diesel because there was a greater range of supported literature values for the cellulosic ethanol technology. The optimistic literature value for F-T diesel comes from the EPA (USEPA, 2010) however, it is not considered due to lack of supporting information. A pessimistic scenario uses pessimistic assessments for both cellulosic biofuel technologies. In the baseline model, F-T diesel is the lower cost pathway of the two cellulosic biofuel technologies. The difference in cost is not large but the "penny switching" nature of linear program leads to a single technology choice not the distribution of choices that may occur when all the performance variability is taken into account. An additional "ethanol dominant" scenario was developed using the baseline ethanol technology along with the pessimistic F-T diesel technology. The ethanol dominant scenario captures the impact of the ethanol technology developing while the F-T diesel technology does not improve.

The second set of scenarios captures the uncertainty in resource availability. High and low feedstock scenarios were developed based on the high and low sets of resource assessments shown in Section 5.1.8. The two resources with the largest range of values among the three assessments (low, middle and high) were agricultural residues and energy crops. The high and low assessments for these two resources were run as four independent scenarios to evaluate the impact of these two important resources.

The model does not currently consider the feedback of biofuel demand on the price of the feedstocks that the industry consumes. This is most important in the case of corn ethanol. With a single price for the procurement of corn the modeled industry will consume as much corn as allowed at high fuel prices. By limiting the corn ethanol to a maximum 15 billion gallons per year the maximum corn consumption for ethanol in the baseline is consistent with the FAPRI projection (2009) from which the corn quantities and prices come. However, there are a number of outside market factors that can impact the price of corn in the future. To show the impact of corn price on the overall supply of biofuels I have developed scenarios with corn prices at $2.50/bushel for the low case and $5.50/bushel for the high case.

The final set of scenarios considers the impact of limits on biofuel demand. The baseline E10 demand limit does not account for all the potential ethanol demand. The EPA ruled in 2020 that vehicles made after the model year 2007 can operate on an E15 blend. If this blend limit is expanded to all vehicles, there would be a significant increase in the potential market for ethanol. An E15 scenario is presented with a limit of 23.56 billion gallons of ethanol.

Ethanol can also be consumed in the form of E85 by flex-fuel vehicles (FFV). There are a limited but growing number of these vehicles on the road. In 2010, 9 million FFVs were on the road in the United States accounting for 4% of the total light-duty vehicle stock. The AEO2010 projects FFVs to grow to 28 million (11.5% of LDVs) in 2018 and 39 million vehicles (15% of LDVs) by 2022. As their name suggests, they can be driven on conventional gasoline or up to 85% blend of ethanol with 15% gasoline. In order to entice the drivers of these vehicles, E85 will need to be both readily available and cost competitive with gasoline. These two conditions are not met any place in the country today. However, as a bounding argument for how far ethanol demand could be pushed without changing the blend limit, a sensitivity scenario is performed with the fleet of FFVs predicted to be on the road in 2018 fueled exclusively on E85. In 2018 FFVs are projected to account for 11.3% of vehicle miles traveled according to the 2010 Annual Energy Outlook Base Case [31]. Assuming that the fleet of FFVs have the same fuel efficiency as the fleet of conventional vehicles, the maximum ethanol demand from FFVs plus the rest of the fleet operating on E10 is 30.38 billion gallons.

For the above scenarios, the blend limit is a maximum constraint on the quantity of biofuels that can be consumed at each terminal. The resulting system will yield a distribution of blends across the country with those terminals near biofuel supplies having higher blends than terminals far from biofuel supplies.

The last fuel demand scenario considers a variable national blend where the blend of each type of biofuel is consistent across the country. This is independent of the volume of fuels produced. For example, if enough ethanol can be profitably produced at a volume that is 5% of the national gasoline demand then every fuel terminal will be using an E5 blend. The blend changes across the supply curve as more biofuel becomes profitable. This scenario does not reflect any expected future but it can highlight improvements to the cost structure of the biofuel supply if blend limits are removed.

Table 19: Summary of the parameter changes in scenarios

	Baseline	High Feedstock	Low Feedstock	High Energy Crop	Low Energy Crop
Parameter					
Cropland - Idle (% of 2007 acres)	50%	50%	**25%**	50%	**25%**
Cropland - Pasture (% of 2007 acres)	50%	50%	**25%**	50%	**25%**
Pastureland (% of 2007 acres)	0%	**5%**	0%	**5%**	0%
Switchgrass yields	2010 upland from ORNL	**2010 lowland from ORNL**	2010 upland from ORNL	**2010 lowland from ORNL**	2010 upland from ORNL
Allow Forest biomass from federal lands	no	**yes**	no	no	no
Ag. Residues	2018 projection (38% harvest eff)	**2018 projection (70% harvest eff)**	**10 yr historical**	2018 projection (38% harvest eff)	2018 projection (38% harvest eff)
Pulpwood	BTS 2018	**BTS 2018 (-20% prices)**	**BTS 2018 (+20% prices)**	BTS 2018	BTS 2018
MSW - food	25.0%	**50%**	**0%**	25.0%	25.0%
MSW - yard	37.5%	**75%**	**0%**	37.5%	37.5%
MSW - wood/c&d	25.0%	**50%**	**25%**	25.0%	25.0%
MSW - paper	25.0%	**50%**	**0%**	25.0%	25.0%
MSW - mixed	37.5%	**75%**	**0%**	37.5%	37.5%
Cellulosic ethanol	baseline	baseline	baseline	baseline	baseline
Cellulosic F-T diesel	baseline	baseline	baseline	baseline	baseline
Ethanol demand limitation	E10	E10	E10	E10	E10
F-T diesel demand limitation	95% of diesel	95% of diesel	95% of diesel	95% of diesel	95% of diesel

	Historical Ag. Residues	**High Ag. Residue**	**Optimistic Cellulosic Technology**	**Pessimistic Cellulosic Technology**	**Ethanol Dominant**
Parameter					
Cropland - Idle (% of 2007 acres)	50%	50%	50%	50%	50%
Cropland - Pasture (% of 2007 acres)	50%	50%	50%	50%	50%
Pastureland (% of 2007 acres)	0%	0%	0%	0%	0%
Switchgrass yields	2010 upland from ORNL	2010 upland from ORNL	2010 upland from ORNL	2010 upland from ORNL	2010 upland from ORNL
Allow Forest biomass from federal lands	no	no	no	no	no
Ag. Residues	**10 yr historical avg.**	**2018 projection (70% harvest eff)**	2018 projection (38% harvest eff)	2018 projection (38% harvest eff)	2018 projection (38% harvest eff)
Pulpwood	BTS 2018	BTS 2018	BTS 2018	BTS 2018	BTS 2018
MSW - food	25.0%	25.0%	25.0%	25.0%	25.0%
MSW - yard	37.5%	37.5%	37.5%	37.5%	37.5%
MSW - wood/c&d	25.0%	25.0%	25.0%	25.0%	25.0%
MSW - paper	25.0%	25.0%	25.0%	25.0%	25.0%
MSW - mixed	37.5%	37.5%	37.5%	37.5%	37.5%
Cellulosic ethanol	baseline	baseline	**optimistic**	pessimistic	baseline
Cellulosic F-T diesel	baseline	baseline	baseline	pessimistic	**pessimistic**
Ethanol demand limitation	E10	E10	E10	E10	E10
F-T diesel demand limitation	95% of diesel	95% of diesel	95% of diesel	95% of diesel	95% of diesel

	National blend	**FFV**	**E15**
Parameter			
Cropland - Idle (% of 2007 acres)	50%	50%	50%
Cropland - Pasture (% of 2007 acres)	50%	50%	50%
Pastureland (% of 2007 acres)	0%	0%	0%
Switchgrass yields	2010 upland from ORNL	2010 upland from ORNL	2010 upland from ORNL
Allow Forest biomass from federal lands	no	no	no
Ag. Residues	2018 projection (38% harvest eff)	2018 projection (38% harvest eff)	2018 projection (38% harvest eff)
Pulpwood	BTS 2018	BTS 2018	BTS 2018
MSW - food	25.0%	25.0%	25.0%
MSW - yard	37.5%	37.5%	37.5%
MSW - wood/c&d	25.0%	25.0%	25.0%
MSW - paper	25.0%	25.0%	25.0%
MSW - mixed	37.5%	37.5%	37.5%
Cellulosic ethanol	baseline	baseline	baseline
Cellulosic F-T diesel	baseline	baseline	baseline
Ethanol demand limitation	**proportional blend**	**E10 + E85 for 100% 2018 flex-fueled vehicles**	**E15**
F-T diesel demand limitation	**proportional blend**	95% of diesel	95% of diesel

6.5 Results

6.5.1 Baseline scenario

The baseline scenario meets the 2018 RFS2 mandate at a fuel price of $2.87/gge at the fuel distribution terminal without subsidies. Local distribution, marketing and taxes would add approximately $0.65/gge on average making the fuel price at the pump approximately $3.52/gge. This is within the range of the projected prices for gasoline ($2.00-$4.71/gge) and diesel ($1.92-$4.46/gge) fuel for 2018 in the AEO2010 low and high oil price scenarios. While the RFS2 mandate is expressed in terms of gallons of ethanol equivalent, I present results in terms of gallons of gasoline equivalent that is more readily comparable to the existing fuel market.

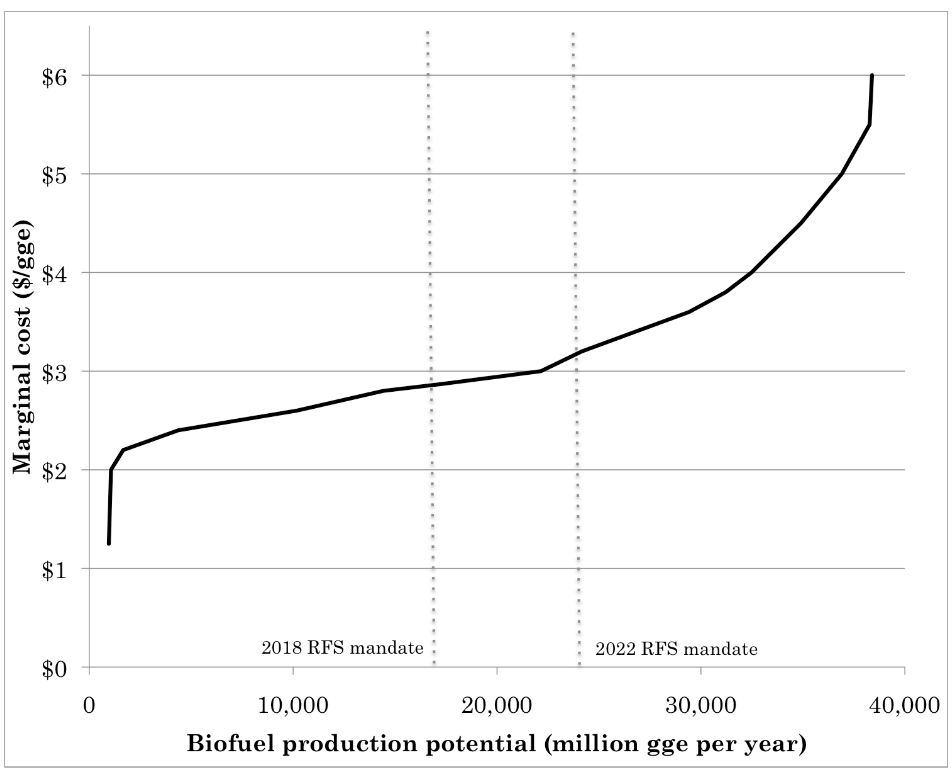

Figure 24: Baseline biofuel supply curve

A variety of biofuel pathways are exploited to meet the mandate. The largest pathway by volume is corn ethanol with 13 billion gallons of ethanol projected. This volume does not reach the mandated limit of 15 billion gallons. A small quantity (200 million gallons) of Brazilian ethanol is also consumed but not enough to reach the E10 blend limit imposed on the model. No cellulosic ethanol production appears in the baseline solution. The model projects 336 million gallons of biodiesel produced from waste greases and animal fats. The remaining 8.3 billion gge of fuel is projected to come from F-T diesel from cellulosic biomass. Three main resources are exploited. Agricultural residues provide the largest fraction (37.5% of F-T diesel). Municipal wastes (33% of F-T diesel) and forest residues (27% of F-T diesel) also provide a significant fraction. While the specific bins within the RFS2 mandate were not explicitly modeled, the resulting system would qualify because the F-T diesel fuels qualify for all bins and none of the other fuels exceed the limit for the bin for which they qualify.

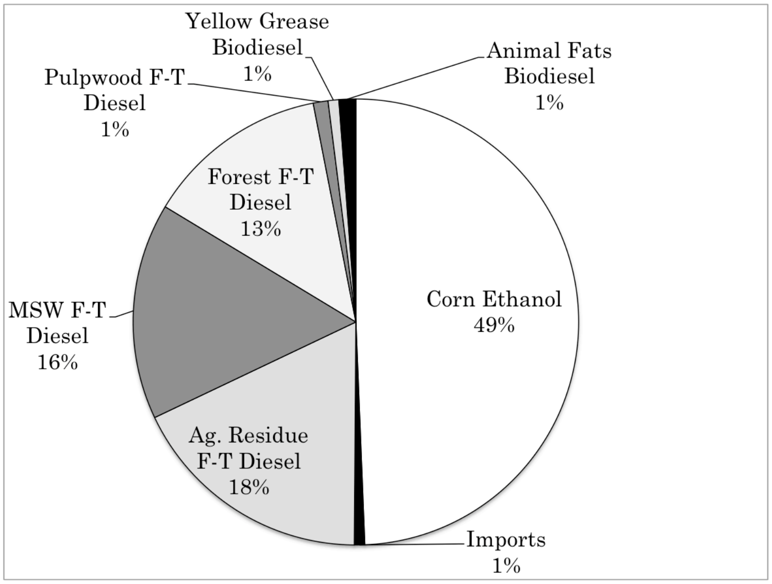

Figure 25: Fuel pathways for meeting 2018 RFS2 mandate under the baseline assumptions

No switchgrass is produced or consumed at this quantity of biofuel. Only the corn ethanol puts pressure on the extent of agricultural land in the United States with 26.5 million acres dedicated to the production of corn for ethanol. Intensification of agriculture – increased fertilizer use and soil erosion – occurs due to the removal of agricultural residues. 47% of the available agricultural residues are consumed in order to meet the mandate.

None of the resources are fully consumed at the national level. However, the solution approaches two resource limits and the corn ethanol limit. The solution contains 13 billion gallons of corn ethanol or 87% of the corn ethanol that is allowed by the formulation. 82% of the forest residue resources are consumed and 86% of the MSW resources are consumed. Free blending of F-T diesel with petroleum diesel was allowed up to 95% by volume meaning the limit on F-T diesel demand is defined by the diesel demand. This limit is not approached but it should be noted that 16% of the projected 2018 diesel demand is met with biomass-based diesel (F-T diesel and biodiesel). At $6/gge – the highest price analyzed – 52% of transportation diesel demand is met with biomass-based diesel while only 7% of the gasoline demand is met with ethanol. Petroleum refineries have limited flexibility in the fraction of diesel versus gasoline that they produce from a barrel of oil. If biofuels provide disproportionate displacement of either diesel or gasoline, they will impact the relative prices between gasoline and diesel.

The infrastructure required to realize the projected supply of biofuels is significant in scale and capital cost. The projected system requires 25 new dry mill corn ethanol biorefineries and 159 new biorefineries producing F-T diesel from cellulosic biomass. The F-T diesel biorefineries range in size from 750 dry tons per day to 5,250 dry tons per day with average size of 3,200 dry tons per day. This system represents $107.9 billion in new capital investment in biorefineries.

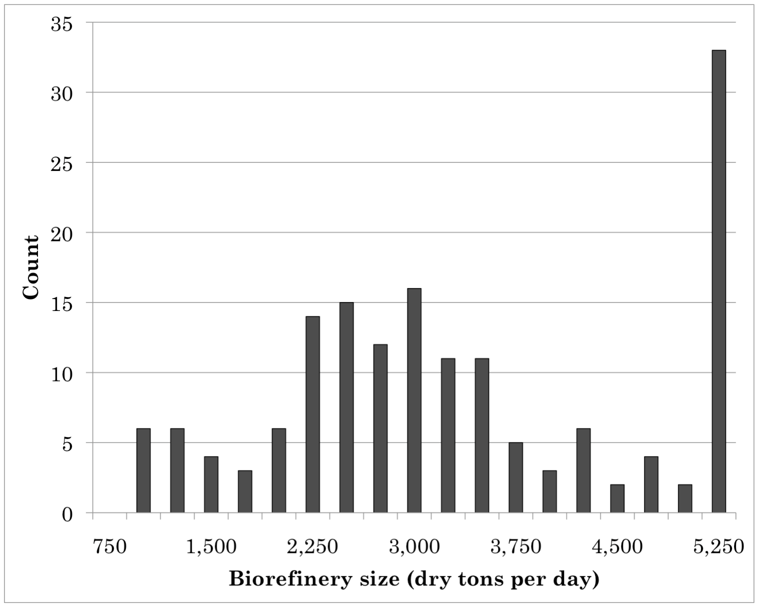

Figure 26: Distribution of F-T diesel biorefinery sizes in baseline

In addition to the F-T diesel, the biorefineries produce 30,277 GWh of renewable electricity and 1.76 billion gallons of renewable naphtha. The electricity represents 0.76% of the projected electricity demand in 2018 and 8% of the projected growth in electricity demand from 2010 to 2018 in the AEO2010 baseline. The naphtha production is not trivial either. It is roughly equal to 1.5% of the refinery naphtha projected to be produced and consumed in North America in 2018 (SRI Consulting, 2010). If the naphtha could be used to produce a renewable gasoline, it would provide a 19.6% increase in the quantity of renewable fuels produced using the F-T diesel technology and reduce the quantity of resource needed met the same level of fuel demand. The impact on the cost of the biofuels will depend on the cost of upgrading the naphtha.

Expanding the analysis to consider the full supply curve, I see that there are discrete regions of the curve that are dominated by the growth of one or a few fuel pathways. Below $2/gge, only existing corn wet mill biorefineries are profitable. From $2/gge to $2.60/gge, existing dry mill corn ethanol and F-T diesel from MSW and forest residues become feasible and reach most of their full potential. At $2.80/gge new dry mill corn ethanol and F-T diesel from agricultural residue enter the market. F-T diesel from agricultural residues accounts for the majority of the growth in supply up to $3.40/gge, when the supply of agricultural residues begins to reach a maximum. At $3/gge, the corn ethanol limit is reached and biodiesel from soy oil enters the market. F-T biofuels from pulpwood and energy crops begin to grow significantly at $3.40/gge and most increases in the supply beyond this point are from energy crops and pulpwood.

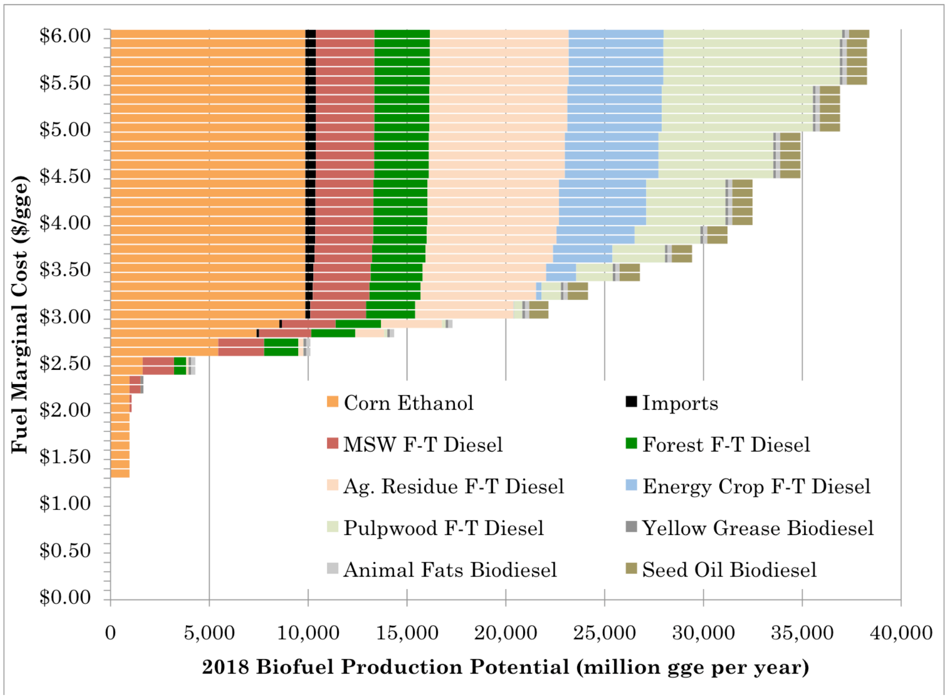

Figure 27: Baseline supply curve by pathway

The supply curve is highly elastic (flat) from $2.20/gge to $3/gge, increasing from 1.7 billion gge per year to 22.2 billion gge per year. This is due in large part to the structure of the resource supply curves. The corn and MSW supplies are available at single prices and the forest and agricultural residue supplies have most of their resources available over small price ranges. For the cellulosic resources, these are simplified supply curves based on estimated costs. The real supply curves are likely less elastic when more of the real variability in cost structure and willingness to participate of the agents who control these resources (waste management companies, timber companies and farmers) are included. The price of corn is not independent of the ethanol industry, as assumed in this analysis. Including these market effects in the supply would cause the curve to become less elastic with more supply becoming available below $2/gge and increasing the slope of the curve.

There are a number of features in this baseline scenario that are dependent on assumptions made about highly uncertain parameters. The dominance of the F-T diesel technology for cellulosic biomass resources is a result of the specific choice of baseline technologies, the discount rate, the value given to the co-products and an assumption that F-T diesel can be freely blended with petroleum diesel. The limit for corn ethanol was not reached due to the availability of cheap MSW and forest residue resources and the existence of a competitive cellulosic conversion technology. In the sections below the sensitivities to these parameters are analyzed.

6.5.2 Resource sensitivities

The supply curves for resource scenarios are shown in Figure 28 along with the baseline. The high and low feedstock scenarios provide bounds for the total supply. It would be possible to meet the 2022 RFS2 mandate at fuel prices between $3/gge and $4/gge. The 2022 volume is 78% of the maximum potential for the low feedstock scenario, leaving little room for meeting the mandate if the available resource is lower than the low scenario analyzed here. In the high scenario, 23% of all transportation fuel demand in 2018 could be met with biofuels at $4/gge.

F-T diesel produced using agricultural residues is the marginal fuel pathway in the baseline case at the 2018 RFS2 mandated volume. Therefore the sensitivities to the agricultural residues have the largest impact on the fuel price needed to meet the 2018 mandated volume. In the high residue scenario, the required fuel price is reduced by 2.4%. Additional reductions in the price come from increased MSW F-T diesel production in the high feedstock scenario bringing the required fuel price down to $2.67/gge. All of these reductions in price come from displacing corn ethanol with additional low cost cellulosic F-T diesel. In the historical residue scenario, the required fuel price increases by 5%. The price is further increased in the low feedstock scenario due to less low cost MSW resources being available. This forces the model to move up the agricultural residue and forest residue supply curves as well as expanding corn ethanol production to the 15 billion gallon per year limit and requiring biodiesel from soy oil. The result is a required fuel price of $3.23/gge.

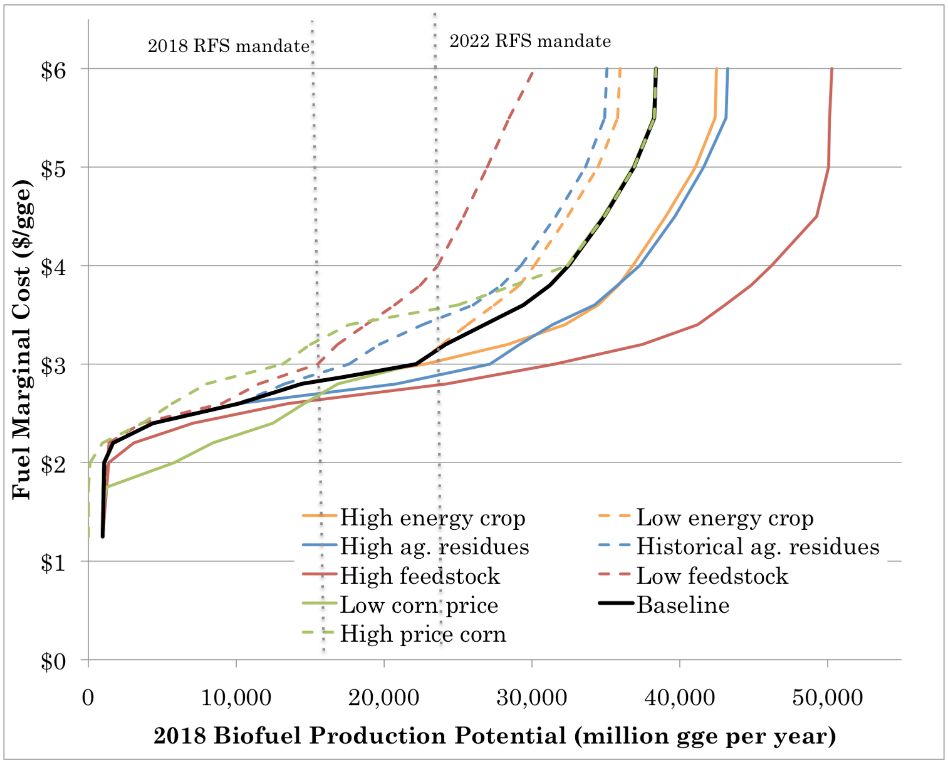

Figure 28: Supply curves for resource sensitivity scenarios

Changing the corn price causes large changes in the supply curve. The corn price shifts the corn ethanol fraction of the biofuel supply up or down depending on direction. Corn ethanol provides one quarter of all supply and 44% of the supply available under $3/gge in the baseline. Shifting this large fraction of supply has a big impact. The low corn price scenario has a limited impact on the required fuel price for the 2018 RFS2 mandate because the baseline is near the 15 billion gallon per year limit and the supply curve is highly elastic at that point. The high corn price, however, has a major impact as it removes all dry mill corn ethanol from the solution forcing the industry to use 58% of all cellulosic resources compared with 32% in the baseline. The required fuel price is the highest of all the feedstock sensitivity scenarios at $3.36/gge.

The shifts in the fuel pathways utilized to meet the mandate would have large impacts on the agricultural sector. In the high feedstock scenario, lands dedicated to production of corn ethanol are reduced to 18.9 million acres while the low feedstock scenario increases lands in corn ethanol to 30.7 million acres. The introduction of seed oil biodiesel presents another demand on agriculture.

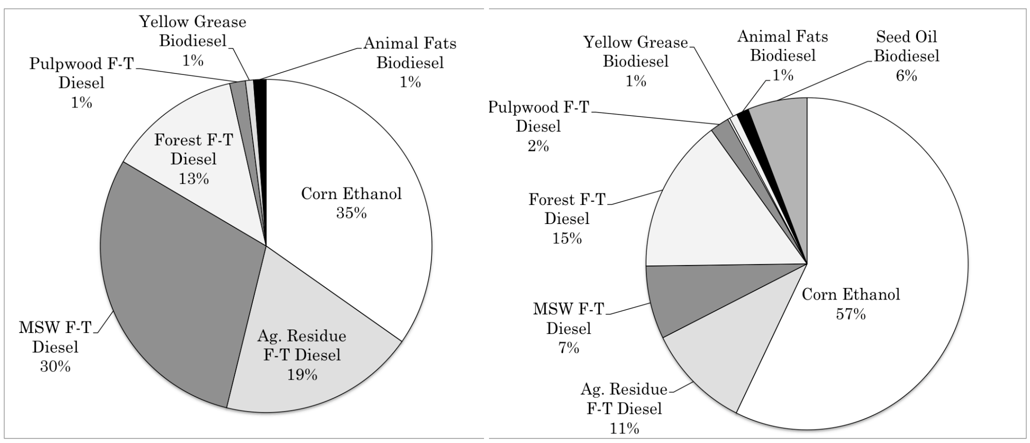

Figure 29: Biofuel pathways for meeting 2018 RFS2 mandate in high (left) and low (right) feedstock scenarios

While energy crops do not play a role in meeting the 2018 RFS2 mandate under any of the scenarios, changes to the energy crop resource assessment result in significant differences in the supply curve above 22 billion gge per year. At $3.80/gge, the difference between the low and high energy crop scenarios is 6.6 billion gge per year, which is similar to the difference between the agricultural residue scenarios.

6.5.3 Technology sensitivities

The technology scenarios lead to a larger range of price outcomes at the 2018 RFS2 mandate. The pessimistic technology results in a 32% increase in the required fuel price. The reason for such a large increase is twofold. First the technology is significantly more expensive. Second, the technology is less efficient at producing fuel. This has two impacts on the cost. First, more feedstock must be purchased per unit fuel produced. Second as more feedstock is consumed the industry is forced to purchase more expensive feedstock as the low cost feedstock are consumed for less fuel produced.

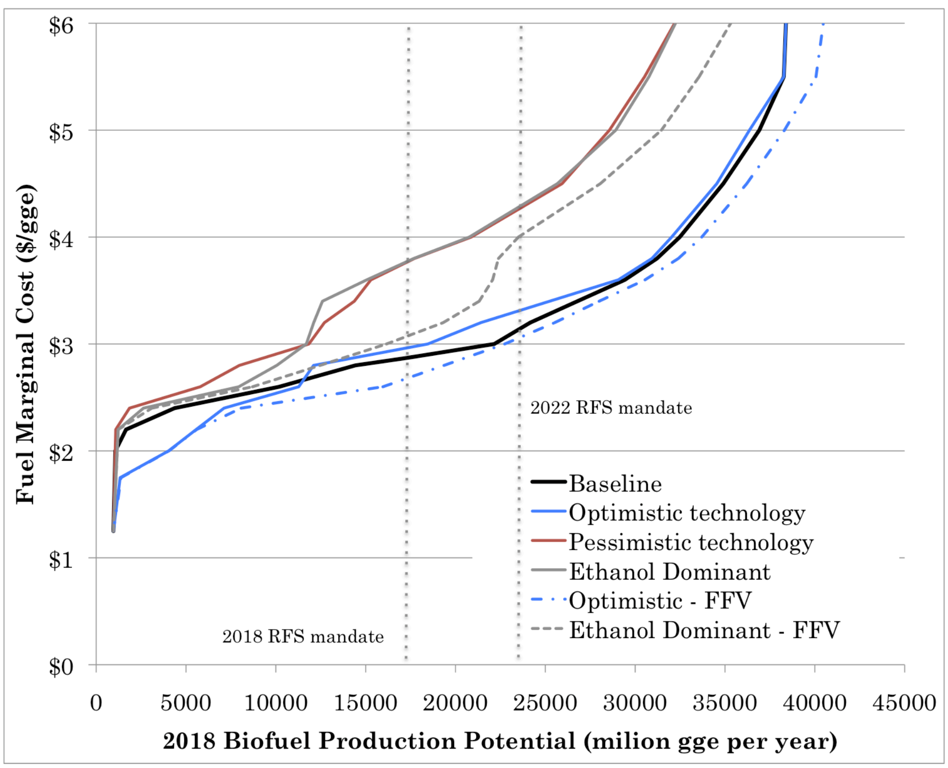

Figure 30: Supply curves for technology sensitivity scenarios

The optimistic case demonstrates an interesting interaction between the ethanol demand limit and the technologies. In the optimistic case, the cellulosic ethanol technology is less expensive than both F-T diesel technology and new dry mill corn ethanol. However, the quantity of ethanol that can be sold is less than the mandated volume when limited to E10. Beyond the ethanol limit, the industry must decide between making cellulosic ethanol with a high profit margin along with F-T diesel from more expensive feedstocks or lower profit margin corn ethanol along with F-T diesel from the lower cost cellulosic feedstocks. Up to $3.60/gge, it is more profitable to make some low cost cellulosic ethanol and increase the marginal cost of F-T diesel than to satisfy the ethanol demand with corn ethanol and imports. The result is that the optimistic technology scenario has a higher required fuel price for the 2018 RFS2 mandate than the baseline despite having a lower cost cellulosic technology. The profit for the industry is 52% higher in the optimistic scenario than the baseline. When the ethanol demand limit is relaxed by allowing all FFVs to consume E85, the optimistic technology scenario has a lower required fuel price at all levels of supply. This does not account for the cost of E85 infrastructure, which would increase the but requires further research to determine how much the costs would increase.

The ethanol dominant scenario uses the baseline cellulosic ethanol technology along with the pessimistic F-T diesel technology. The result is similar to the optimistic technology in that the ethanol dominant scenario has a portion of the supply curve that is more expensive than the pessimistic case despite utilizing lower cost technology. At the 2018 mandate the ethanol dominant scenario is identical to the pessimistic technology scenario. When the ethanol demand constraint is relaxed, the ethanol dominant scenario performs better than the pessimistic technology increasing the fuel price by 7% relative to the baseline.

While the ethanol dominant with FFV scenario results in higher required fuel prices compared with the baseline, the infrastructure investments are lower. It requires $45 billion in investment compared to the $107.9 billion for the baseline. This result suggests that in a scenario where E85 is a viable competitor for fueling FFVs (adequate availability), a higher rate of return on investment may come from the cellulosic ethanol technology as opposed to the F-T diesel technology.

6.5.4 Demand sensitivities

In the scenarios where the cellulosic ethanol technology is preferred to the F-T diesel technology on a production cost basis, the blending limits on ethanol play a large role in shaping the supply curve. To demonstrate this, the supply curves for the ethanol dominant scenario are shown in Figure 31 with an E10 blend limit, an E15 blend limit, a blend limit with 100% FFVs using E85 and E10 for conventional vehicles and finally a proportional blend limit where all terminals get the same blend but the total ethanol is not limited. For all but the proportional blend, there is a sharp increase in the supply curve where the ethanol limit is reached and the cellulosic resources are shifted to a more expensive F-T diesel technology. The pessimistic F-T diesel technology produces less fuel (on an energy basis) per unit of biomass than the cellulosic ethanol technology. This translates into greater biofuel potential in scenarios where more ethanol demand exists.

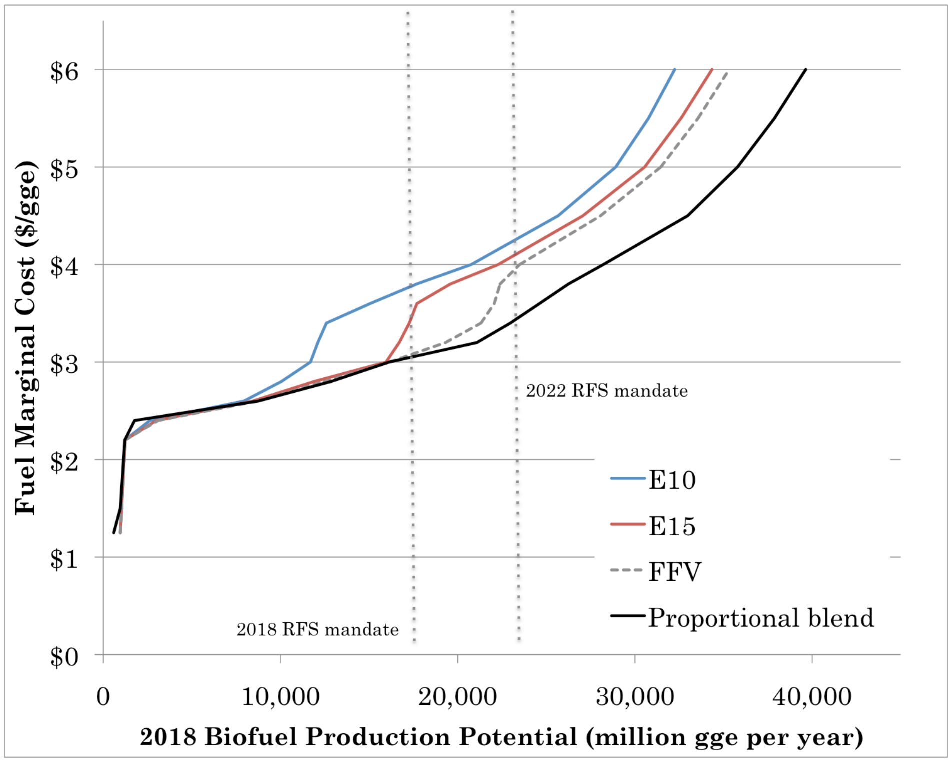

Figure 31: Supply curves for the fuel demand sensitivity scenarios with the ethanol dominant technology scenario

The technology assumptions and ethanol limits impact how biofuels will be used in different subsectors of the transportation system. In scenarios where cellulosic ethanol is the low cost cellulosic technology and there is ethanol demand in the form of E85, then most biofuels replace gasoline. In scenarios where F-T diesel is the low cost cellulosic technology or there is not ethanol demand in the form of E85, then cellulosic biofuels replace diesel.

6.5.5 Results summary

All of the scenarios analyzed achieve the 2018 RFS2 mandate below the projected fuel price in the AEO2010 high oil price scenario ($3.81/gge for diesel and $4.06/gge for gasoline at fuel terminal). The range of possible outcomes are from $2.65/gge to $3.78/gge with the bounds coming from technology scenarios.

While the required fuel prices deviate at most 32% from the baseline, the fuel pathways used to meet the mandate vary wildly. Corn ethanol meets 58% of the mandate in some cases and only 4% in the high corn price case. The cellulosic resources switch between ethanol and F-T diesel leading to large difference in the quantities of ethanol versus biomass-based diesel between scenarios. In all scenarios, the majority of available MSW and forest residue resources are consumed.

The capital investment required for the biorefineries is highly variable. The highest capital investment is more than twice the lowest capital investment. In scenarios that depend on F-T diesel for large quantities of fuel the capital intensity is high. In scenarios where conventional technologies and/or cellulosic ethanol provide the majority of the fuel, the capital investment is lower.

Table 20: Summary of baseline and resource sensitivity scenarios for meeting 2018 RFS2 mandate

Scenario	Baseline	High Feedstock	Low Feedstock	High Residue	Historic Residue
Fuel Price ($/gge)	$2.87	$2.67	$3.23	$2.73	$2.94
Total Biofuel (MGGEY)	17,300	17,265	17,213	17,562	17,106
Biomass-based Diesel	8,630	11,269	7,358	11,279	7,221
% of Diesel Demand	15.93%	20.79%	11.69%	20.81%	11.44%
Ethanol	8,671	5,995	9,855	6,283	9,885
% of Gasoline Demand	5.82%	4.02%	6.61%	4.22%	6.63%
Number of biorefineries needed					
Cellulosic Ethanol Biorefineries	0	0	0	0	0
F-T Diesel Biorefineries	159	188	112	183	133
Biodiesel Biorefineries	16	16	27	16	27
Dry Mill Biorefineries	157	112	173	115	170
Wet Mill Biorefineries	9	9	9	9	9
Required Capital Investment in Biorefineries (million $)					
Total Capital	$107,897	$138,134	$65,484	$132,683	$76,586
Cellulosic Ethanol Capital	$0	$0	$0	$0	$0
F-T Diesel Capital	$103,686	$137,913	$64,729	$132,462	$75,831
Biodiesel Capital	$221	$221	$755	$221	$755
New Corn Ethanol Capital	$3,989	$0	$7,072	$0	$6,543
Biofuel production by pathway (MGGEY)					
Corn Ethanol	8,540	5,995	9,855	6,152	9,629
Imported Ethanol	131	0	0	131	256
Ag. Residue Ethanol	0	0	0	0	0
MSW Ethanol	0	0	0	0	0
Forest Ethanol	0	0	0	0	0
Pulpwood Ethanol	0	0	0	0	0
Energy Crop Ethanol	0	0	0	0	0
Ag. Residue F-T Diesel	3,085	3,299	1,791	6,282	384
MSW F-T Diesel	2,716	5,113	1,227	2,537	2,755
Forest F-T Diesel	2,297	2,246	2,598	2,057	2,420
Pulpwood F-T Diesel	186	265	331	57	289
Energy Crop F-T Diesel	0	0	38	0	0
Yellow Grease Biodiesel	135	135	135	135	135
Animal Fats Biodiesel	211	211	212	211	212
Seed Oil Biodiesel	0	0	1,026	0	1,026
Co-products					
Electricity (GWh/yr)	30,277	40,410	19,583	38,404	22,423
Naphtha (MGY)	1,763	2,353	1,140	2,236	1,306

Table 22: Summary of baseline and resource sensitivity scenarios for meeting 2018 RFS2 mandate (continued)

Scenario	Baseline	High Feedstock	Low Feedstock	High Residue	Historic Residue
Consumption of Biomass (1,000 dry tons per year)					
Agricultural Residue	56,189	61,920	29,062	123,575	0
Energy Crops	0	0	742	0	0
Forest Residues	42,845	41,882	48,450	38,370	45,131
Orchard/Vineyard Waste	7,508	6,277	7,789	6,485	7,673
Pulpwood	3,468	4,938	6,180	1,063	5,384
MSW – Wood	8,123	16,105	8,277	7,963	8,149
MSW – Paper	12,102	25,013	0	11,568	12,270
MSW – C&D	15,142	30,380	15,372	14,902	15,164
MSW – Yard	3,101	6,015	0	2,803	3,179
MSW – Mixed	19,350	28,475	0	16,057	20,045
Corn grain	131,732	93,006	151,751	95,393	148,315
Animal Fats	789	789	793	789	793
Yellow Grease	521	521	521	521	521
Seed Oils	0	0	3,830	0	3,830

Table 21: Summary of technology scenarios

Scenario	Optimistic Technology	Pessimistic Technology	Optimistic w/E85 in FFV	Baseline w/E85 in FFV
Fuel Price ($/gge)	$2.99	$3.78	$2.65	$2.83
Total Biofuel (MGGEY)	17,305	17,161	17,315	17,194
Biomass-based Diesel	6,936	6,801	1,185	7,752
% of Diesel Demand	12.81%	10.67%	2.21%	14.31%
Ethanol	10,369	10,360	16,130	9,443
% of Gasoline Demand	6.96%	6.95%	10.82%	6.34%
Number of biorefineries needed				
Cellulosic Ethanol Biorefineries	114	0	208	0
F-T Diesel Biorefineries	117	125	21	145
Biodiesel Biorefineries	16	27	16	16
Dry Mill Corn Ethanol Biorefineries	108	173	108	166
Wet Mill Corn Ethanol Biorefineries	9	9	9	9
Required Capital Investment (million $)				
Total Capital	$106,236	$140,781	$57,714	$93,132
Cellulosic Ethanol Capital	$17,846	$0	$41,685	$0
F-T Diesel Capital	$88,169	$140,026	$15,808	$92,910
Biodiesel Capital	$221	$755	$221	$221
New Corn Ethanol Capital	$0	$0	$0	$5,798
Biofuel production by pathway (MGGEY)				
Corn Ethanol	5,716	9,855	5,790	9,312
Imported Ethanol	131	505	131	131
Ag. Residue Ethanol	649	0	5,256	0
MSW Ethanol	1,114	0	1,615	0
Forest Ethanol	2,389	0	2,835	0
Pulpwood Ethanol	369	0	502	0
Energy Crop Ethanol	0	0	0	0
Ag. Residue F-T Diesel	4,318	1,264	0	2,350
MSW F-T Diesel	1,800	2,001	839	2,664
Forest F-T Diesel	398	1,927	0	2,244
Pulpwood F-T Diesel	64	236	0	148
Energy Crop F-T Diesel	10	0	0	0
Yellow Grease Biodiesel	135	135	135	135
Animal Fats Biodiesel	211	213	211	211
Seed Oil Biodiesel	0	1,026	0	0
Co-products				
Electricity (GWh/yr)	37,220	107,335	32,223	27,220
Naphtha (MGY)	1,454	2,428	256	1,585

Table 23: Summary of technology scenarios (continued)

Scenario	Optimistic Technology	Pessimistic Technology	Optimistic w/E85 in FFV	Baseline w/E85 in FFV
Consumption of Biomass (1,000 dry tons)				
Agricultural Residue	93,352	24,480	89,860	41,190
Energy Crops	202	0	0	0
Forest Residues	47,306	43,740	47,336	41,844
Orchard/Vineyard Waste	7,850	7,151	7,865	7,264
Pulpwood	7,349	5,351	8,389	2,766
MSW - Wood	8,319	8,103	8,319	8,099
MSW - Paper	12,410	10,795	10,981	12,006
MSW - C&D	15,464	15,089	15,464	15,101
MSW - Yard	3,224	2,598	2,525	3,022
MSW – Mixed	20,720	14,188	10,116	18,228
Corn grain	88,755	151,751	89,885	143,483
Animal Fats	789	794	789	789
Yellow Grease	521	521	521	521
Seed Oils	0	3,830	0	0

6.6 Conclusions

The potential for biofuel production in the United States is large relative to the current production. Cellulosic biofuels can be produced from a range of resources that do not inflict major land use impacts. In the scenarios for the meeting the RFS2 mandates cellulosic energy crops are a minor contributor. They make up less than 1% of the biofuel production in all cases because switchgrass and pulpwood-based biofuels are the most expensive pathways. The bulk of the cellulosic biofuels comes from waste and residue resources.

Not surprisingly, the industry is expected to site biorefineries concentrated in the Midwest to take advantage of corn and agricultural residue resources, near metropolitan areas to take advantage of municipal wastes, and in regions with large forestry operations to utilize the residues of that industry.

The results are particularly sensitive to corn price, the development of a low cost lignocellulosic biofuel technology, blending limitation for ethanol (if the low cost lignocellulosic technology is ethanol) and the availability of low cost waste and residue resources. Corn ethanol provides approximately one-quarter of the biofuel potential. The importance of the price of corn falls logically from this fact. A dollar per bushel increase in the corn price shifts one third of the supply up $0.66/gge and a dollar per bushel decrease does the opposite.

The modeled performance of conversion technologies represents significant learning and rapid deployment of lignocellulosic biofuels. This is a great challenge for the industry. The nascent cellulosic biofuel industry would need to build more plants over the next 8 years than the already mature corn ethanol industry built between 2002 and 2010. A supply of experienced labor needed for this rapid deployment also may not be available. Early biorefineries will necessarily have higher costs than the nth of kind facilities modeled here unless technology develops faster than expected. These dynamic factors should be considered in applying model results.

Ethanol demand limitations become a factor if a low cost technology to convert lignocellulosic biomass into hydrocarbons does not exist. The E10 blend wall directs lignocellulosic biomass toward the production of hydrocarbon fuels (e.g. by Fischer-Tropsch processes) even if it is a significantly more expensive route. Extensive use of E85 in flex-fueled vehicles can provide enough ethanol demand for the 2018 target if all biofuels are ethanol. However, the 2022 target would require all FFVs projected to be on the road in 2022 to use E85 exclusively.

This modeling effort provides an initial look at the spatial design of the future biofuel industry. There are two main advantages of this modeling approach compared to other national scale efforts that I are aware of. First, it allows for the spatial distributions of supply and demand to impact the optimization of the predicted industry. Second, competition between technologies and between potential locations for a given resource is allowed with the most profitable configuration being chosen.

The model predictions are fully tied to the quality of the data used and the assumptions made. With the cellulosic biofuel industry in its infancy, the range of uncertainty is very large for conversion technologies and feedstock production. I have made an effort to use the best information available and to indentify where data limitations can impact the interpretation of the results. Many of these limitations can be addressed through additional research and as knowledge about the industry develops.

7 CASE STUDY 2: HIGH RESOLUTION CALIFORNIAN MODEL WITH EMISSIONS ESTIMATATION

7.1 Introduction

This case study seeks to develop comparisons of biofuel pathways (feedstock-fuel combinations) from waste and residue resources in California. There is a fundamental difference between this case study and the previous in that it considers each pathway separately in the supply chain optimization model in order to compare the economic costs and emissions benefits for each pathway with optimized supply chains. The potential for these pathways to provide compliance options for the California Low Carbon Fuel Standard (LCFS) is calculated.

A refinement on the model for this case study is the use of high resolution resource data. Where the national study in Chapter 6 uses county-level resource data sets which includes county areas from 34 km^2 to 52,071 km^2, this study uses approximately a 5 km x 5 km pixel resolution. This higher resolution allows for better accounting of the transportation cost and emissions. In doing so, it allows for improved accounting of the conversion economies of scale and the transportation costs in the sizing of biorefineries. In California, the high resolution data is especially important due to the size, shape and heterogeneity of the counties. Locating resources at the centroid of many California counties leads to a very poor spatial representation of the resource. For example, in Fresno County, the agricultural residue is produced in the western half of the county and the forest resources are produced in the eastern half.

The scope of the case study is biofuel production pathways from waste and residue biomass resources in California using projections for technology cost and performance appropriate for the time period before 2020. The State of California has adopted a low carbon fuel standard (LCFS), which will likely lead to a high value for any low carbon biofuel that can be delivered to the state prior to 2020. The state's waste and residue biomass resources are large and diverse with approximately 32 million tons produced and 83 million tons technically available per year (Williams, 2008). Biofuels produced from these waste and residue resources are expected to qualify as low carbon fuels. Given this resource is the most probable source of biofuel to meet the LCFS produced within California (Yeh *et al.*, 2009), the case study analyzes different pathways to produce biofuels from these resources using optimized supply chains. A comparison between the pathways is presented in terms of levelized cost, capital cost, carbon intensity of the fuels (g CO_2-equivalent emitted per MJ of lower heating value of the fuel), emissions relative to a gasoline baseline and total fuel production potential.

This work considers the two major pathways for producing biofuels from cellulosic materials: biochemical and thermochemical. The biochemical process modeled is the production of ethanol through dilute acid hydrolysis and fermentation. The thermochemical route is the production of middle distillates and naphtha through gasification and the Fischer-Tropsch synthesis.

7.2 Pathway Descriptions

7.2.1 Overview

Six pathways combining three resource sets and two conversion technologies were analyzed. The resources are woody feedstocks from forest thinnings and slash and prunings from orchards and vineyards; harvestable straws and stovers from rice, corn, wheat, sorghum, barley and oats; and the organic fraction of municipal waste that is currently being landfilled. The conversion technologies are ethanol via dilute acid hydrolysis and fermentation as a representative biologically based conversion process and production of diesel and naphtha blend stocks via gasification and Fischer-Tropsch synthesis as a representative thermochemical conversion process. For both conversion processes the feedstock production, harvest, storage and logistics are assumed to be the same except for potential differences in the distances traveled to a biorefinery. From the biorefinery the fuels are transported to a distribution terminal for blending with petroleum-based fuels and distribution to local refueling stations.

7.2.2 Forest residues

Forest residues are produced from commercial logging, pre-commercial stand thinning, fire hazard reduction activities, and as mill residue. Each of these resources is produced from distinct forest management operations and is thus available in a variety of conditions ranging from loose slash scattered throughout the stand to uniform sawdust or hog fuel at a mill or secondary processing facility. There are a number of different frameworks that can be taken in considering the allocation of costs and emissions for this resource. For this work, the starting point for the analysis is the harvest landing in the forest where tops and branches are available for loading and transport. The cost and emissions are calculated from this point forward. The biomass is chipped into chip vans for transport to the biorefinery. For long distance transport, transfer to rail or marine transportation may occur along the way to a biorefinery. This last is true for all feedstocks.

7.2.3 Agricultural residues

For straw and stover resources, the biomass is assumed to be a by-product of production agriculture with emissions calculations starting with operations after the harvest of the grain crop. Total harvest systems are not explored here. The straw or stover is harvested, baled and taken to the roadside where it is stored. Additionally, when residues are removed nutrients that are removed with them need to be replaced. The fertilizers required to replace the full value of the nutrients removed are included in the cost and the emissions analysis. Bales are wrapped in plastic and stored at the roadside at the site of production. Bales are loaded onto trucks for delivery to the biorefinery. Short-term storage is provided at the biorefinery.

7.2.4 Municipal waste

Municipal wastes can either be source separated yard wastes or construction/demolition debris or mixed wastes. The wastes are brought to a material recovery facility (MRF) where they are sorted for recyclables and fractions that could be used for energy production. This classification step is included in the estimation of cost and emissions. The fractions that are separated for energy production are then transported to a biorefinery. No long-term storage has been included in the supply chain for MSW as the volume of feedstock is expected to be large enough year-round to support the biorefinery. In practice, the feedstock composition will change over the course of the year but this complication is not considered here.

7.2.5 Biological conversion

The model biological conversion technology is based on the Antares near-term technology characterization (Antares, 2009) – see Figure 8. It uses dilute acid pretreatment to hydrolyze the hemicellulosic fraction to sugars and an enzymatic hydrolysis to convert the cellulosic fraction to sugars [1]. Hydrolysis results in both five and six carbon sugars, which are fermented into ethanol. The acid from the pretreatment is recycled to the extent possible with lime used to neutralize the remaining acid before the enzymatic hydrolysis step. The fraction of the feedstock that is not converted to sugars (lignin plus the hemicellulose and cellulose that did not hydrolyze) is separated, dried and burned in biomass boilers to produce heat and electricity. The process model used here produces excess electricity for sale to the grid at a rate of 2.63 kWh/gallon of ethanol produced (Antares, 2009).

Ethanol yields from different feedstocks depend on the fraction of the feedstock that is cellulose or hemicellulose and the process efficiency. The process efficiencies assumed in this work are shown in Table 22. Using these conversion efficiencies, the ethanol produced per ton of feedstock varies from 63.9 gallons of ethanol per dry ton of yard wastes to 80.9 gallons per ton of softwoods (forest residue) (Antares, 2009). The conversion of biomass to ethanol and electricity occurs at an efficiency of 37 – 41% (lower heating value basis). Approximately 4% of the energy in the biomass becomes electricity while 33 – 37% becomes ethanol.

Table 22: Conversion efficiency of cellulosic ethanol technology

Process	Percent of maximum theoretical yield (Antares, 2009)
Hemicellulose conversion to xylose, etc.	82.5%
Cellulose conversion to glucose	75%
Xylose to ethanol	86%
Glucose to ethanol	92.5%

7.2.6 Thermochemical conversion

The model thermochemical conversion technology is the production of diesel and naphtha blendstock via gasification and Fischer-Tropsch synthesis (F-T). The conversion technology is based on the F-T technology reported in (Antares, 2009). This is the same as the pessimistic F-T diesel technology used in Chapter 6. Specifically, it uses an indirectly fired gasifer operating at atmospheric pressure to convert the biomass to a syngas. A steam methane reformer and water gas shift reactors convert the syngas to a 2:1 H_2 to CO ratio for the F-T reactors. The F-T reactors have Co catalysts and a CO conversion rate of 42%. Unconverted syngas is used for electricity and heat production in a combined cycle power plant.

The yields for the thermochemical process are modeled to be dependent on the heating value of the fuel. The conversion of biomass to liquid fuels occurs at an efficiency (lower heating value basis) of 42% with the production of 0.43 gallons of naphtha per gallon of diesel produced. The electricity is co-produced at a rate of 19 kWh/gallon of diesel. Including the electricity production brings the overall efficiency of the biorefinery to 58% of the energy in the feedstock distributed as 30% of the input energy in diesel fuel, 12% in naphtha and 16% in electricity.

7.3 Methodology

The methodology follows from the general formulation presented in Chapter 3 with small changes for considering one pathway at a time and to incorporate emissions accounting. The emissions accounting model was used solely to aggregate emissions metrics. It was not used to introduce a cost for carbon or any other emissions.

7.3.1 Emissions accounting

This work considers fuel pathways that are to the location of the resource providing the fuel. With this level of spatial detail, an analysis of the impacts of the particular system modeled is possible as opposed to an average system.

The emissions accounting model is incorporated into the optimization model in order to provide that analysis.

Emissions are calculated at all points along the supply chain for the waste biomass to fuel pathways. The major stages are the production/harvest of the biomass, the transport of the biomass, the conversion of the biomass to fuel, co-product credits, fuel transmission to distribution terminals and local fuel delivery. At each of these stages emissions due to energy use and inputs are recorded and then aggregated to find the total emissions for the pathway measured in grams of pollutant per MJ of fuel delivered to the fuel terminal.

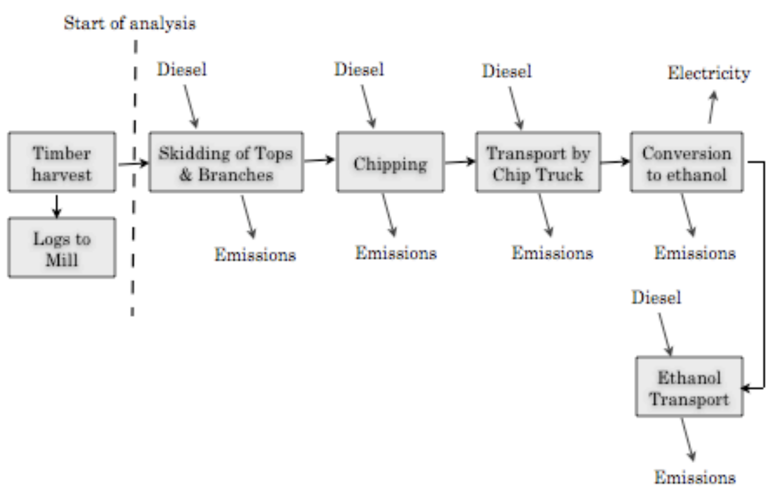

Figure 32: Accumulation of inputs and emissions along the supply chain

The impact model has its foundation in Argonne National Laboratory's GREET model (ANL, 2009). Where possible, emissions factors were obtained from GREET 1.8c. California GREET, used by the Air Resources Board, is based on GREET 1.8b with changes to some input parameters that are mostly geographic (such as transport distances) but the basic emission factors are the similar. Some parts of the system are not modeled in GREET and values for these were taken from additional literature and are described below in section 0.

7.4 Data

7.4.1 Resource assessment

A California-specific resource assessment was performed at high resolution by Tittmann *et al* (2009). The assessment differs from the national case study in order to make use of high resolution data sets that are available for California. Available forestry residues were taken from a CalFire assessment of available forest biomass (CBC, 2006) with collection costs calculated using the Fuel Reduction Cost Simulator (Fight *et al.*, 2006). Municipal waste resources were taken from the Solid Waste Information System (CIWMB, 2009). The agricultural residues assessment uses the methods described in section 5.1.1 for calculating the gross residue production by county which were then assigned proportionally by area to field plots within the county. The field boundaries were taken from the Department of Water Resources land use maps (DWR, 2000-2003). The quantity of residues available and their cost were found using the INL feedstock logistics model with a 38% harvest efficiency. The assessment is a refinement on the California Biomass Collaborative report on biomass supplies in California (CBC, 2006) in disaggregating supplies to the field, landfill, or forest plot level.

This assessment found approximately 16.9 million tons of organic municipal wastes currently being land filled; 4.1 million dry tons of biomass potential from agricultural production in straws, stovers and prunings; and 5.9 million dry tons of potential unused forest biomass. A couple of changes were made to the resource assessment. First, residues from cotton fields were removed. Discussions with an expert in the field convinced the authors that no cotton residue was sustainably removable.[9]

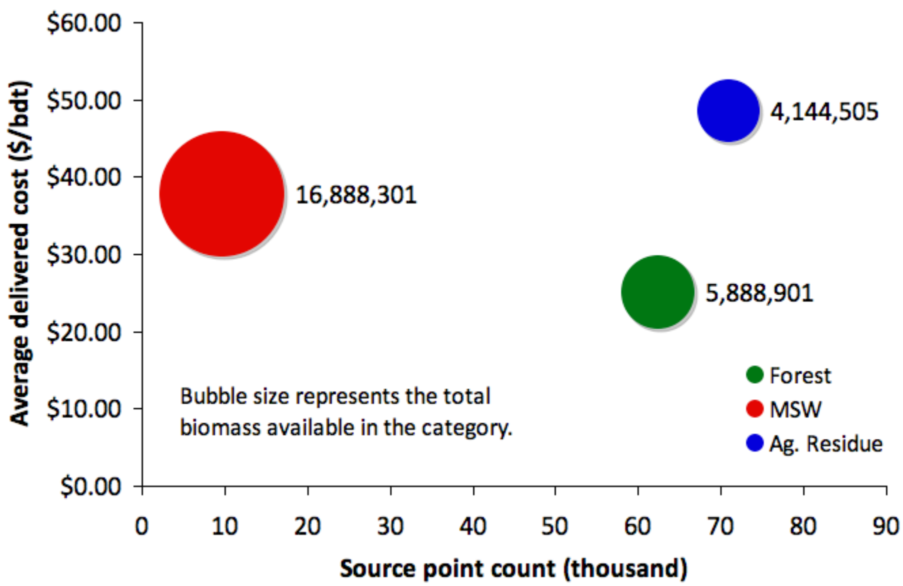

Figure 33: Biomass cost ($/dry ton), volume (dry tons) and number of discrete supply points by type

The original assessment used a very high spatial resolution. The forest data was reported using a 40 by 40 meter grid. The agricultural data uses Department of Water Resources field level data and the municipal wastes are reported by landfill location. The resolution of this resource assessment is greater than the resolution of the road network. The resolution of the

[9] Personal communication with Dr. Richard Nelson, 2009.

transportation costs is what defines the spatial resolution for the model. The extra resolution for the resource assessment is lost when the transportation costs are calculated. To address this, the forest and agricultural data sets were aggregated to a 5 by 5 km resolution using k-means algorithm using SAS statistical package. K-means is a statistical method that groups observations into "k" clusters by allocating each observation to the cluster with the nearest mean. Efficient heuristics have been developed to find good approximation for the best clusters (Kanungo *et al.*, 2002). For this analysis the data were clustered by their x and y coordinates and by the resource type (e.g. rice straw, forest thinnings, wheat straw). Clustering reduced the source points to 23,723 distinct locations. An alternative would be to increase the resolution of the road network but the original assessment with more than 140,000 distinct source points result in a difficult optimization model that is not feasible to solve with the available methods.

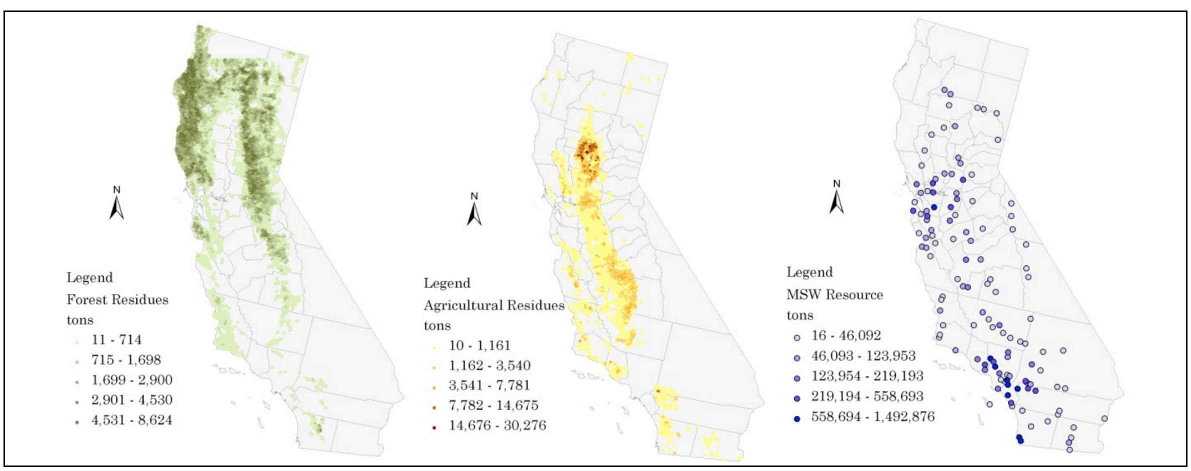

Figure 34: Location of biomass resources - forest, agricultural and municipal

7.4.2 Transportation Network

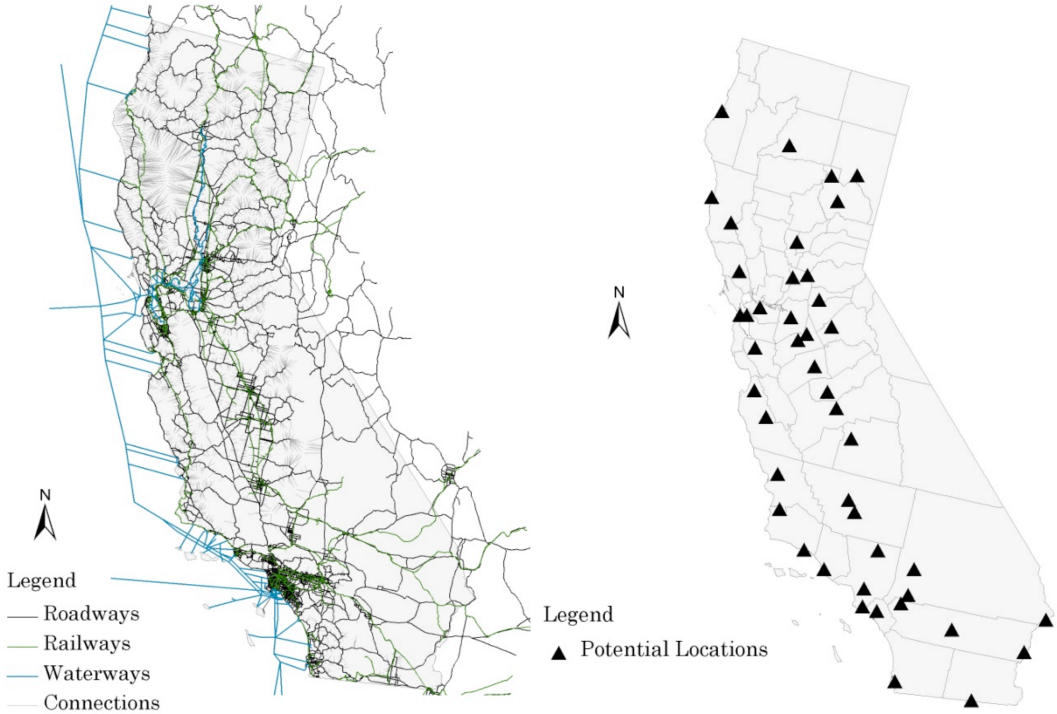

Figure 35: Transportation network showing the connections to the resource locations and the set of potential locations

The sources of biomass were located on the transportation network as point sources. The municipal waste resources are located as points at the nearest municipality to the landfill although some municipalities are known to transport their wastes long distances for landfill disposal. The centroid of the clusters of agricultural fields or forest grid cells were used as the starting point for these resources. If these points are not on the network, connectivity is provided by drawing lines representing the shortest distance from the point source to the nearest point on any road in the network. These lines are considered part of the road network with a low speed of travel (25 MPH). These data were incorporated into a geodatabase in the ArcGIS software environment (McCoy, 2005). The Network Analyst extension was used to create an origin-destination cost matrix from all source destinations to all potential facility locations.

7.4.3 Cost

Conversion technology cost models

The conversion technology models are adapted from work by the Antares Group (Antares, 2009). Spreadsheet models of the conversion technology performance (yields of all products by feedstock type) and costs were developed by the Antares Group based on the available literature on biofuel production. The F-T diesel technology model is the same as the pessimistic technology used in the national case study. The cellulosic ethanol technology is different for any of the technologies considered in the national case study. A summary of the cost parameters is provided below.

Accounting for economies of scale, the capital cost for a biorefinery is described by the equation:

$$C_x = C_b*(S_x/S_b)^{\alpha} \tag{23}$$

Table 23: Capital cost parameters for biorefineries (Antares, 2009)

Technology	Base Cost C_b	Base Scale S_b	Scaling factor α
Cellulosic Ethanol	$340 million	40.7 MGY	0.8
F-T Diesel	$759 million	658,752 tons/yr	0.74

Table 24: Process description (Antares, 2009)

	F-T diesel	Cellulosic ethanol
Biomass input	550 – 13,700 tons/day	550 – 3,600 tons/day
Products	F-T Diesel 37-42 gal/ton biomass Naphtha 16-18 gal/ton biomass Electricity 19 kWh/gallon Diesel	Ethanol 63.9-80.9 gal/ton biomass Electricity 2.63 kWh/gallon ethanol
Energy conversion efficiency (LHV basis) % of biomass input energy as product	30% diesel fuel 12% naphtha 16% electricity	33-37% ethanol 4% electricity
Cost	F-T diesel	Cellulosic ethanol
Maintenance	2.3% of initial capital	$0.35/gallon capacity
Labor	$0.33*(Feedstock_Capacity)0.75	
Variable operating	$9.45/bbl products	$0.29/gallon ethanol

The operating costs for the F-T diesel process includes a fixed maintenance cost, labor and variable operating costs. The labor cost is scaled by the biorefinery size. For the ethanol, the variable costs are a function of the output capacity of the biorefinery.

Table 25: Operating cost parameters (Antares, 2009)

Cost	FT diesel	Cellulosic ethanol
Maintenance	2.3% of initial capital	$0.35/gallon capacity
Labor	$0.33*(Feedstock_Capacity)$^{0.75}$	
Variable operating	$9.45/bbl products	$0.29/gallon ethanol

An annualized cost of production was found for each conversion technology over the range of feedstock input capacities that the cost models are valid. A linear fit to the annualized cost as a function feedstock input capacity was found for both technologies. The linear fit gives the values of the parameters a_t and b_t that are used in the model formulation as previously discussed.

The economic parameters in this case were different than in the national case study. A higher electricity price reflects higher electricity prices in California compared to the national average (EIA, 2011). A higher discount rate is used because this case study was developed with a nearer term focus which results in higher risk for the investments in the earliest cellulosic biorefineries. It is also a crude method to bring nth of a kind conversion costs reported in literature closer to the cost for the first few biorefineries.

Table 26: Additional economic parameters

Parameter	Value
Discount rate	15%
Economic lifetime of biorefinery	20 years
Price of electricity co-product	$0.08/kWh
Constant year 2008 dollars	

7.4.4 Emission factors

The majority of the emissions data was taken from the GREET model (ANL, 2009) in order to provide a consistent comparison with petroleum based fuels. The emissions inventory is meant to be analogous to the GREET model but using inputs from the optimized system rather than the average or best estimate inputs that are used in GREET. However, there were a few instances where I have deviated from or augmented the GREET emission factors. They are described in detail below.

Embodied emissions for feedstock

In the framework of this research, none of the feedstocks are the primary product from the operations that produce them and therefore the emissions accounting begins at the point in their lifecycle that their fate is differentiated as becoming an energy product. For residues, this is harvesting for agricultural residues and roadsiding/chipping for forest. For municipal wastes this is the classification step where the biomass is separated from the inert material. This is in agreement with the approach taken in the GREET model.

Energy input requirements for harvesting, roadsiding, and chipping were derived from the resource assessments (INL, 2010; Fight *et al*, 2006; Kalogo *et al.,* 2007). Emission factors from GREET were applied to the energy input requirements. The removal of agricultural residues is assumed to induce an additional fertilizer requirement, which are described in Table 13. The embodied emissions for the fertilizers were allocated to each ton of straw or stover removed using emission factors found in the GREET model. Emissions for classification of biomass from municipal waste were taken from Kalogo *et al*. (2007). GREET does not have emission factors for municipal waste as a feedstock. The emission factors used can be found in Appendix B.

Transportation emissions

The transportation network model reports miles by mode as well as cost for each link. These data along with the energy intensity of each mode and the emissions factors from GREET for burning diesel fuel in each of the modes of transport are used to find the emissions for each link of the transportation network.

Conversion emissions

Due to the lack of existing facilities producing cellulosic biofuels, data for the air pollutant emissions are highly speculative. I was not able to identify a study with the criteria air pollutants estimated for the dilute acid hydrolysis and the Fischer – Tropsch diesel processes that were modeled other than the GREET model (ANL, 2009). These emissions estimates rely on published engineering design studies that are proof of concept level with values obtained from Aspen chemical engineering process flow models (Wu *et al.*, 2006). The emissions are calculated based on average emissions factors for individual pieces of equipment. There are two main issues with the GREET model emissions factors for use in this study of California. One is that in California these biorefineries will be required to use the best available control technology (BACT) in order to obtain permits to construct and operate due to California's environmental regulations and the large fraction of the state that is in non-attainment with ambient air quality standards. GREET uses emissions factors representative of national average production not BACT emission factors. The second issue is that some data have recently become available have not been used to update GREET. Proposed biorefineries have submitted permit applications stating their potential to emit, the control technologies they plan to use and provide some detail on the major sources of pollutants at the biorefinery.

I have acquired documentation (Environmental Impact Reports (EIR) or air permit applications) for three proposed cellulosic biorefineries (Bluefire, 2009; AMEC Earth & Environmental, 2009; Range Fuels, 2007). Two (Bluefire and Verenium) use an acid hydrolysis pretreatment technology for producing ethanol via a biochemical route. One (Range Fuels) is a gasification-based technology producing alcohols via a thermochemical synthesis. None of these processes is an exact match with the conversion processes that were modeled in the economic optimization model but they provide a basis for comparison. Due to the locations of the facilities, each faced different levels of reporting requirements. Table 27 shows the emissions factors that were calculated based on the information provided by dividing the annual potential to emit reported by each facility by the annual feedstock input for the facility. Differences in the yields and the production of co-products impact the emissions per MJ of fuel produced.

The default GREET values for cellulosic ethanol are based on the NREL study by McAloon et al (2000). The technology modeled here uses more conservative estimates on the yield of ethanol from biomass and correspondingly a greater production of electricity. I have adjusted the GREET model to address these differences. The major source of air pollutants at the cellulosic biorefinery is the biomass boiler accounting for

12.5-17% of VOCs, 52-93% of PM, 99.98-100% of SO_x and 83-99.5% of NO_x (See Appendix B for breakdown). By applying BACT to the biomass boilers the emissions for the biorefinery can drop significantly, the most likely outcome for facilities sited in California. BACT emission factors for biomass boilers were found via the EPA clearinghouse (CATC, 2009). These emissions factors were used in replacement of the default GREET values. The adjusted GREET values are generally lower than the values reported by the proposed biorefineries. This can be partially explained by scale. The BACT technologies employed in the adjusted GREET values may not be cost effective at the small scale for the pilot plants listed in Table 7. The biggest difference is in sulfur oxide emissions. The important factor here is how much of the sulfur from the acid pretreatment ends up in the biomass boiler versus being recirculated. The adjusted numbers, shown in Table 8, are the values used in the emissions analysis.

Table 27: Potential to emit for various proposed biorefineries (g/ton feedstock)

	Range Fuels (ethanol via gasification-100 MGY)	**Verenium (ethanol/acid hydrolysis – 36 MGY)**	**Blue Fire (ethanol/acid hydrolysis— 3 MGY)**
VOC	27.15	123.06	515.18
CO	89.73	331.39	482.71
NO_x	98.96	270.12	515.18
PM_{10}	96.37	57.99	270.58
$PM_{2.5}$	42.69	42.63	270.58
SO_x	0.75	179.68	474.05
CH_4	27.15		
N_2O	2.96		

Default GREET values for Fischer – Tropsch diesel from biomass are based on a facility with higher conversion of biomass to fuels and less electricity production than the facility modeled here. The appropriate changes were made to the efficiency of conversion and the quantity of electricity produced. Additionally, the default values were questionable for other reasons. The value of zero for VOCs is highly unlikely in a facility that stores significant quantities of biomass and fuel; the sulfur oxide emission rate is approximately equal to maximum potential production of sulfur oxides given the sulfur content of the pine (the modeled feedstock for the F-T technology in GREET). I estimate the maximum sulfur oxides emissions to be approximately 363 grams per ton of feedstock if all of the sulfur in pine (0.02% S by mass) is converted to SO_2. Not all sulfur will become sulfur oxides especially when pollution control technologies are applied. For our estimates I have taken the values reported by Range Fuels to be representative of thermochemical biorefinery using modern control technologies.

The most significant co-product for both processes is electricity. For the purposes of this study, I report the emissions with and without a credit taken for displaced electricity. The electricity displaced is taken to be produced from natural gas in a combined cycle power plant (NGCC). The emissions factors for NGCC electricity were taken from GREET and are reported in Table 28.

Table 28: Emission factors for conversion technologies

	Cellulosic Ethanol		**Fischer - Tropsch Diesel**		**Displaced Electricity**
	GREET default	Adjusted GREET	GREET default	Adjusted	Natural Gas Combined Cycle
	g/ton feedstock				g/kWh
VOC	137.0	98.8	0.000	27.2	0.07
CO	434.8	242.9	141.5	89.7	0.29
NO_x	625.1	228.2	534.9	99.0	0.25
PM_{10}	153.4	105.7	85.2	96.4	0.02
$PM_{2.5}$	50.1	54.1	42.6	42.7	0.02
SO_x	23.6	31.5	368.6	0.8	0.08
CH_4	23.4	30.5	0.000	27.2	1.26
N_2O	62.0	44.8	9.6	3.0	0.01

7.5 Results

The results are divided into four sections. The economic results are discussed first and provide information on the total potential for the pathway and the costs. Second, the emissions results are discussed. Third, I present the optimal layout of biorefineries for each pathway along with the location of the resources exploited. Finally a summary comparison is provided.

7.5.1 Economic results

A total of 988 million gallons of gasoline equivalent ethanol or 1,070 million gallons of gasoline equivalent F-T diesel and naphtha could be produced from waste and residue biomass resources in California below $4/gge. For reference, approximately 15 billion gge of gasoline and 4 billion gge of diesel were sold in California in 2007 (Schremp *et al.*, 2010). The F-T diesel pathways produce more overall fuel than the ethanol pathways with the same resource base but the ethanol pathways are less expensive. The ethanol pathways are $0.20 per gge less expensive on average than the F-T diesel for the same quantity of fuel energy produced using the assumptions of this case study. The assumptions on the technology cost and the discount rate favor the cellulosic ethanol pathway compared to the assumptions in the national case study. In general, the costs of the biofuels are higher than most historical wholesale prices of gasoline and diesel. However, they may be a relatively low cost pathway for compliance with government mandates such as the Low Carbon Fuel Standard and the Renewable Fuel Standard compared to purpose grown crop-based biofuels as seen in Chapter 6.

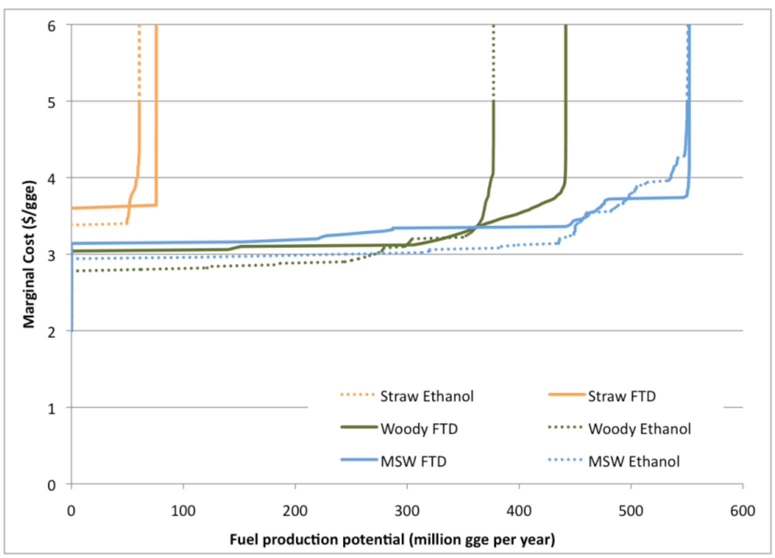

Figure 36: Potential supply of biofuels by pathway – FTD and ethanol lines for a specific resource are not additive

Comparing the three resource types (Figure 36), the straws and stovers lead to the most expensive pathways with the least potential for petroleum displacement. This is due to the high cost of procurement of the feedstock relative to the other feedstock options. The woody resources (forest residues and prunings from orchards and vineyards) have the lowest cost pathways. The longer transport distances of the forest residues are compensated by low procurement costs and high fuel yields. The municipal waste resource is the largest source of biomass in California. It is the only resource where ethanol produces as much fuel as F-T diesel. This is due to the assumption about yields of food wastes, which were prohibited from the F-T diesel pathway due to their high moisture content.

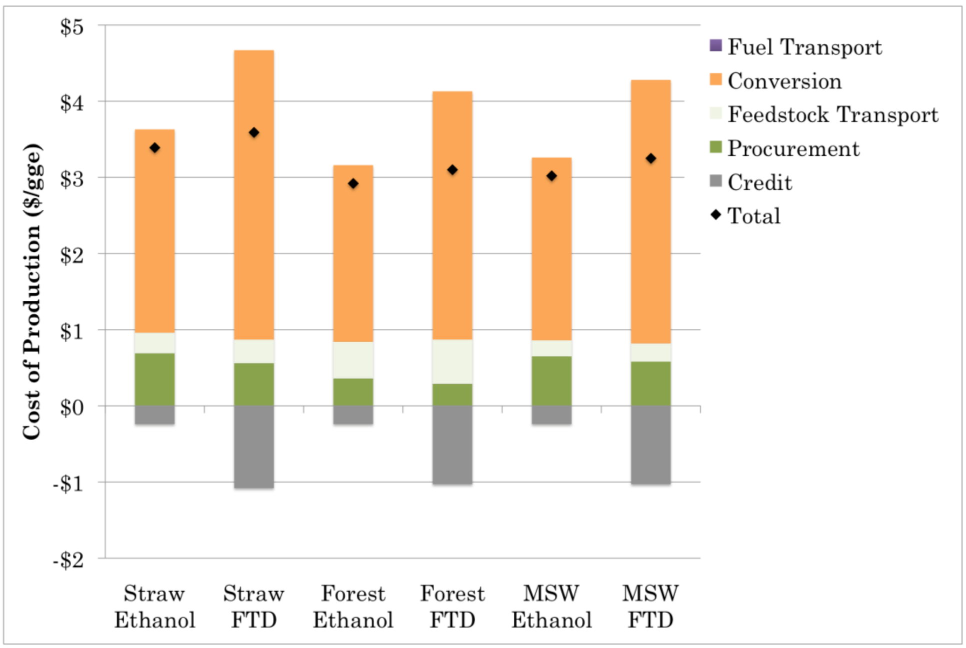

Figure 37: Breakdown of levelized cost of fuel by stage of the supply chain

The components of the levelized cost of producing biofuels and delivering them to fuel terminals is seen in Figure 37. The costs of the pathways considered are dominated by the conversion step. Large credits are generated for electricity production by the F-T diesel technology. The net cost (total cost minus the co-product credit) is given by the black diamond.

Despite higher transportation costs, the delivered feedstock contribution to the finished fuel costs is less for the F-T diesel pathways due to higher conversion efficiencies and therefore more fuel produced per ton of feedstock processed. None of the optimal supply chains had a significant average fuel transport cost to reach a fuel distribution terminal because most biorefineries were sited at existing fuel terminals. Whether the space is available at these fuel terminals to accommodate the biorefineries was not determined for this study.

Electricity co-product value is an important factor in determining which conversion technology is economically optimal. If a premium is paid for renewable electricity, the F-T diesel pathway becomes cost competitive with the ethanol pathway at an electricity price of $0.10/kWh.

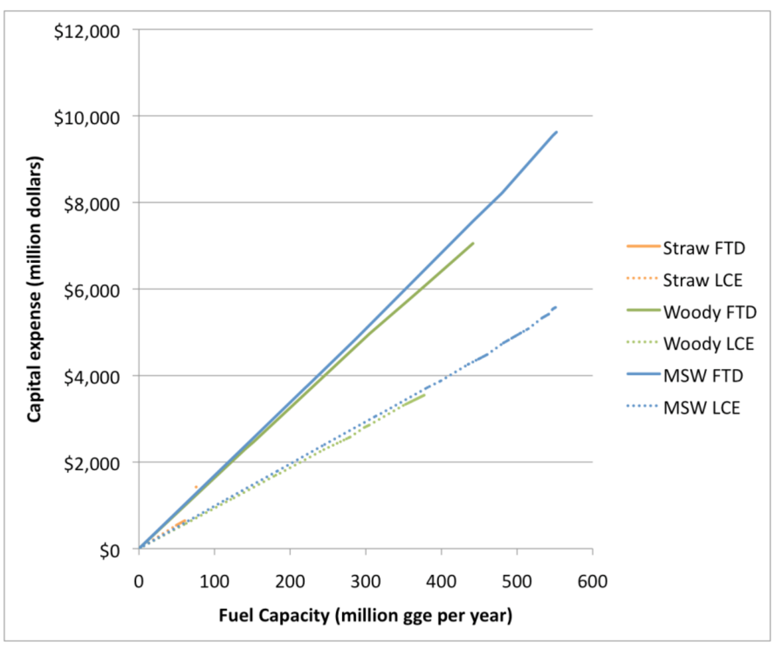

Figure 38: Required capital investment for a given annual production of biofuel by pathway

There is a large difference in capital expenditure for the F-T diesel biorefineries compared to the ethanol biorefineries. For the same annual fuel energy production capacity, the F-T diesel biorefineries required approximately 1.7 times the capital investment compared to ethanol biorefineries.

7.5.2 Emissions results

The emissions inventory for biofuels production depends on the allocation of emissions between the electricity co-product and the fuel product. In California, the two most reasonable allocations are 1) no allocation to electricity or 2) allocation of emissions via the displacement method with the electricity assumed to displace electricity produced using natural gas combined cycle power plants. The no allocation for electricity is appropriate if the electricity is used to meet the Renewable Portfolio Standard (RPS) and is therefore displacing other renewable forms of electricity. If the electricity from these biorefineries provide electricity above the RPS then the electricity displaced would be from natural gas combined cycle. These two allocation methods yield significantly different levels of emissions for the biofuel pathways.

For all emissions and both allocation methods, the ethanol pathways have higher emissions than the F-T diesel pathways. The lowest emission pathway is the thermochemical conversion of municipal wastes to diesel and naphtha with significant co-production of electricity.

Compared to the gasoline baseline, the ethanol pathways have significantly higher CO, N_2O and $PM_{2.5}$ emissions. The straw pathways have higher emissions than the other pathways especially for SO_x and N_20 emissions. Emissions of VOCs are improved in all pathways expect the straw ethanol pathway.

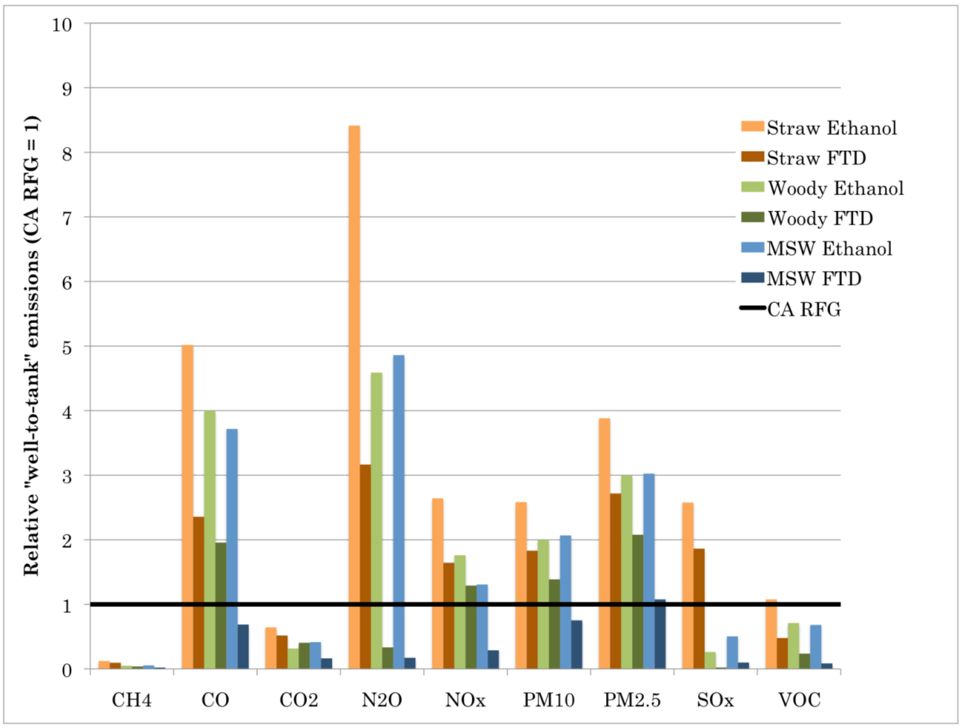

Figure 39: Emissions by pathway normalized by California reformulated gasoline without credit for electricity production

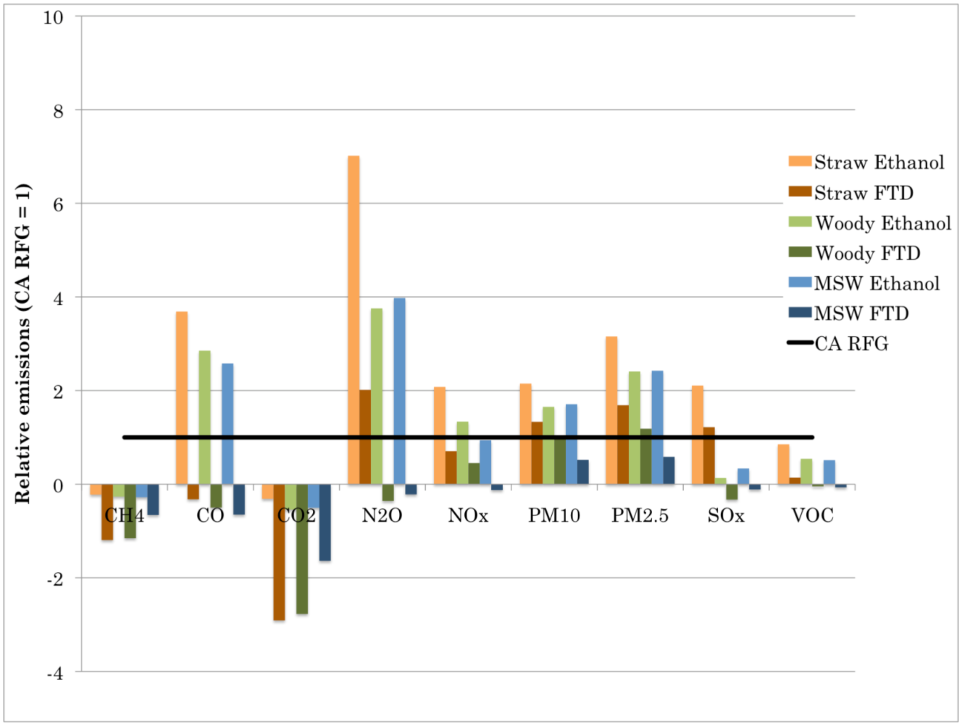

Figure 40: Emissions by pathway normalized by California reformulated gasoline emissions with credit for electricity production displacing natural gas combined cycle electricity

The sign of the difference between biofuel NO_x emissions and gasoline emissions depends on the allocation method. Without credits for electricity production, most pathways make NO_x emissions worse compared to gasoline. With the credit, all F-T diesel pathways and the MSW ethanol pathway result in improvements in well-to-tank NO_x emissions.

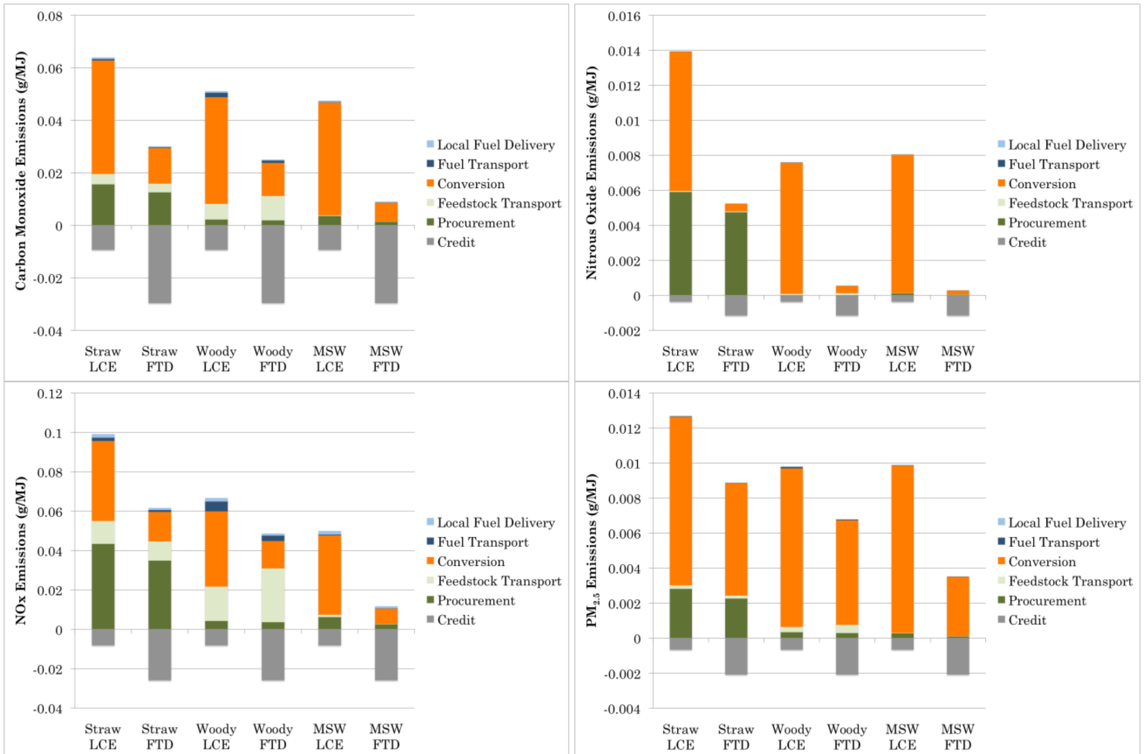

Figure 41: Breakdown of emissions of CO, N_20, NO_x and $PM_{2.5}$

The impacts are different for greenhouse gases. All biofuel pathways make significant reductions in fuel carbon intensity compared to gasoline or diesel with or without the credits for electricity co-production. Credits for electricity result in very negative carbon intensity biofuels. This is due to significant reductions in both CO_2 and CH_4 lifecycle emissions for the displaced electricity. CO_2 makes up approximately 93% of the credit. To better understand how such a large credit comes about, consider the total energy produced by product type. For the F-T diesel process, 0.37 MJ of electricity are produced for every 1 MJ of biofuels. For the ethanol process, 0.12 MJ of electricity are produced for every 1 MJ of ethanol. Since the natural gas-based electricity being displaced has high carbon intensity (~134.7 g CO_2-

eq/MJ), every MJ of electricity displaced has a large impact on the lifecycle emissions of the biofuels.

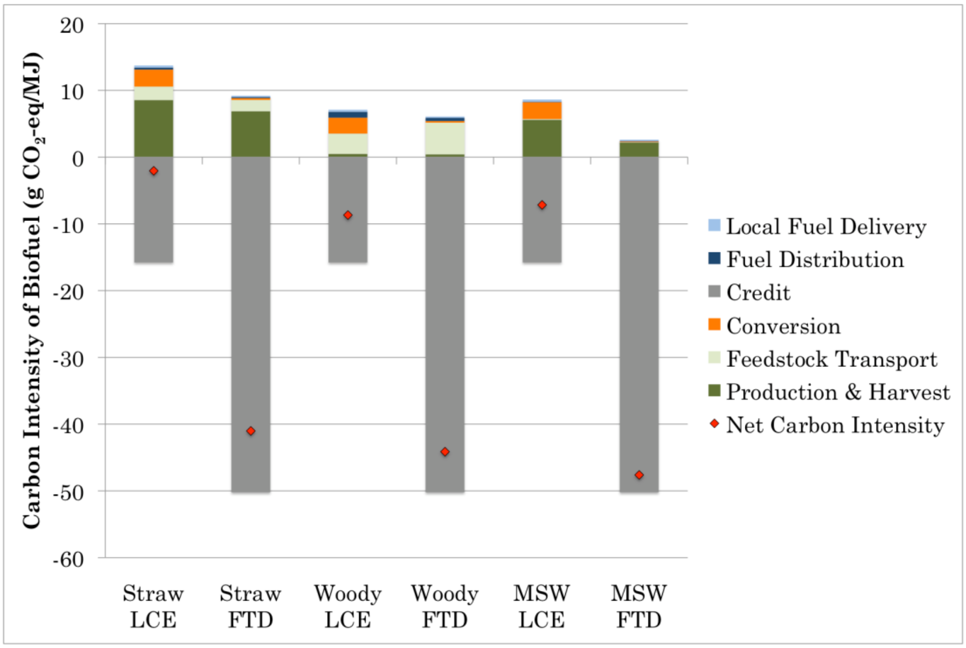

Figure 42: Carbon intensity of biofuel pathways – for reference the CI of CA gasoline (CARBOB) is 95.86 g/MJ and diesel is 94.71 g/MJ

7.5.3 System layout

Cellulosic ethanol favors many medium scale biorefineries while the F-T diesel process favors fewer larger biorefineries. The optimal systems result in 3 to 4 ethanol biorefineries for every F-T diesel biorefinery. This result has both positive and negative implications for the F-T diesel pathways. Fewer facilities mean fewer permit applications in order to produce the same amount biofuels. The larger biorefineries are more expensive on an individual project basis and so incur greater risk at least during initial build out with commercially unproven technologies and markets. Permitting may also be more difficult for larger size facilities due to local transport and other impacts. Development of standardized permitting procedures may improve permitting times for multiple facilities of similar type, however. These uncertainties are not yet addressed through this modeling effort.

The maps below present the system configurations at the point in their supply curves where additional biofuel production comes at significantly steeper costs. This gives a picture of the potential industry at the largest size that might reasonably be expected.

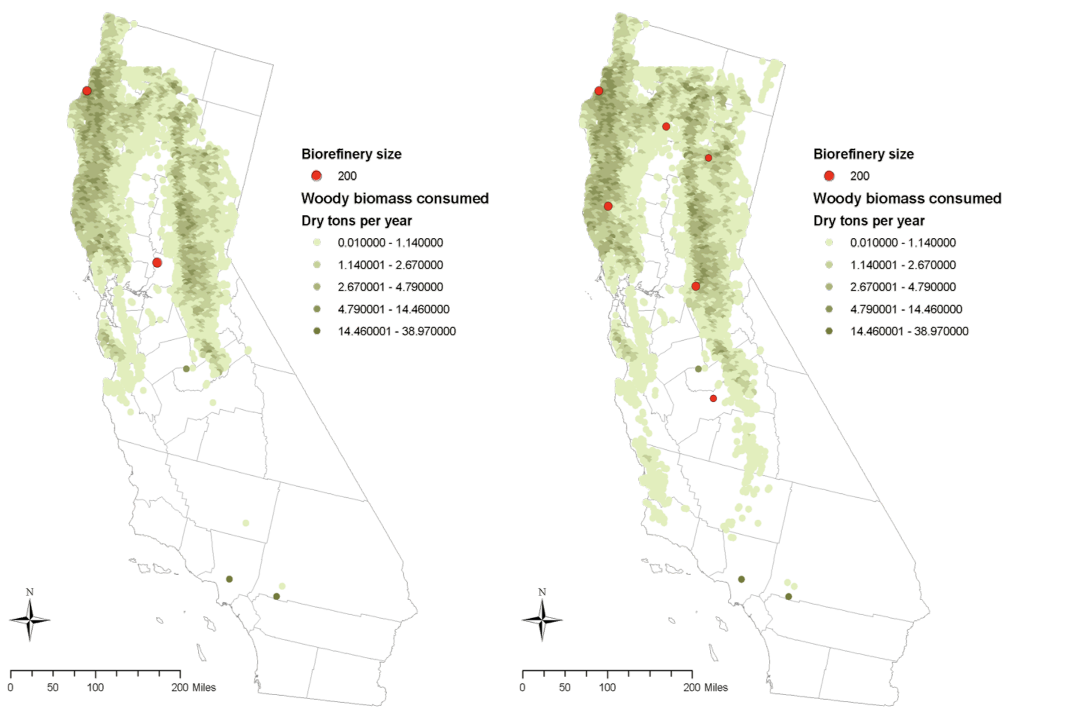

Figure 43: Optimal configuration for biofuel production for forest and wood wastes at $3.25/gge - F-T diesel (left) and ethanol (right)

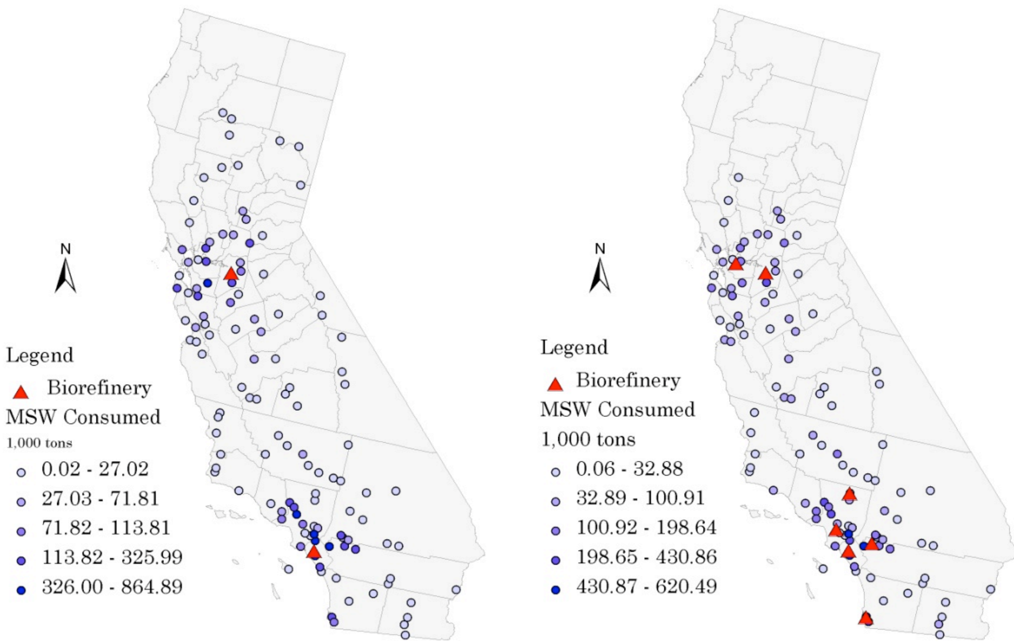

Figure 44: Optimal configuration for biofuel production from MSW - F-T diesel (left) and ethanol (right)

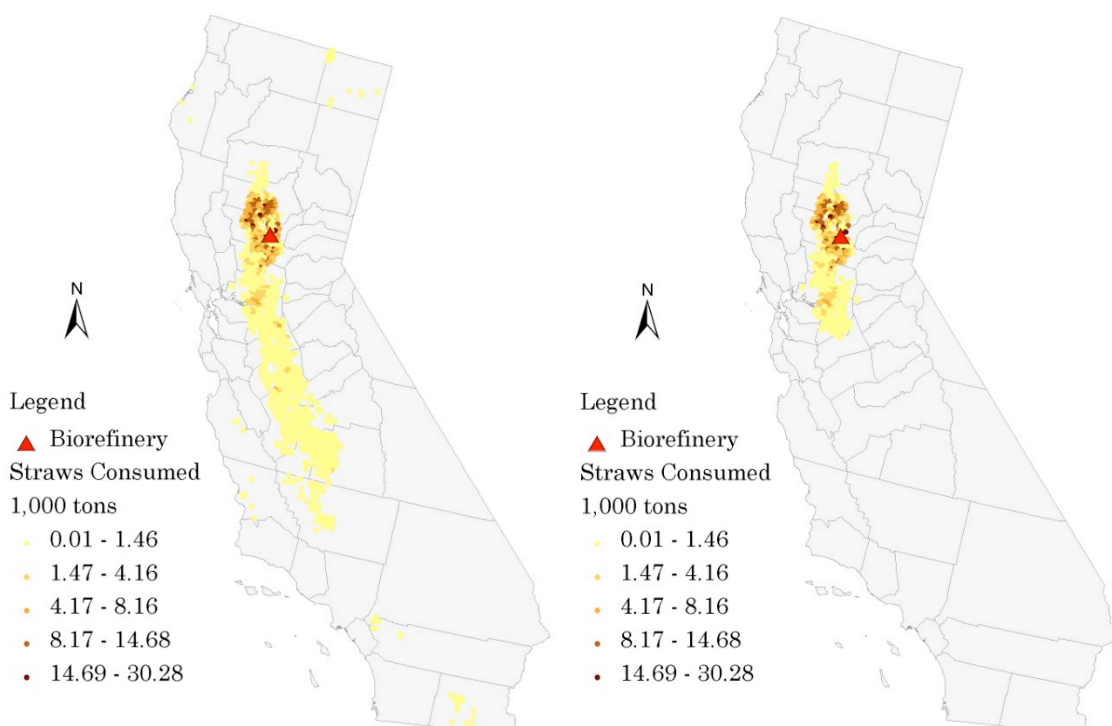

Figure 45: Optimal configuration for biofuel production from agricultural straws and stovers - F-T diesel (left) and ethanol (right)

7.5.4 Summary

There is no pathway that is the most attractive on all metrics of comparison. The F-T diesel from MSW pathway has clear environmental advantages over the other pathways but it has the highest capital cost per gallon of biofuel capacity of all the pathways. Additionally there has been great difficulty in getting innovative projects producing energy from MSW through the permitting process in California.

The ethanol pathways provide a mix of low capital cost; lower levelized costs but higher greenhouse gas and criteria air pollutant emissions compared with F-T diesel pathways using the same resource base. The increases in CO, NO_x and PM compared with the gasoline baseline are high and pose a serious hurdle for these biorefineries to be sited in California where many air basins are in non-attainment.

All the biofuel pathways are low carbon fuels. The value of the low carbon fuels will need to be weighed against the potential for mixed results on air pollutant emissions and higher costs in comparison to petroleum fuels.

Table 29: Summary of biofuel pathway performance

	Straw Ethanol	Straw FTD	Woody Ethanol	Woody FTD	MSW Ethanol	MSW FTD
Petroleum displacement potential (MGGEY)	50-60	76	63-374	140-440	117-533	153-547
Levelized Cost ($/gge)	$3.40-4.12	$3.64	$2.80-3.92	$3.06-3.92	$2.96-3.96	$3.16-3.74
Capital cost ($/annual gge)	$10.66-10.92	$18.80	$9.23-9.47	$15.97-16.37	$9.71-10.12	$16.89-17.44
Number of biorefineries	1	1	6	2	7	2
Carbon intensity (g/MJ)[1]	13.73/-2.05	9.20/-41.02	7.10/-8.68	6.08/-44.14	8.62/-71.6	2.60/-47.61
Emissions[1,2]						
CH_4	++/++	++/++	++/++	++/++	++/++	++/++
CO	--/--	--/++	--/--	--/++	--/--	+/++
CO_2	+/++	+/++	++/++	++/++	++/++	++/++
N_2O	--/--	--/--	--/--	++/++	--/--	++/++
NO_x	--/--	-/+	-/-	-/+	-/+	++/++
PM_{10}	--/--	-/-	--/-	-/+	--/-	+/++
$PM_{2.5}$	--/--	--/-	--/--	--/-	--/--	-/++
SO_x	--/--	-/-	++/++	++/++	+/++	++/++
VOC	-/+	+/++	+/+	++/++	+/+	++/++

[1]Emissions are shown without and with credit for displaced electricity

[2]Qualitative score for the impact of the biofuel pathway on total well-to-tank emissions compared with a gasoline baseline. -- More than twice the emissions as gasoline, - more emissions than gasoline, + less emissions than gasoline and ++ less than half the emissions of gasoline.

7.6 Discussion

The production of biofuels from waste and residue resources in California can provide limited petroleum displacement. For the year 2009, California consumed 19 billion gallons of gasoline equivalent of petroleum gasoline and diesel (Schremp *et al.,* 2010). At maximum the total ethanol pathways could provide for 5.1% of this total demand. The F-T diesel pathways could provide and maximum of 5.6% of this total demand. The biofuel pathways considered here are not major sources of petroleum displacement for California.

Biomass from residues and wastes can go a long way towards meeting the policy goals laid out by the Low Carbon Fuel Standard (LCFS). According to Yeh *et al*. (2009) the LCFS 2020 target translates to a reduction of 25.5 million tonnes of the carbon dioxide emissions. At maximum the F-T diesel pathways can provide 46% of the total emissions reductions required by the LCFS without the carbon credit for electricity co-production and 71% with the credit for electricity co-production. The ethanol pathway leads to lower LCFS compliance potential. With the electricity co-production carbon credit the total ethanol pathways result in 40% of the LCFS emissions reduction goals. Including the electricity credits increases the LCFS compliance potential to 47%. To make up the rest of the LCFS reductions, fuels will need to be imported to California from other states or countries. In the case of ethanol pathways, the ethanol produced from the in-state resources account for most of the ethanol that could be sold as E10. Therefore, either E85 strategies or fuels other than ethanol will need to be pursued.

A major finding of the research is that the co-production of electricity might greatly improve the environmental performance of biofuels if the electricity that is displaced is made from fossil sources without carbon capture and sequestration. One possible implication of this result is that the best use of biomass may be to produce electricity. Other researchers have argued this point (Campbell *et al.,* 2009). However, research to date does not explicitly account for costs of fuel production or the value of co-products, nor have the aviation or heavy transport markets been expressly addressed in terms of supplies of low-carbon fuels. I see this as an area for future work.

The air pollutant emissions data for advanced biofuel conversion technologies are not yet known. I have made a simple estimate given existing data at the time of the study. As can be seen in Figure 41, the majority of emissions that were found in the emission inventory occur at the biorefinery. If these emissions can be controlled or prevented through technology not considered here, the environmental performance of biofuels could be made positive on most, if not all, air pollutants. It is possible that uncontrolled air pollution emissions associated with biorefineries are worse than shown here and more expensive control technologies will be needed in order for the biorefineries to acquire permits to construct and operate. As cellulosic biofuels come closer to commercialization, emissions will be better known and an update of this study may be useful.

In summary, biofuels from waste and residue resources in California have limited potential for petroleum displacement, could contribute 40-70% of the LCFS emissions reductions but with mixed and uncertain results on air quality. This study is limited by lack of information on commercial scale conversion technology performance – especially for emissions.

8 CONCLUSIONS AND DISCUSSION

In this concluding chapter, I summarize the main findings. Additional discussion is given for the choice of cellulosic biofuel technology and the computational issues encountered in the implementation of the national scale model. Next I discuss limitations of the work present here with comment on the resulting basis in the reported results and methods that may be employed to address the limitations. The chapter concludes with a discussion of the future work that I plan to undertake utilizing the methodology developed here as a basis.

8.1 Main Findings

In this dissertation, I set out to develop methodology that makes explicit the spatial features of biofuel supply chain in projecting future biofuel supplies. The spatial features include the locations of the supplies of biomass and demands for fuels, and the trade off between economies of scale in conversion and additional feedstock collection costs in sizing biorefineries. These features have been greatly simplified in large scale analysis of future biofuels supply to date. The method was demonstrated at the national scale considering the Renewable Fuel Standard mandate for 2018. Additional refinements of high resolution and emissions accounting were demonstrated for California.

The methodology developed expands the use of facility siting and supply chain optimization modeling to include the entire United States biofuel industry. Explicitly modeling of the infrastructure required to bring about biofuel supply provides several advantages over previous methods for projecting biofuels. First, it guarantees that the modeled system is anchored to a realistic supply system. Second, it allows the analysis of regional differences in supply. Third, the data intensive approach based in engineering estimates of costs provides a transparent and flexible model for analyzing the sensitivity of the highly uncertain parameters involved in projecting future fuel supplies.

The potential for biofuel production in the United States is large relative to the current production. The national case study found biofuel potentials ranging from 20 to 46 billion gallons of gasoline-equivalent below $4/gge in 2018 depending on the resource scenario. This represents 10 to 23 percent of the projected transportation fuel demand and an increase of at 300% of 2009 production levels. Below $3/gge, between 12 and 32 billion gge are projected to be feasible. Constraints on the supply of biomass restrict growth of biofuels to not much more than the quantities available at $4/gge. The maximum supply found was 50 billion gge at $6/gge in the high feedstock scenario.

Waste and residue biomass can provide quantities of biofuels that assist with policy goals. Nationally, waste and residue resources are projected to provide between 35 and 64 percent of the RFS2 mandate in both 2018 and 2022. The remaining biofuels are predominantly corn ethanol (up to 15 billion gallons) and soy biodiesel (up to 1 billion gge) in the 2018 case and expanding to include switchgrass and pulpwood-based biofuels at the higher volumes of the 2022 mandate. In California, biofuels from waste and residue resources have limited potential for petroleum displacement, but could contribute 40-70% of the LCFS emissions reductions with mixed and uncertain results on air quality.

Investment in biorefineries required to meet mandated volumes of biofuels are large and depend on the specific pathways chosen. Greater reliance on cellulosic technologies requires higher capital investment than systems that rely on conventional biofuel technologies such as corn ethanol or FAME biodiesel. The total investment in biorefineries to required meet the 2022 RFS2 mandate is between $100 and $360 billion with the baseline estimate of $160 billion. This would represent an investment of $9 to $30 billion ($13 billion in baseline) annual investment over the next 12 years. To put this in perspective with the cost of past biofuel policies, the volumetric ethanol excise tax credit (VEETC) provided roughly $5 billion to the industry in 2009 and $5.8 billion in 2010.

The diverse set of biofuels have different policy values. All provide petroleum displacement but the magnitude of the potential displacement and the cost of that displacement varies. Corn ethanol was shown to provide significant quantities of fuel at relatively low prices. However, the net climate impact of corn ethanol is uncertain with a strong probability that large production of corn ethanol will increase global greenhouse gas emissions (Plevin *et al.*, 2010). The projected cellulosic biofuels from municipal wastes and forest residues have limited potential for petroleum displacement in the same cost range as corn ethanol with larger and more certain greenhouse gas reductions. Other cellulosic biofuels that offer significant greenhouse gas reductions are feasible only at costs higher than corn ethanol. This result highlights the challenge in providing a balance between two primary goals of biofuels policies; petroleum displacement and reductions in greenhouse gases.

8.1.1 Optimal choice of cellulosic biofuel technology

Two cellulosic biofuel technology classes – thermochemical processes to hydrocarbons (F-T diesel) and biochemical processes to alcohol (cellulosic ethanol) – were considered in the case studies above. Each have distinct advantages and disadvantages. Unlike the biochemical process, the thermochemical process is expected to produce fuels that are fungible with petroleum fuels. This is a distinct advantage as the F-T diesel technology does not require the roll out of alternative refueling infrastructure or the adoption of E85 by consumers. The biochemical technologies have the advantage of lower capital intensity. Lower capital requirements reduce the exposure to risk for those investing in the developing biofuels industry.

The cellulosic ethanol biorefineries capital costs in the baseline are between $8.50 and $9.25 per gge of annual fuel capacity. They range from

$5.5-6.5 per gge of annual fuel capacity in the optimistic case to $14-17 per gge of annual fuel capacity in the pessimistic case. F-T diesel biorefineries have capital costs of between $12 and $16 per gge of annual capacity in the baseline and $27-35/gge annual capacity in the pessimistic scenario. In the national case study, the baseline system favors the F-T diesel despite the higher capital cost due the high variable costs for the cellulosic ethanol and higher co-product credits for the F-T diesel technology. However, at higher discounts the optimal system would favor cellulosic ethanol. Discount rates above 20% result in optimal systems where the cellulosic ethanol technology is more attractive.

Capital constraints may play a large role in the biofuel industry for several reasons. First, biofuels are not expected to provide a consistently lower cost alternative to petroleum fuels in the early build out of cellulosic biofuels industry. The market for cellulosic biofuels is being created at least in part as a response to government policy and is therefore subject to the additional uncertainty in the durability and stringency of the policy. This is likely to increase the perceived risk of investments in biofuels. The uncertainty in technology performance will also result in a high premium on capital. There are two implications from this increased cost of capital. First, capital intensive technologies will be at a disadvantage in the marketplace relative to the results presented here. Second, policy instruments that lower the risk to capital – such as, loan guarantees – may be necessary compliments to the current mandate in order to launch the cellulosic biofuels industry.

The ethanol demand scenarios in Chapter 6 demonstrate that a low cost cellulosic ethanol technology provides no benefit in terms of biofuel supply unless actions are taken to either increase the blend limit or induce drivers of FFVs to use E85. Increasing E85 availability may not be profitable owners of refueling stations. In 2018, slightly more than 10% of vehicle miles travelled are expected to be by vehicles that are flexibly fueled. This is a small volume at any given refueling station that can also be met with gasoline that does not require the station owner to make any changes or sacrifices of existing pumps. While there will be more vehicles on the road in 2018 that can consume ethanol than any other alternative fuel, there is not a business model to serve them without some form of market shift towards a preference for E85 or financial incentives. Easing the blend limits and/or accelerating the growth of FFVs in the vehicle fleet are policy actions that may change the long-term outlook for cellulosic ethanol.

Technology development is a function of the investment in research and development of the technology. Path dependencies will develop as the private sector and the government agencies select which technologies are worthy of funding. In light of this, the cellulosic ethanol technology is attractive for research and development investment due to capital cost differential that increases at small scales. On the other hand, the current ethanol market with near saturation of the E10 demand may discourage investment in ethanol technologies. Of the 14 current commercial and demonstration cellulosic biorefineries that have received funding from the United States Department of Energy, ethanol is the main product for 10 and renewable diesel is the product of only two. The cellulosic pilot projects receiving some funding from the U.S. Department of Energy are more evenly distributed with half producing ethanol and half producing hydrocarbon fuels (USDOE, 2010).

The suite of technologies considered in the modeling exercise is necessarily limited. In part, this is due to a dearth of good data for the performance and capital requirements of alternative biofuels. The industry is experimenting with a large suite of technologies and the eventual biofuels industry will be comprised of many biorefineries utilizing a variety of technologies, and in all likelihood none will be the exact technologies modeled here. However, the results of the work here can inform what types of technologies would be preferred. First, technologies that produce fuels that can be blended to a high fraction of the fuel content have a major advantage over ethanol. Second, technologies that can make use of municipal wastes have a limited but important role to play in the biofuels market, potentially providing low carbon fuels using a low cost feedstock.

8.2 Computational issues

The national implementation of the model pushed limits of the computational power using commercial mixed integer programming solvers. I limited the problem size by solving a series of smaller regional screening models first, that allowed for a manageable national model. Despite this, some models still required greater than 15 hours to converge to an acceptable solution. The run model time is dependent on the exact parameterization of the model. Some runs found solutions easily (under one hour) while others required more than 10 hours. The scenarios that posed the greatest computational difficulties were either scenarios where two fuel pathways had similar costs or where the demand limits were binding and the next best production pathway needed to be found. For example, the E10 blend limit constrained growth of cellulosic ethanol beyond 7 billion gge in the optimistic scenario forcing the model to shift cellulosic resources to the F-T diesel technology that more expensive than the cellulosic ethanol technology.

The models were not run to proven optimality as the computation time would have exceeded 36 hours for most price points and provided limited benefit for a model of national policy. The algorithm generally progressed to a 1% optimality gap within 5 hours but progress slowed significantly below 0.5%. I consider the optimality gap of 0.5% an acceptable solution. The optimality gap can be interpreted as that the algorithm has not ruled out the possibility of a another feasible solution existing with 0.5% greater profit.

There may be multiple solutions that are within this gap. The maximum possible error introduced by terminating the optimization at an optimality gap of 0.5% increases with increasing profit because the gap is a percentage of the profit. For the baseline scenario in the national case study the maximum possible error is 100 million gge at the $6/gge price point and less than 12.5 million gge for the $2.87/gge price point.

Some of the more interesting extensions to the work presented here would require larger models. Extending the model to consider uncertainty, time dynamics or competition from other sectors for biomass feedstock all represent significant increases in model size (number of variables and constraints). These extensions, especially modeling uncertainty, will require improvements in algorithm development that take advantage of the structure of this specific problem. This is an open question that will need further exploration in order to develop a national scale stochastic model based on the deterministic formulation given in this dissertation

8.3 Limitations

There are several limitations to the modeling framework that impact the results of the analysis. First, there is no interaction between facility siting and land use. This impacts the results by not allowing cropping patterns to respond to the spatially differentiated energy crop value due to the existence of a facility. Second, the model does not account for the temporal evolution of the industry as supplies, technologies and demands change over time. A third and related limitation is that this framework ignores uncertainty inherent in the system. The use of a deterministic model with an implied constant supply and demand over time, leads to optimizations that do not account for robustness and underutilized capacity.

Several of the limitations to the current modeling framework can be overcome by extension of the model in future work. Methods that may be used to extend the model are briefly described below along with the expected outcome of addressing the limitations of the model.

8.3.1 Time dynamics

The dynamic build of a biofuel industry can be modeled using the existing modeling framework as the base for a dynamic simulation model. The simulation would step through time in 1 to 5 year increments with decisions made at each time step based on the result of the supply chain optimization model and expected changes in fuel demands. Costs, prices and supplies can be updated to reflect learning as in de Wit, *et al* (2010).

Including the path dependence for developing the biofuel industry over time would make explicit a number of important issues with the introduction of a cellulosic biofuel industry. Explicitly modeling the learning needed to reduce the cost of biofuel production would highlight the buy down cost for biorefineries and the delivery infrastructure scale up. The learning is assumed to happen over the next 8 years but no cost is assigned for this development under the current modeling framework. Additionally using short time horizons along with current technology cost will lead to some entrenched capital in inferior 1st of a kind biorefineries and path dependencies for technology development. In theory, the cost of accelerated deployment of the technologies could be captured as well. Construction cost would be a function of the current stock of biorefineries and the number of biorefineries to be constructed in the current time step.

The expected outcome from explicit inclusion of time dynamics would be a higher but more realistic estimate of the cost of biofuels to account for entrenched capital in early biorefineries and the costs of rapid industry deployment.

8.3.2 Competition between biomass consumers

Biomass may play a large role in other industries, most notably electricity and heat. The competition from these sectors could be included in the modeling framework conditional on the availability of the appropriate data. A model that included all energy sectors as potential consumers of biomass would help answer questions about the most economical use of the feedstock and whether a single pathway is likely to dominate the biomass industry or a suite of uses will be the end result and what policies might be most effective. With respect to the results presented here, the additional competition for feedstock will either increase the cost of biofuels or make no change if biofuels are the dominant biomass technology.

8.3.3 Links to agricultural economic model

A dynamic link between the biorefinery siting model and an agricultural economic model for modeling biomass producers would provide improvements on two fronts. First it would allow for local markets of biomass induced by the placement of biorefineries to impact the production decisions for the modeled farmers. This would lead to denser production of biomass feedstock near the biorefineries than is seen in the unlinked models and a reduction in the total cost of production. For example, farmers in a given county may plant equal areas of soy and corn under current markets. However, if a corn stover biorefinery is sited in the county, the farmers have an incentive to produce more corn than soy and would likely do so. By planting more corn near the biorefinery, the farmers reduce the cost of transporting corn stover to the biorefinery. This effect is not currently captured in the model. Second, the market impacts on land rents, input prices and agricultural commodity prices could be explicitly modeled. Market feedback loops would lead to increased prices as the demand for biomass places additional pressure on scarce resources of land, water and agricultural inputs. This in turn would lead to higher biofuel prices than are predicted in the preceding case studies.

8.3.4 Uncertainty

There is a great deal of uncertainty on a number of levels in the system modeled. There is year to year uncertainty in feedstock availability and price, fuel price and supporting policies. Uncertainties also exist for the technology performance development over time.

A result of the deterministic model is that biorefineries are sited to utilize all the feedstock in a region leaving little slack in the supply to account for the inevitable down year in supply. This is not a robust infrastructure design and will lead to volatile fuel prices for profitability of the industry. The existing biomass power industry has accommodated year-to-year supply variations, mostly due to the relatively low fraction of biomass currently utilized. As industry demands on supplies increase toward the maximum available, shortfalls will likely result in sharp price increases and greater demand on feedstock imports, if not increased facility shutdowns and business failures. A better method would be to account for the volatility of supply and petroleum prices in the design of the system. This requires a stochastic model with higher computational effort. The resulting system from the stochastic model would be less aggressive in consuming biomass leading to a higher required fuel price for the same volume of fuel in the expected scenario but would be more robust in face of changes in supply and fuel prices.

8.4 Future research directions

There are four research directions that are immediately interesting. First, the omission of the electricity sector as a competitor for biomass must be addressed. Demand for biomass in the electricity sector is expected to rise sharply as a number of states have enacted Renewable Portfolio Standards and the Northeastern states have implemented a regional cap-and-trade policy in the electricity sector. A minimum these new demands for biomass in electricity and fuels sectors need to be considered together in order to understand the degree to which the available biomass can support all existing policies. Taking the analysis a step further, the use of limited biomass resources should maximize the benefits to society. The electricity sector has been shown to be the most efficient use of biomass for carbon reductions if used as a replacement to coal fired electricity (Campbell *et al.*, 2009). However, the picture is less clear when considering low carbon alternatives in the electricity and transportation sectors (Rhodes, 2007; Lemoine *et al.*, 2010). An expanded version of the modeling framework presented here can provide good insight into where biomass would be best used. It would provide a compliment to full energy systems models, such as MARKAL, considering the same question as it would be able to accommodate greater spatial detail in the analysis.

Second, the ethanol demand limit scenarios highlighted the importance of E85 in a world where ethanol is the dominant cellulosic technology. However, the costs of provide the E85 infrastructure and the relative prices of E85 and gasoline that would be needed to induce the required level of E85 demand were not analyzed. The spatially-explicit nature of the supply chain optimization provides a good framework for exploring the extent to which the limits on ethanol demand cause a cost premium relative to a hydrocarbon biofuel.

Third, the path to cost competitive biofuels will require investment in and the development of technologies that are not competitive in order to develop the learning that is needed. Additional cost are incurred in the form of infrastructure scale up for the deliver of both the fuels and the biomass feedstocks. The buy down cost representing the investment required to make the industry is self-sustaining is an important metric for comparing the diverse set of alternative fuels that exist (hydrogen, electric drive, biofuels). A dynamic implementation of the model is an ideal candidate for calculating this metric as it tracks infrastructure investments at in a detailed manner.

Fourth, air quality restrictions may limit the ability of facilities to operate within regions that are currently in non-attainment of Federal EPA air quality standards. These regions, which include many major urban areas in the U.S., are required to restrict emissions of criteria air pollutants. Most biofuel production facilities emit significant amounts of multiple criteria pollutants and while these emissions can be mitigated through utilization of emissions control technology (Brady and Pratt, 2007) no facility can be completely emission-free. In some situations, meeting emissions permit requirements or providing emission offsets may be too costly to allow for ethanol production at realistic prices, which serves as a functional constraint. The model can be used to explore the impact of non-attainment regions on the siting of biorefineries and the cost of producing biofuels.

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APPENDIX A: FEEDSTOCK LOGISTICS COST MODEL

The "Pioneer Feedstock Logistics Chain" developed by Idaho National Laboratory (INL, 2010) is used to describe the cost of harvesting, storing, and transporting straw and stover feedstocks. The transportation cost model is used for all biomass resources. The equations below describe the model.

There are a few parameters that are maintained outside of the hard coded model to allow for variation between states and over time. These are labor rates, fuel costs and land rents. The INL model assumptions can be found in the "State-specific" sheet of the excel model.

Parameter notation

LC_f	Farm labor rate ($/hr)
LC_{td}	Truck driver labor rate ($/hr)
LC_{pl}	Plant loader operator labor rate ($/hr)
LC_{bh}	Bulk handling labor rate ($/hr)
LC_{go}	Grinder labor rate ($/hr)
FC_r	On-road fuel cost ($/gallon)
FC_o	Off-road fuel cost ($/gallon)
Rent	Land rent ($/acre)

Straw bale truck transportation

Truck costs are calculated for a 26 bale truckload. The bale density (**bd**) and moisture content (**MC**) will impact the cost per dry ton. For generic model, use 17 wet tons per load (**bd** = 0.65445 tons/bale) and leave moisture content adjustment for post processing of network outputs.

Loading Costs (spatially located at farm gate)

load_cost ($/dry ton) = {(0.325 hrs)*[$6.71/hr + 1.67*$LC_{pl}$ + (1.725 gal/hr)*FC_o] + (0.56 hrs)*1.67*LC_{td}} / [26***bd**/(1-**MC**)]

Unloading Costs (spatially located where bale trucks unload)

unload_cost (\$/dry ton) = {(0.325 hrs)*[\$6.71/hr + 1.67*LC_{pl} + (1.725 gal/hr)*FC_o] + (0.59 hrs)*1.67*LC_{td}} / [26***bd**/(1-**MC**)]

Travel Cost (spatially located on road links) –includes roundtrip

travel_cost (\$/dry ton) = 2*{[\$0.29/mile + (1/6 mpg)*FC_r]*road_miles + 1.67*LC_{td}*travel_time(hours)} / [26***bd**/(1-**MC**)]

Bulk material transport

Truck costs are calculated for a single truckload (4371 ft^3). The per dry ton cost will depend on the density (**d**) and the moisture content (**MC**). For generic model, use 19.9 wet tons per load (**d** = 9.1 lbs/ft^3) and leave moisture content adjustment for post processing of network outputs.

Loading Costs (spatially located at depot)

load_cost (\$/dry ton) = {(0.22 hrs)*1.67*LC_{td}} / [(4371/2000)***d**/(1-**MC**)]

Unloading Costs (spatially located at biorefineries or intermodal facilities)

unload_cost (\$/dry ton) = {(0.16667 hrs)*[\$44.31/hr + 1.6*LC_{bh}] + (0.2 hrs)*1.67*LC_{td}} / [(4371/2000)***d**/(1-**MC**)]

Travel Cost (spatially located on road links) –includes roundtrip

travel_cost (\$/dry ton) = 2*{[\$0.35/mile + (1/6 mpg)*FC_r]*road_miles + 1.67*LC_{td}*travel_time(hours)} / [(4371/2000)***d**/(1-**MC**)]

Rail transportation

Rail costs in the INL model follows a simplified format. There is just a fixed cost plus a per mile cost.

Rail Fixed Cost (spatially located at origin Intermodal facility)

fixed_rail_cost (\$/dry ton) = \$17.10/(1-**MC**)

Rail per mile cost (spatially located on the links) – no roundtrip required

var_rail_cost ($/dry ton) = $0.0172/(1-**MC**)

Straw & Stover Harvest Cost (Bales)

The Pioneer and Pioneer Uniform scenarios in the INL model have the same harvest system. The residue remaining on the field after grain harvest is windrowed

The parameters that impact the harvest cost are the effective yield ($\mathbf{y_e}$) measured in dry tons per acre (BDT/acre) and the field radius ($\mathbf{r_f}$) measured in miles.

Effective yield is the minimum of the sustainably removable fraction biomass and the biomass that can be technically harvested. The biomass that can be technically harvested is the gross residue production times the harvest efficiency (eff_h), which accounts for mechanical harvest limitations of the equipment. In the Pioneer stover and straw models the harvest efficiency is 38%.

$\mathbf{y_e}$ (BDT/acre) **= min**{[gross residue yield – residue required on field], [gross residue * eff_h]}

Windrowing & Baling

Residues are cut during grain harvest and therefore residue cutting is not charged to the cost of residue removal. The residues are windrowed to improve drying and in preparation of baling. The costs of the windrowing and baling operations are dependent on the area of the field to be traveled by the equipment. The equipment capacity is assumed to be purely a function of the speed and the width of the equipment for the windrowing. Baling capacity is the minimum of the field operating capacity and the rated capacity. Higher yields are not assumed to slow down the equipment up to the rated capacity.

Windrow_cost ($/BDT) = [$40.82/hr + 1.1*LC_f + 9.96gal/hr*FC_o]/[$\mathbf{y_e}$*7.3 acres/hr]

Bale_cost ($/BDT) = [$115/hr + 1.1*LC_f + 12.46 gal/hr*FC_o]/[**min**{21.89 BDT/hr, $\mathbf{y_e}$*10.72 acres/hr}] + $1.28/BDT

Roadsiding

The INL model assumes an average distance to storage site of 0.5 miles. The costs below are for roadsiding to storage at each farm to be consistent with the network analyst beginning at each pfarm.

Roadsiding_cost ($/BDT) = [$55.97/hr + 1.1*LC_f + 8.85 gal/hr*FC_o]/[(5.184 BDT/load)/(0.0413 hr/load + $\mathbf{r_f}$*0.1893 hr/load)]

Storage

The costs below are for storage at each pfarm roadside in wrapped bales. There are three main costs in storage as the INL model is designed. First is the cost of placing the bales in the bale wrap. Second is the land rent and insurance for the feedstock during storage. And finally there are losses of feedstock in storage. I believe the best way to handle the third cost is to calculate all harvest costs and then reduce the quantity of biomass leaving the pfarms to account for storage losses.

Wrapping_cost ($/BDT) = [$38.35/hr + 2.2*LC_f + 2.88*LC_o]/[46.08 BDT/hr] + $4.96/BDT

Land_ins_cost ($/BDT) = Rent*(0.00063769 acres/BDT) + $0.05/BDT

Storage losses = 5% of feedstock

Total Procurement Cost

The total procurement cost for the stover or straw resource will be the sum of the windrowing, baling, roadsiding and storage costs. The per BDT procurement cost will include an adjustment to the quantity that accounts for the storage losses.

Procurement_cost ($/BDT) = {Windrow_cost ($/BDT) + Bale_cost ($/BDT) + Roadsiding_cost ($/BDT) + Wrapping_cost ($/BDT) + Land_ins_cost ($/BDT)}/ 0.95

The total quantity of biomass available from the pfarms for the biorefineries is given as.

biomass (BDT) = $\mathbf{y_e}$*farm_size(acres)*0.95

Preprocessing

The preprocessing costs include the costs of grinding, densifying and storing biomass at a depot. In the case of the pioneer feedstock supply chain the depot is part of the biorefinery. On additional parameter is needed for calculating the preprocessing costs. The **depot_size** is the size of the depot in dry tons per year. This can be calculated by summing the biomass delivered to a depot (or biorefinery).

Grinding

Grinding_Cost ($/BDT) = {$73.3/hr + 1.03*LC_{go}}/{min(14.6*(1-**MC**), **depot_size**(BDT/yr)/8400)}

Grinding loader

Loader_Cost($/BDT) = {$6.08/hr + 1.03*LC_{pl} + 1.725*FC_{o}}/{min(39.3*(1-**MC**), **depot_size**(BDT/yr)/8400)}

Miscellaneous depot equipment

Misc_depot ($/BDT) = $47.16/{min(14.6*(1-**MC**), **depot_size**(BDT/yr)/8400)}

Plant Handling and Queing

Plant handling and queing costs are incurred at the biorefinery and represent the cost of the receiving equipment beyond unloading. This includes a truck scale and asphalt pad for receiving.

PHQ_Costs ($/BDT) = [($1.89/hr + 1.67*LC_{bh})/{min(255.3*(1-MC),**brfn_size**(BDT/yr)/4200)}] +$178,151/**brfn_size**(BDT/yr)

APPENDIX B: ADDITIONAL EMISSIONS DETAILS

The emissions acounting model in Chapter 7 is based on emissions factors from Argonne National Laboratory's GREET Model where possible and data from peer-reviewed articles or environmental impact reports of proposed biorefineries. In this Appendix, the emissions factors not reported in Chapter 7 are given and the raw potential to emit data from two biorefineries are shown broken down by process to highlight the contribution of the boiler to the overall emissions of the facility.

Table 30 gives the emissions factors for fertilizer applications from the GREET model. The fertilizer required to replace nutrients lost from the removal of agricultural residues are given in Table 13 in the Chapter 5.

Table 30: Emission factors for fertilizers (ANL, 2009)

	Fertilizer (per gram of nutrient)			
Total Emissions: grams per gram	Nitrogen	P2O5	K2O	Induced soil emissions
VOC	0.0061	0.0004	0.0001	
CO	0.0057	0.0013	0.0004	
NOx	0.0034	0.0072	0.0018	0.0139
PM10	0.0009	0.0017	0.0006	
PM2.5	0.0005	0.0011	0.0002	
SOx	0.0018	0.0637	0.0013	
CH4	0.0029	0.0018	0.0010	
N2O	0.0016	0.0000	0.0000	0.0030
CO2	2.4260	0.9784	0.6519	

MSW classification emissions were taken from Kalogo *et al.* (2007). They were reported with a basis of wet-ton of MSW sorted. To account for this adjustments have been made for each MSW resource type due to its moisture content and are reported in Table 31.

Table 31: Emission factors for MSW classification

	MSW Food g/ton	**MSW Paper** g/ton	**MSW Other** g/ton	**MSW Yard** g/ton	**MSW Wood** g/ton
VOC	2.1	0.7	0.7	1.2	0.7
CO	54.2	18.1	16.9	30.7	18.5
NOx	93.4	31.1	29.2	52.9	31.8
PM10	6.0	2.0	1.9	3.4	2.0
PM2.5	4.1	1.4	1.3	2.3	1.4
SOx	77.8	25.9	24.3	44.0	26.5
CH4	3.3	1.1	1.0	1.9	1.1
N2O	1.9	0.6	0.6	1.1	0.6
CO2	83,666.2	27,888.7	26,145.7	47,358.2	28,522.6

The emissions from the operation of harvest equipment, trucks, locomotives and barges were found using emissions factors for each class and the diesel consumption found by the harvest and transport models described in Appendix A and Chapter 5.

Table 32: Emission factors for diesel consumed by mode (grams/mmBtu diesel) (ANL, 2009)

	Off-road	Marine	Rail	Truck
VOC	69.25	40.99	73.95	30.03
CO	363.20	119.64	213.33	153.08
NOx	684.96	1,045.69	1,517.11	450.74
PM10	62.32	26.03	35.94	8.38
PM2.5	55.68	13.02	32.35	7.71
SOx	8.04	8.04	8.04	5.21
CH4	0.63	2.01	3.94	1.43
N2O	0.92	2.00	2.00	2.00
CO2	77,410.76	77,877.76	77,622.52	77,860.99

The biomass boiler is a significant fraction of the emissions. From the two air permit applications with detailed emissions reporting, the boiler is responsible for the majority of emissions for all pollutants except volatile organic compounds. The VOC emission are significant from a number of operations.

Table 33: Potential to emit by process unit for proposed Bluefire MSW-to-ethanol biorefinery (Bluefire, 2009)

Blue Fire	Potential to emit (tpy)					
Process Unit	**VOC**	**CO**	**NOx**	**PM10**	**PM2.5**	**SOx**
Biomass Storage and Processing	2.027			0.013		
Dryer	14.334					
Lignin Processing	0.57			0.249		
Biomass Bioler	4.118	22.176	23.76	11.722		21.859
Cooling Tower				0.356		
Emergency Fire ICE	0.03	0.068	0.122	0.006		
Fermentation	0.726					
Valves, fittings, pumps & compressors	1.614					
Gasoline Storage	0.009					
Ethanol Storage	0.167					
Ethanol Tank and Loadout	0.167					
Ash Silo and Handling				0.084		
Lime Slacking System				0.084		
Limestone Storage Silo				0.003		
Total	23.762	22.244	23.882	12.517	0	21.859
Boiler Percent	17.33%	99.69%	99.49%	93.65%	-	100.00%

Table 34: Potential to emit for proposed Verenium energycane-to-ethanol biorefinery (AMEC Earth & Environmental, 2009)

Verenium	**Potential to emit (tpy)**					
	VOC	**CO**	**NOx**	**PM10**	**PM2.5**	**SOx**
Fermentation	16.5					
Distillation	2.3					
Ethanol Storage	0.7					
Product Loadout Flare	5.3	2.3	0.4	0.02	0.02	0.004
Gasolne Storage	0.9					
Misc. Storage Silos				4.7	4.7	
Wastewater Treatment	5.4	0.3	0.1	0.002	0.002	0.0005
Cooling Tower	4.1			0.7	0.7	
Biomass Boilers	8.7	173.4	130.1	17.3	17.3	104.1
Fire Pump ICE	0.1	0.5	0.5	0.03	0.03	0.001
Backup Generator ICE	2.8	15.4	25.4	0.8	0.8	0.02
Stillage Loadout	2.8					
Equipment Leaks	19.6					
Road Dust				9.9	1	
Total	69.2	191.9	156.5	33.452	24.552	104.1255
Boiler %	12.57%	90.36%	83.13%	51.72%	70.46%	99.98%

APPENDIX C: MODEL CODE

The model code for the national model is presented below. The model is written in the GAMS language. There are two models presented. First is the national model. Second is a sample regional production model. Between running the regional production models and the national model the output files of the regional models are combined to form a reduced transportation cost file for the national model and a list of location/technology combinations that were choosen in the regional models.

National model

```
$ontext
This is the baseline model for dissertation modeling.
$offtext

*Sets a parameter that can be used to change all output file names
$set scenario baseline

*Turns off default GAMS output display
Option   Solprint = off;
Option   Limrow = 0;
Option   Limcol = 0;

*Create set indices for all supply locations plus a single supply point for Brazilian ethanol
sets     plot   biomass source locations  /
$include plot_list_all.csv
B99999
/
         brfn    biorefinery sites /
$include brfn_all.csv
/
         feed    /ag_res, hec, forest, ovw, pulpwood, msw_wood, msw_paper, msw_constr_demo,
msw_yard, msw_food, msw_dirty, corngrain, animal_fats, grease, seed_oils, sugar/
*Biorefineries are specified by site/technology/feedstock class combinations
         class   feedstock classification        /herb, woody, pulp, msw, new, exist1*exist6, virgin,
waste, brazil/
*Set used in table of feedstock composition which is needed to calculate yields
         comp    feedstock composition component /cellulose, hemicellulose, lignin, HHV/
*Define discrete price levels
         plev    /
$include price_list_all.csv
$include brazilian_etoh_price_list.csv
/
```

```
        tech          tech type   /lce, ft_diesel, fame, fahc, dry_mill, wet_mill, sugar_etoh/
        term            terminal locations  /
$include terminal_list.csv
/
        trans        transportation mode /total_cost, road_miles, rail_miles, water_miles/;

*Create subsets of the above sets
sets     bulk(feed)      /ag_res, hec, forest, ovw, pulpwood, msw_wood, msw_constr_demo,
msw_paper, msw_yard, msw_food, msw_dirty/
       woody(feed)     /forest, ovw, pulpwood, msw_wood, msw_constr_demo/
       herb(feed)      /ag_res, hec/
       msw(feed)       /msw_paper, msw_yard, msw_food, msw_dirty/
        liquid(feed)    / animal_fats, grease, seed_oils/
*Technologies are group by fuel chemistry for demand limits
        etoh(tech)            /lce, dry_mill, wet_mill, sugar_etoh/
        ftd(tech)       /ft_diesel, fahc/
        biodiesel(tech) /fame/
*Biorefienery sites that are in port cities are considered as potential import locations for
Brazilian ethanol
        ports(brfn)     /
$include ports4brazilian_etoh1.csv
/;

alias (tech, tech2);

*Define transportation cost parameters
Parameters       pbcost(plot, brfn, feed)        '$ per ton for feedstock transport'
                      pbcost_base(plot, brfn, feed)
                      btcost(brfn, term)
                      pbcost_dry(plot, brfn) '$ per wet ton'
                      pbcost_liq(plot,brfn)   '$ per 100 gallon'
*Import supply data sets
                      supply(plot, feed, plev) 'matrix of supply quantities' /
$ondelim
$include ag_residues_38.csv
$include ovw_supplies.csv
$include hec_base.csv
$include msw_supply.csv
$include forest_nofed.csv
$include 2017_BTS_pulpwood.csv
$include lipids.csv
$include supply_corn.csv
$include brazilian_etoh_supply.csv
$offdelim
/
*Import file giving a dollar value for each price level
        prices(plev)    'values for price levels'    /
$ondelim
$include prices_all.csv
$include brazilian_etoh_prices.csv
$offdelim
/
```

```
       feed_MC(feed)                  moisture content of dry biomass feedstocks   /
ag_res          0.15
hec             0.15
msw_paper       0.1
msw_wood        0.12
msw_yard        0.465
msw_dirty       0.186
msw_food        0.7
ovw             0.35
forest          0.5
pulpwood        0.5
/
       feed_density(feed)                 transfers cost per 100 gallons to costs per ton  /
grease          3.085
seed_oils       2.588
animal_fats     3.0
/

       conv_eff(feed, tech, class)          conversion efficiency for converting feedstock to fuel
/

$ondelim
$include conv_eff_with_class.csv
$offdelim
sugar.sugar_etoh.brazil  1
/

       conv_factor(tech, comp)    converts conversion efficiencies into gallons product per ton
feedstock           /
lce.hemicellulose    176.9
lce.cellulose        172.85
ft_diesel.HHV        6.84/

       tech_eff(tech, comp)       conversion efficiency for cellulosic technologies     /
lce.hemicellulose    0.765
lce.cellulose        0.72
ft_diesel.HHV        0.387/

       electricity(tech, feed)              electricity produced per ton of biomass
       elec_eff(tech)         /
lce             0.0366
ft_diesel       0.0366/

       naptha(tech, feed)                   naptha produced per ton of biomass
       naptha_eff(tech)                /
ft_diesel       0.072/

       gge_conversion(tech)         converts fuel quanitities into equivalent gallons of gasoline
/
lce             0.657
dry_mill        0.657
wet_mill        0.657
sugar_etoh      0.657
```

```
ft_diesel       1.065
fame            1.03
fahc            1.065/

        vmt_fraction(term)      'fraction of 2015 vmt allocated to each terminal'  /
$ondelim
$include terminal_vmt_fraction.csv
$offdelim
/

        fuel_price              fuel price for each model run                          /2.8/
        naptha_price                    price of naphtha defined below
        elec_price              price of electricity in dollars per kWh                   /0.05/

        Ethanol_demand          total ethanol demand limit for scenario (units=10MGY)
/1580.5/
        Diesel_demand           total diesel demand limit for scenario (units=10MGY)
/5091/
        diesel_use(plot, brfn, feed);

*Define naphtha price as function of fuel price
naptha_price = 0.86*fuel_price;

*Insert table giving composition and HHV (GJ/Mg) of feedstocks
Table    biomass_composition(feed, comp)
$ondelim
$include feedstock_composition.csv
$offdelim
;

*Insert regional model-limited feedstock transport cost matrix
Table    feedstock_od_table(plot, brfn, feed, trans)
$ondelim
$include source2refine_production_links_limited.csv
$include source2refine_corn_links_limited.csv
$offdelim
;

*Fuel transport cost matrix
Table        terminal_od_table(brfn, term, trans)
$ondelim
$include brfn2term_national.csv
$offdelim
;

*Table of assigned cost for each terminal adding each type of biofuel on a per gallon basis
($/gal)
Table           terminal_cost(term, tech)
$ondelim
$include terminal_cost.csv
$offdelim
;
```

```
*Extract the base feedstock transport cost from table
pbcost_base(plot, brfn, feed) = feedstock_od_table(plot,brfn, feed, 'total_cost');

*Extract fuel transportation cost from table
btcost(brfn, term) = terminal_od_table(brfn, term, 'total_cost');

*Define any missing links as having a high cost
btcost(brfn, term)$(btcost(brfn, term) lt 0.5) = 500;

*Caluclate diesel use in 0.01 gge per ton-link
diesel_use(plot, brfn, feed) = (feedstock_od_table(plot,brfn, feed, 'road_miles')*1084.5 +
feedstock_od_table(plot,brfn, feed, 'rail_miles')*341 + feedstock_od_table(plot,brfn, feed,
'water_miles')*510)/(1-feed_MC(feed))/116093;

*Calculate the conversion yield for cellulosic technologies (gallons/ton)
conv_eff(herb(feed), tech, 'herb') = sum(comp, biomass_composition(feed, comp)*tech_eff(tech,
comp)*conv_factor(tech, comp))/1000;
conv_eff(msw(feed), tech, 'msw') = sum(comp, biomass_composition(feed, comp)*tech_eff(tech,
comp)*conv_factor(tech, comp))/1000;
conv_eff(woody(feed), tech, 'woody') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(woody(feed), tech, 'pulp') = sum(comp, biomass_composition('pulpwood',
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;

*Calculate the coproduct yields by feedstock type
electricity(tech, feed) = elec_eff(tech)*biomass_composition(feed, 'HHV')/1.1023/.0036/1000;
naptha(tech, feed) = naptha_eff(tech)*biomass_composition(feed,
'HHV')/1.1023/0.1216089/1000;

*Input potential locations and links from regional models to limit national locations
Parameters      regional_locations(brfn, tech, class)   /
$ondelim
$include regional_locations_distinct.csv
$include locations_corn.put
$offdelim
/;

*Add brazilian ethanol at port cities
regional_locations(ports, 'sugar_etoh', 'brazil') = 1;

*Existing facility information (corn ethanol plant sizes)
Parameters      remaining_cap(brfn, class, tech)        remaining capital for existing facilities
                existing_cap(brfn, class, tech)         existing capacity of ethanol facilities  /
$ondelim
$include existing_ethanol_capacity.csv
$offdelim
/

*Parameter that defines which technologies can use which feedstocks (0,1)
                feed_tech_match(feed, tech)     /
$ondelim
hec             lce             1
ag_res          lce             1
```

```
ovw             lce            1
forest          lce            1
pulpwood        lce            1
msw_wood        lce            1
msw_yard        lce            1
msw_paper       lce            1
msw_dirty       lce            1
msw_constr_demo  lce            1
pulpwood        ft_diesel      1
ovw             ft_diesel      1
ag_res          ft_diesel      1
forest          ft_diesel      1
hec             ft_diesel      1
msw_paper       ft_diesel      1
msw_yard        ft_diesel      1
msw_wood        ft_diesel      1
msw_dirty       ft_diesel      1
msw_constr_demo  ft_diesel      1
msw_food        lce            1
grease          fame           1
grease          fahc           1
seed_oils       fame           1
seed_oils       fahc           1
animal_fats     fame           1
animal_fats     fahc           1
corngrain       dry_mill       1
corngrain       wet_mill       1
sugar           sugar_etoh     1
$offdelim
/;
*Give all existing facilities zero capital burden
remaining_cap(brfn, class, tech) = 0;

*Create subsets that will prevent the model from creating extra variables
sets spar(plot, feed, brfn)  set used to eliminate unnecessary links
     spar1(plot, feed, plev)      set used to eliminate unnecessary supplies
        spar2(brfn, tech, class)
        spar4(feed, brfn)
        spar3(brfn, tech);


*Only allow links that have cost in regional model-limited transport cost matrix or Brazilian
ethanol to port cities
spar(plot, feed, brfn)$(pbcost_base(plot, brfn, feed) gt 0.5 and smax(plev, supply(plot, feed,
plev)) > 10)=yes;
spar('B99999', 'sugar', ports) = yes;

*Only consider feedstocks that are in the supply file and connected to the network
spar1(plot, feed,  plev)$(supply(plot, feed, plev)*sum(brfn, pbcost_base(plot, brfn, feed)) gt
10)=yes;
spar1('B99999', 'sugar', plev)$(supply('B99999', 'sugar', plev) gt 0.01) = yes;

*Only consider potential biorefineries that were chosen by the regional models
```

```
spar2(brfn, tech, class)$(regional_locations(brfn, tech, class) gt 0.5) = yes;
spar3(brfn, tech)$(sum(class, regional_locations(brfn, tech, class)) gt 0.5) = yes;

*Only consider supply point-biorefinery site combinations with a cost
spar4(feed, brfn)$(sum((plot, plev), pbcost_base(plot, brfn, feed)) gt 0.5) = yes;

*Assign missing links a very high cost (should be redundant with spar4)
pbcost_base(plot, brfn, feed)$(pbcost_base(plot, brfn, feed) lt 0.05) = 200;

*Model scaling - Fix the parameters to have units of $10M, 10M gallons, and 10k tons
pbcost_base(plot, brfn, feed) = pbcost_base(plot, brfn, feed)/1000;
supply(plot, feed, plev) = supply(plot, feed, plev)/10000;
btcost(brfn, term) = btcost(brfn, term)/100;
prices(plev) = prices(plev)/1000;

*Make feedstock transport cost reflect fuel price of a given model run
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;

*Define model variables
Positive Variables
        biomass_consumed(feed, plot, plev)          annual quantity of feedstock consumed from
plot "i" at price level "plev"
        p2b(feed, plot, brfn)          annual quantity of biomass from plot "i" taken to biorefinery
"k"
        Qb(brfn, tech, class)                 quantity of fuel "b" produced at biofinery "k"
        T(brfn, term, tech)                       Fuel deliveries
        x1(feed, brfn, tech, class)          quantity of feedstock consumed at each biorefinery  ;

*Define economic variables that can be used as objective
Variables
        total_cost
        profit;

*Define binary biorefinery variable (build or don't build)
Binary variable
        xi(brfn, tech, class);

Equations
        annual_cost                   total annual cost for biofuel supply
        annual_profit
        xi_constraint(brfn, tech, class)      constraint for integer variable xi
        Qb_constraint(brfn, tech, class)       relates Qb to x1's

*Constraints to set up biofuel networks
        supply_constraint(plot, feed, plev)     limits biomass leaving a plot at a price level to
what is available
        plot_flow(feed, plot)                  constrains feedstock leaving plot to what is consumed
        brfn_cap(feed, brfn)                  limits fuel production capcity at biorefinery to be less
than or equal to the feedstock inputs
        brfn_flow(brfn, tech)                   limits the fuel leaving the brfn to be less than the fuel
produced
        terminal_max(term)          upper bound on ethanol delivered to terminal
```

```
        terminal_max2(term)      upper bound on ft diesel delivered to terminal
        terminal_max3(term)   upper bound on biodiesel delivered to terminal
            corn_limit                                       upper bound on corn ethanol
        commodity_fraction(feed)       upper bound on commodity feedstock consumption
;

*Technology cost parameters
Parameters
        aa(tech, class)                        fixed cost component in linearized biorefinery costs      /
$ondelim
fame       virgin       0.18106
fame       waste        0.09317
fahc      virgin       1.3783
$offdelim
/

        bb(tech, class)                        feed capacity depedent component in linearized biorefinery
costs     /
$ondelim
fame       virgin       0.06032
fame       waste        0.1704
fahc      virgin       0.068699
$offdelim
/;



Parameters
        ac(tech)                       fixed cost component in linearized biorefinery costs      /
dry_mill        0.7504670
wet_mill       12.4830588
fame            0.72619
fahc            7.1564
lce            8.0794
ft_diesel       7.9022/

        bc(tech)                       feed capacity depedent component in linearized biorefinery costs
/
dry_mill        0.15337
wet_mill        0.124006
fame            0.13238
fahc            0.3668
lce            0.3517
ft_diesel       0.55098/
        iir            /0.1/
        lifetime       /20/
        CRF

        ao(tech)                       fixed cost component in linearized biorefinery costs      /
dry_mill        0.0863381
wet_mill        0
fame            0.0576
fahc            0.3936
```

```
lce            0.4476
ft_diesel       0.3477/

        bo(tech)                    tech cap dependent component in linearized biorefinery costs    /
dry_mill        0.01308
wet_mill        -0.079505
fame           0.06694
fahc           0.008
lce            0.03548
ft_diesel       0.024243/

        MM(tech)                            big number used in constraints
/
dry_mill        100
wet_mill        400
lce            131
ft_diesel       172
fame            32
fahc            78.5
sugar_etoh      200/

        a(brfn, tech, class)
        b(brfn, tech, class)
        M(brfn, tech, class);

CRF = iir*(1+iir)**lifetime/((1+iir)**lifetime - 1);

*Fixing the remaining capital parameter to reflect new and exisiting plants
remaining_cap(brfn, class, tech) = 1;
remaining_cap(brfn, class, 'dry_mill') = 0;
remaining_cap(brfn, class, 'wet_mill') = 0;
remaining_cap(brfn, 'new', 'wet_mill') = 1;
remaining_cap(brfn, 'new', 'dry_mill') = 1;



a(brfn, tech, class) = (CRF*ac(tech)*remaining_cap(brfn, class, tech) + ao(tech));

b(brfn, tech, class) = (CRF*bc(tech)*remaining_cap(brfn, class, tech) + bo(tech));

M(brfn, tech, class) = MM(tech);

M(brfn, 'dry_mill', class) = existing_cap(brfn, class, 'dry_mill');
M(brfn, 'wet_mill', class) = existing_cap(brfn, class, 'wet_mill')*1.12;
M(brfn, 'dry_mill', 'new') = MM('dry_mill');
M(brfn, 'wet_mill', 'new') = MM('wet_mill');

a(brfn, tech, 'virgin') = aa(tech, 'virgin');
b(brfn, tech, 'virgin') = bb(tech, 'virgin');
a(brfn, tech, 'waste') = aa(tech, 'waste');
b(brfn, tech, 'waste') = bb(tech, 'waste');

*Objective
```

```
annual_cost..           total_cost =e= sum((spar(plot, feed, brfn)), pbcost(plot, brfn,
feed)*p2b(feed, plot, brfn)) + sum((spar1(plot, feed, plev)),
prices(plev)*biomass_consumed(feed, plot, plev)) + sum((feed, brfn, tech, class), b(brfn, tech,
class)*x1(feed, brfn, tech, class)) + sum((brfn, tech, class), a(brfn, tech, class)*xi(brfn, tech,
class)) + sum((brfn, term, tech), T(brfn, term, tech)*(btcost(brfn,term)+ terminal_cost(term,
tech)));

annual_profit..         profit*100 =e= fuel_price*sum((brfn, term, tech),
gge_conversion(tech)*T(brfn, term, tech))+ elec_price*sum((brfn, tech, class, feed),
electricity(tech, feed)*x1(feed, brfn, tech, class)) + naptha_price*sum((brfn, tech, class, feed),
naptha(tech, feed)*x1(feed, brfn, tech, class)) - total_cost;

*Subject to:
supply_constraint(plot, feed, plev)$spar1(plot, feed, plev)..    biomass_consumed(feed, plot,
plev) =l= supply(plot, feed, plev);

plot_flow(feed, plot)..      sum(spar1(plot, feed, plev), biomass_consumed(feed, plot, plev))
=g= sum(spar(plot, feed, brfn), p2b(feed, plot, brfn));

brfn_cap(feed, brfn)..       sum(spar(plot, feed, brfn), p2b(feed, plot, brfn))
=g= sum((tech, class), x1(feed, brfn, tech, class));

brfn_flow(brfn, tech)..        sum(term, T(brfn, term, tech)) =l= sum(class, Qb(brfn, tech,
class));

terminal_max(term)..      sum((brfn, etoh(tech)), T(brfn, term, tech)) =l=
vmt_fraction(term)*Ethanol_demand;

terminal_max2(term)..      sum((brfn, ftd(tech)), T(brfn, term, tech)) =l=
vmt_fraction(term)*Diesel_demand*0.95;

terminal_max3(term)..      sum((brfn, biodiesel(tech)), T(brfn, term, tech)) =l=
vmt_fraction(term)*Diesel_demand*0.05;

corn_limit..                 sum((brfn, term), T(brfn, term, 'dry_mill')) + sum((brfn, term), T(brfn,
term, 'wet_mill')) =l= 1500;

commodity_fraction('seed_oils')..       sum((plot, plev), biomass_consumed('seed_oils', plot,
plev)) =l= 383;

xi_constraint(brfn, tech, class)..     sum(feed, x1(feed, brfn, tech, class)) =l= M(brfn, tech,
class)*xi(brfn, tech, class);

Qb_constraint(brfn, tech, class)..     Qb(brfn, tech, class) =l= sum(feed, x1(feed, brfn, tech,
class)*conv_eff(feed, tech, class));

*Limit the upper bound of the binary variable to the regional locations
xi.up(brfn, tech, class) = regional_locations(brfn, tech, class);
x1.up(feed, brfn, tech, class) = feed_tech_match(feed, tech)*M(brfn, tech, class);

*Set solver to CPLEX and set time and iteration limits for the model runs
Option MIP = cplex;
Option iterlim = 1000000;
```

```
Option reslim = 54000;

*Define model as all equations
Model USDA /ALL/;

*Create CPLEX option file to control algorithm
FILE opt "Cplex option file" / cplex.opt /;
PUT opt;
PUT
'workmem 100000'/
'brdir 1'/
'cuts    2'/
'probe   3'/
'parallelmode -1'/
'threads=0'/;
PUTCLOSE OPT;

USDA.optfile=1;

*Set the optimality criteria to a 0.5% relative gap
USDA.OptCR = 0.005;

*Define a looping set to create supply curve
Set      run  /run1*run18/ ;

alias  (class,class2);
alias    (term, term2);

*Define the fuel price for each model run
Parameter fprice(run)   defines the fraction of the max demand for each run /
run1            1.25
run2            1.5
run3            1.75
run4            2
run5            2.2
run6            2.4
run7            2.6
run8            2.8
run9            3
run10           3.2
run11           3.4
run12           3.6
run13           3.8
run14           4
run15           4.5
run16           5
run17           5.5
run18           6/

         biogenic_mass(feed)
       biogenic_energy(feed);

*Define the biogenic mass and energy fractions for mixed MSW, everything else is 1
```

```
biogenic_mass(feed) = 1;
biogenic_mass('msw_dirty') = 0.517;
biogenic_energy(feed) = 1;
biogenic_energy('msw_dirty') = 0.408;

*Define a set for States to aggregate results to state level
set     state         /
$include state_list.csv
/;

*Indicate which state each terminal and biorefinery is in
Parameter state_terminals(term, state)     /
$ondelim
$include terminal_fips.csv
/
            state_brfn(brfn, state)     /
$ondelim
$include state_brfn.csv
/
*Yields of corn and energy crops for calculating land use
      yield(plot, feed)      /
$ondelim
$include corngrain_yield.csv
$include ornl_upland_yields_thinned.csv
$offdelim
/;

*Create results output files
file status_%scenario%;
file results_%scenario%   ;
file results_%scenario%_brfn;
file results_%scenario%_feedstock_links;
file state_results_%scenario%;
file results_%scenario%_fuel_links;
file results_%scenario%_biomass_consumed;
file update;

*Make results files CSV format
results_%scenario%.pc=5;
results_%scenario%_brfn.pc=5;
results_%scenario%_feedstock_links.pc=5;
state_results_%scenario%.pc=5;
results_%scenario%_biomass_consumed.pc=5;

*Increase width of files so that all results fit
results_%scenario%_brfn.pw= 1500;
results_%scenario%.pw=1500;

*$onend turns on a coding option for using loop-do-endloop format
$onend

*Define headings for state specific results file
put state_results_%scenario%;
```

```
put "scenario", "state_fips", "fuel_price ($/gge)", "pathway", "fuel_consumption (MGGEY)",
"fuel_production (MGGEY)"/;

*Define headings for feedstock delivery results file
put results_%scenario%_feedstock_links;
put "scenario", "fuel_price ($/gge)", "source_id", "dest_id", "type", "quant_tons"/;

*Define headings for fuel delivery results file
put results_%scenario%_fuel_links;
put "scenario", "fuel_price ($/gge)", "source_id", "dest_id", "pathway", "fuel_deliveries
(MGY)"/;

*Define headings for feedstock consumption results file
put results_%scenario%_biomass_consumed;
put "scenario", "fuel_price ($/gge)", "source_id", "type", "price_id", "quantity (bdt/yr)"/;

*Define headings for biorefinery results file
put results_%scenario%_brfn;
put "scenario", "fuel_price ($/gge)", "brfn_id", "technology", "class", "fuel_output (MGY)",
"electricity output (GWh/yr)", "naptha (MGY)", "feedstock_cap (bdt/day)",  ;
        loop (feed)     do
        put feed.tl,
        endloop;
put "capital_cost (M$)", "annual_cost (M$/yr)", "annual_capital (M$/yr)", "O&M (M$/yr)",
"feedstock_procurement (M$/yr)", "feedstock_transport (M$/yr)", "fuel_distribution (M$/yr)",
"marginal_feedstock ($/GJ)", "mc ($/gge)", "ac ($/gge)", "max_trans_dist (miles)",
"feed_truck_freight (ton-miles/yr)", "feed_rail_freight (ton-miles/yr)", "feed_barge_freight
(ton-miles/yr)"/;

*Define column headings for summary statistics file (two rows used)
put results_%scenario%;
put "scenario", "fuel_price", "total_biofuel", "electricity", "naptha",;
        loop (tech, feed)$(feed_tech_match(feed, tech) gt 0.5)        do
        put tech.tl,
        endloop;
        loop (tech)     do
        put tech.tl,
        endloop;
        loop (feed)     do
        put feed.tl,
        endloop;
put "annual_profit", "annual_cost",;
        loop (tech) do
        put tech.tl,
        endloop;
put "cellulosic truck freight", "cellulosic rail freight", "cellulosic barge freight", "corn truck
freight", "corn rail freight", "corn barge freight", "lipid truck freight", "lipid rail freight", "lipid
marine freight", "hec land", "corn land"/;
put " ", "$/gge", "MGGEY", "GWh/yr", "MGY",
        loop (tech, feed)$(feed_tech_match(feed, tech) gt 0.5)        do
        put feed.tl,
        endloop;
        loop (tech)     do
```

```
        put "# brfns",
        endloop;
        loop (feed)     do
        put "consumption ktons/yr",
        endloop;
put "billion $", "billion $",;
        loop (tech) do
        put "brfn capital (M$)",
        endloop;
put "million ton miles/yr", "million ton miles/yr", "million ton miles/yr", "million ton miles/yr",
"million ton miles/yr)", "million ton miles/yr", "million ton miles/yr", "million ton miles/yr",
"million ton miles/yr", "million acres", "milion acres"/;

*Create parameters used for calculating outputs
Parameter
                feedstock_consumption(feed)
                brfn_production(brfn, tech, class)
                brfn_consumption(brfn, tech, class, feed)
                links(plot, brfn, feed)
                term_links(brfn, term, tech)
                consumed_biomass(plot, feed, plev)
                quant
                quant_last_run
                brfn_quant(brfn, tech, class)
                state_consumption(state, tech)
                state_fraction(state, brfn, tech)
                state_by_pathway(state, tech, feed)
                state_production(state, tech, feed)
                brfn_count(tech)
                elect_quant
                naptha_quant
                fuel_by_pathway(tech, feed)
                total_annual_cost
                brfn_capital_total(tech)
                cellulosic_truck_freight
                cellulosic_rail_freight
                cellulosic_barge_freight
                corn_truck_freight
                corn_rail_freight
                corn_barge_freight
                lipid_truck_freight
                lipid_rail_freight
                lipid_marine_freight
                hec_lands
                corn_lands
                brfn_electricity(brfn, tech, class)
                brfn_naptha(brfn, tech, class)
                feedstock_cap(brfn, tech, class)
                capital_cost(brfn, tech, class)
                brfn_annual_cost(brfn, tech, class)
                annual_capital(brfn, tech, class)
                O_M(brfn, tech, class)
                feedstock_procurement(brfn, tech, class)
```

```
        avg_feed_pc(plot, feed)
        feedstock_transport(brfn, tech, class)
        fuel_distribution(brfn, tech, class)
        marginal_feedstock(brfn, tech, class)
        mc(brfn, tech, class)
        avg_cost(brfn, tech, class)
        max_trans_dist(brfn, tech, class)
        feed_truck_freight(brfn, tech, class)
        feed_rail_freight(brfn, tech, class)
        feed_barge_freight(brfn, tech, class);

*The model is looped over the set 'run' which defines the price points that are solved along
the supply curve.

Loop run do

*Set a new fuel price for next solve statement.
fuel_price = fprice(run);

*Update naphtha credit to reflect new fuel price.
naptha_price = fuel_price*.86;

*Update transportation costs to reflect new fuel price.
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;

*Create an update file to let alert the user of the current run
put update;
put "Working on " run.tl /
putclose;


*Solve statement

Solve USDA using MIP maximizing profit;

*Calculate results for export

*Calculate production for each biorefinery
brfn_production(brfn, tech, class)$(regional_locations(brfn, tech, class) gt 0.5) = sum(feed,
10*gge_conversion(tech)*conv_eff(feed, tech, class)*biogenic_energy(feed)*x1.l(feed, brfn,
tech, class));

*Calculate total production
quant = sum((spar2(brfn, tech, class)), brfn_production(brfn, tech, class));

*Calculate sumary statistics for each biorefinery
feedstock_consumption(feed) = sum((brfn, tech, class), 10*biogenic_mass(feed)*x1.l(feed,
brfn, tech, class));
brfn_quant(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum(feed,
10*conv_eff(feed, tech, class)*biogenic_energy(feed)*x1.l(feed, brfn, tech, class));
brfn_consumption(brfn, tech, class, feed)$(brfn_production(brfn, tech, class) gt 0.1) =
10*biogenic_mass(feed)*x1.l(feed, brfn, tech, class);
```

```
brfn_electricity(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum(feed,
electricity(tech, feed)*x1.l(feed, brfn, tech, class)*10);
brfn_naptha(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum(feed,
naptha(tech, feed)*x1.l(feed, brfn, tech, class))*10;
feedstock_cap(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum(feed,
brfn_consumption(brfn, tech, class, feed))/365/.9;
capital_cost(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) =  10*(sum(feed,
bc(tech)*x1.l(feed, brfn, tech, class)) + ac(tech)*xi.l(brfn, tech, class));
annual_capital(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) =
CRF*capital_cost(brfn, tech, class);
O_M(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = 10*(sum(feed,
bo(tech)*x1.l(feed, brfn, tech, class)) + ao(tech)*xi.l(brfn, tech, class));
avg_feed_pc(plot, feed)$(sum(plev, biomass_consumed.l(feed, plot, plev) gt 0.05)) =
sum((plev), prices(plev)*biomass_consumed.l(feed, plot, plev))/sum((plev),
biomass_consumed.l(feed, plot, plev));
feedstock_procurement(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) =
10*sum((feed)$(x1.l(feed, brfn, tech, class) gt 0.1), sum((plot)$(p2b.l(feed, plot, brfn) gt 0.1),
avg_feed_pc(plot, feed)*p2b.l(feed, plot, brfn)));
feedstock_transport(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) =
sum((feed)$(x1.l(feed, brfn, tech, class) gt 0.1), sum((plot), pbcost(plot, brfn, feed)*p2b.l(feed,
plot, brfn)))*10;
fuel_distribution(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum((term),
T.l(brfn, term, tech)*(btcost(brfn,term)+ terminal_cost(term, tech)))/sum((term), T.l(brfn,
term, tech))*Qb.l(brfn, tech, class)*10;
brfn_annual_cost(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) =
annual_capital(brfn, tech, class) + O_M(brfn, tech, class) + feedstock_procurement(brfn, tech,
class) + feedstock_transport(brfn, tech, class) + fuel_distribution(brfn, tech, class);
marginal_feedstock(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = smax((plot,
feed, plev)$(x1.l(feed, brfn, tech,class) gt 0.1 and p2b.l(feed, plot, brfn) gt 0.1 and
biomass_consumed.l(feed, plot, plev) gt 0.1), 10*(prices(plev)*biomass_consumed.l(feed, plot,
plev) + pbcost(plot, brfn, feed)*p2b.l(feed, plot, brfn))/conv_eff(feed, tech,
class)/gge_conversion(tech));
mc(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = (annual_capital(brfn, tech,
class) + O_M(brfn, tech, class))/brfn_production(brfn, tech, class) + marginal_feedstock(brfn,
tech, class) + smax((term)$(T.l(brfn, term, tech) gt 0.1), (btcost(brfn,term)+
terminal_cost(term, tech)))/gge_conversion(tech);
avg_cost(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = brfn_annual_cost(brfn,
tech, class)/brfn_production(brfn, tech, class);
max_trans_dist(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = smax((plot,
feed)$(x1.l(feed, brfn, tech,class) gt 0.1 and p2b.l(feed, plot, brfn) gt 0.1),
feedstock_od_table(plot, brfn, feed, 'road_miles') + feedstock_od_table(plot,brfn, feed,
'rail_miles') + feedstock_od_table(plot,brfn, feed, 'water_miles'));
feed_truck_freight(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum((plot,
feed)$(x1.l(feed, brfn, tech,class) gt 0.1 and p2b.l(feed, plot, brfn) gt 0.1),
feedstock_od_table(plot, brfn, feed, 'road_miles')*p2b.l(feed, plot, brfn)/100);
feed_rail_freight(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum((plot,
feed)$(x1.l(feed, brfn, tech,class) gt 0.1 and p2b.l(feed, plot, brfn) gt 0.1),
feedstock_od_table(plot, brfn, feed, 'rail_miles')*p2b.l(feed, plot, brfn)/100);
feed_barge_freight(brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.1) = sum((plot,
feed)$(x1.l(feed, brfn, tech,class) gt 0.1 and p2b.l(feed, plot, brfn) gt 0.1),
feedstock_od_table(plot, brfn, feed, 'water_miles')*p2b.l(feed, plot, brfn)/100);

*Calculate summary statistics on a national level
```

```
feedstock_consumption(feed) = sum((brfn, tech, class), 10*biogenic_mass(feed)*x1.l(feed,
brfn, tech, class));
brfn_count(tech) = sum((brfn, class), xi.l(brfn, tech, class));
elect_quant = sum((brfn, tech, class, feed), electricity(tech, feed)*x1.l(feed, brfn, tech,
class)*10);
naptha_quant = sum((brfn, tech, class, feed), naptha(tech, feed)*x1.l(feed, brfn, tech,
class))*10;
fuel_by_pathway(tech, feed) = sum((brfn, class), 10*gge_conversion(tech)*conv_eff(feed, tech,
class)*biogenic_energy(feed)*x1.l(feed, brfn, tech, class));

total_annual_cost = annual_cost.l/100;#error in units

*Calculate the capital cost of biorefineries by technology

brfn_capital_total(tech) =  10*sum((feed, brfn, class), bc(tech)*x1.l(feed, brfn, tech, class)) +
sum((brfn, class), ac(tech)*xi.l(brfn, tech, class));

*Calculate the sum of freight movements in the model

cellulosic_truck_freight = sum((plot, brfn, bulk(feed)), feedstock_od_table(plot, brfn, feed,
'road_miles')*p2b.l(feed, plot, brfn)/(1-feed_MC(feed)))/100;

cellulosic_rail_freight = sum((plot, brfn, bulk(feed)), feedstock_od_table(plot, brfn,
feed,'rail_miles')*p2b.l(feed, plot, brfn)/(1-feed_MC(feed)))/100;

cellulosic_barge_freight = sum((plot, brfn, bulk(feed)), feedstock_od_table(plot, brfn,
feed,'water_miles')*p2b.l(feed, plot, brfn)/(1-feed_MC(feed)))/100;

corn_truck_freight = sum((plot, brfn),
feedstock_od_table(plot,brfn,'corngrain','road_miles')*p2b.l('corngrain', plot, brfn)/(1-
feed_MC('corngrain')))/100;

corn_rail_freight = sum((plot, brfn),
feedstock_od_table(plot,brfn,'corngrain','rail_miles')*p2b.l('corngrain', plot, brfn)/(1-
feed_MC('corngrain')))/100;

corn_barge_freight = sum((plot, brfn),
feedstock_od_table(plot,brfn,'corngrain','water_miles')*p2b.l('corngrain', plot, brfn)/(1-
feed_MC('corngrain')))/100;

lipid_truck_freight = sum((plot, brfn, liquid(feed)), feedstock_od_table(plot,brfn, feed,
'road_miles')*p2b.l(feed, plot, brfn)*feed_density(feed))/100;

lipid_rail_freight = sum((plot, brfn, liquid(feed)), feedstock_od_table(plot,brfn,
feed,'rail_miles')*p2b.l(feed, plot, brfn)*feed_density(feed))/100;

lipid_marine_freight = sum((plot, brfn, liquid(feed)), feedstock_od_table(plot, brfn,
feed,'water_miles')*p2b.l(feed, plot, brfn)*feed_density(feed))/100;

*Calculate resulting land use for corn and energy crop production

hec_lands = sum((plot, plev), yield(plot, 'hec')*biomass_consumed.l('hec', plot, plev));
```

```
corn_lands = sum((plot, plev), yield(plot, 'corngrain')*biomass_consumed.l('corngrain', plot,
plev));

*Correct units for feedstock delieries and limit to biogenic fraction

links(plot, brfn, feed)$(sum((tech, class), x1.l(feed, brfn, tech, class)) gt 0.05) =  sum(plev,
biogenic_mass(feed)*p2b.l(feed, plot, brfn)*10000);

*Calculate fuel deliveries on a MGGEY basis for only the biogenic portion of fuels

term_links(brfn, term, tech)$(sum(class, Qb.l(brfn, tech, class) gt 0.001)) = T.l(brfn, term,
tech)*10*sum((feed, class), gge_conversion(tech)*conv_eff(feed, tech,
class)*biogenic_energy(feed)*x1.l(feed, brfn, tech, class))/sum(class, Qb.l(brfn, tech, class));

*Correct units for output of results.

consumed_biomass(plot, feed, plev) = biomass_consumed.l(feed, plot, plev)*10000;

*Calculate state specific statistics on optimal system

state_consumption(state, tech) = sum((brfn, term), state_terminals(term,
state)*term_links(brfn, term, tech));

state_fraction(state, brfn, tech)$(sum(class, Qb.l(brfn, tech, class)) gt 0.001) =  sum(term,
state_terminals(term, state)*term_links(brfn, term, tech))/sum(term, term_links(brfn, term,
tech));

state_by_pathway(state, tech, feed) = sum((brfn, class), state_fraction(state, brfn,
tech)*10*gge_conversion(tech)*conv_eff(feed, tech, class)*biogenic_energy(feed)*x1.l(feed,
brfn, tech, class));

state_production(state, tech, feed) = sum((brfn, class), state_brfn(brfn,
state)*10*gge_conversion(tech)*conv_eff(feed, tech, class)*biogenic_energy(feed)*x1.l(feed,
brfn, tech, class));

*Write files to save the results.

*Model and solver status output file

put status_%scenario%;
put run.tl, "Model status", USDA.modelstat, "Solver status", USDA.solvestat/;

*Output summary statistics of national results

put results_%scenario%;
put      "base", fuel_price, quant, elect_quant, naptha_quant,
        loop (tech, feed)$(feed_tech_match(feed, tech) gt 0.5)        do
        put fuel_by_pathway(tech, feed),
        endloop;
        loop (tech)     do
        put brfn_count(tech),
        endloop;
        loop (feed)     do
```

```
        put feedstock_consumption(feed),
        endloop;
put profit.l, total_annual_cost,
        loop (tech) do
        put brfn_capital_total(tech),
        endloop;
put cellulosic_truck_freight, cellulosic_rail_freight, cellulosic_barge_freight,
corn_truck_freight, corn_rail_freight, corn_barge_freight, lipid_truck_freight,
lipid_rail_freight, lipid_marine_freight, hec_lands, corn_lands/;

*Output description of each biorefinery

put results_%scenario%_brfn;
loop    (brfn, tech, class)$(brfn_production(brfn, tech, class) gt 0.5)        do
put "base", fuel_price, brfn.tl, tech.tl, class.tl, brfn_quant(brfn, tech, class),
brfn_electricity(brfn, tech, class), brfn_naptha(brfn, tech, class), feedstock_cap(brfn, tech,
class),
        loop (feed)     do
        put brfn_consumption(brfn, tech, class, feed),
        endloop
put capital_cost(brfn, tech, class), brfn_annual_cost(brfn, tech, class), annual_capital(brfn,
tech, class), O_M(brfn, tech, class), feedstock_procurement(brfn, tech, class),
feedstock_transport(brfn, tech, class), fuel_distribution(brfn, tech, class),
marginal_feedstock(brfn, tech, class), mc(brfn, tech, class), avg_cost(brfn, tech, class),
max_trans_dist(brfn, tech, class), feed_truck_freight(brfn, tech, class), feed_rail_freight(brfn,
tech, class), feed_barge_freight(brfn, tech, class)/
endloop;

*Output the resulting feedstock deliveries between plots and biorefinieries

put results_%scenario%_feedstock_links;
loop (plot, brfn, feed)$(links(plot, brfn, feed) gt 0.01) do
        put "base", fuel_price, plot.tl, brfn.tl, feed.tl, links(plot, brfn, feed)/
        endloop;

*Output the resulting fuel deliveries between biorefineries and terminals
put results_%scenario%_fuel_links;
loop (brfn, term, tech)$(term_links(brfn, term, tech) gt 0.01) do
        put "base", fuel_price, brfn.tl, term.tl, tech.tl, term_links(brfn, term, tech) /
        endloop;

put results_%scenario%_biomass_consumed;
loop (plot, feed, plev)$(biomass_consumed.l(feed, plot, plev) gt 0.05)  do
        put "base", fuel_price, plot.tl, feed.tl, plev.tl, consumed_biomass(plot, feed, plev)/
        endloop;

put state_results_%scenario%;
loop (state, tech, feed)        do
        put     "base", state.tl, fuel_price, tech.tl, feed.tl, state_by_pathway(state, tech, feed),
state_production(state, tech, feed)/
        endloop;
endloop;
```

Sample regional model for woody feedstocks in the west

```
$ontext
This is the template for regional production models. The msw, lipid and corn models are
similiarly designed.  The herbaceous feedstock model has more scenarios run.
$offtext

*Set parameters that define the regional model
$set scenario baseline
$set region   west
$set fdstk    woody

*Turn off GAMS default output
Option   Solprint = off;
Option   Limrow = 0;
Option   Limcol = 0;


*Create set indices for all feedstock plots, biorefinery sites, feedstocks, price levels, and
technologies
sets      plot   biomass source locations  /
$include plot_list_all.csv
/
        brfn    biorefinery sites /
$include brfn_all.csv
/
        feed    /ag_res, hec, forest, ovw, pulpwood, msw_constr_demo, msw_wood, msw_paper,
msw_yard, msw_food, msw_dirty, corngrain, animal_fats, grease, seed_oils/
        class   feedstock classification        /herb, woody, msw, new, exist1*exist6, virgin, waste/
        comp    feedstock composition component /cellulose, hemicellulose, lignin, HHV/
        plev    /
$include price_list_all.csv
/
        tech         tech type   /lce, ft_diesel, fame, fahc, dry_mill, wet_mill/
        trans        transportation mode /total_cost, road_miles, rail_miles, water_miles/;


*Create subsets for feedstock, fuels and the region of interest
sets     bulk(feed)      /ag_res, hec, forest, ovw, pulpwood, msw_wood, msw_constr_demo,
msw_paper, msw_yard, msw_food, msw_dirty, corngrain/
       woodyf(feed)     /forest, ovw, pulpwood, msw_wood, msw_constr_demo/
       herbf(feed)      /ag_res, hec/
       mswf(feed)       /msw_paper, msw_yard, msw_food, msw_dirty/
        liquid(feed)    / animal_fats, grease, seed_oils/
        etoh(tech)            /lce, dry_mill, wet_mill/
        ftd(tech)       /ft_diesel/
        biodiesel(tech) /fame, fahc/
       west(brfn)      /
$include brfn_west.csv
/
       west_plot(plot);

alias (tech, tech2);
```

```
Parameters       pbcost(plot, brfn, feed)        '$ per ton for feedstock transport'
                 pbcost_base(plot, brfn, feed)        '$ per ton for feedstock transport'
             pbdist(plot, brfn)              'distance traveled on link'
       pbcost_dry(plot, brfn) '$ per wet ton'
       pbcost_liq(plot,brfn)   '$ per 100 gallon'
*Import all supplies for baseline scenario
       supply(plot, feed, plev) 'matrix of supply quantities' /
$ondelim
$include ag_residues_38.csv
$include ovw_supplies.csv
$include hec_base.csv
$include msw_supply.csv
$include forest_nofed.csv
$include lipids.csv
$include supply_corn.csv
$offdelim
/
*Make a parameter of prices that is feedstock specific so that the prices can be changed by a
% as a sensitivity
       prices_feed(plev, feed)
       prices(plev)    'values for price levels'    /
$ondelim
$include prices_all.csv
$offdelim
/

       feed_MC(feed)                  moisture content of dry biomass feedstocks   /
ag_res          0.15
hec             0.15
msw_paper       0.1
msw_wood        0.12
msw_yard        0.465
msw_dirty       0.186
msw_food        0.7
ovw             0.35
forest          0.5
pulpwood        0.5
/
       feed_density(feed)                  transfers cost per 100 gallons to costs per ton  /
grease          3.085
seed_oils       2.588
animal_fats     3.0
/

       conv_eff(feed, tech, class)           conversion efficiency for converting feedstock to fuel
/
$ondelim
$include conv_eff_with_class.csv
$offdelim
/
```

```
        conv_factor(tech, comp)    converts conversion efficiencies into gallons product per ton
feedstock            /
lce.hemicellulose    176.9
lce.cellulose        172.85
ft_diesel.HHV        6.84/

*Define baseline technology assumptions
        tech_eff(tech, comp)       conversion efficiency for cellulosic technologies     /
lce.hemicellulose    0.765
lce.cellulose        0.72
ft_diesel.HHV        0.387/

        electricity(tech, feed)              electricity produced per ton of biomass
        elec_eff(tech)          /
lce             0.0366
ft_diesel       0.0366/

        naptha(tech, feed)                   naptha produced per ton of biomass
        naptha_eff(tech)                               /
ft_diesel       0.072/
        gge_conversion(tech)         converts fuel quanitities into equivalent gallons of gasoline
/
lce             0.657
dry_mill        0.657
wet_mill        0.657
ft_diesel       1.065
fame            1.03
fahc            1.065/

*Define the initial fuel price of $3/gge
        fuel_price             fuel price for each model run                              /3/
        naptha_price

        elec_price             price of electricity in dollars per kWh                      /0.05/

        diesel_use(plot, brfn, feed);

naptha_price = 0.86*fuel_price;


Table    biomass_composition(feed, comp)
$ondelim
$include feedstock_composition.csv
$offdelim
;


Table    feedstock_od_table(plot, brfn, trans)
$ondelim
$include source2refine_lceft_lt45.csv
$offdelim
;
```

```
Table    liq_feedstock_od_table(plot, brfn, trans)
$ondelim
$include source2refine_lipid.csv
$offdelim
;

*Limit the transportation costs extracted frm the table to only include the biorefineries
within the region
pbcost_dry(plot, %region%) = feedstock_od_table(plot, %region%,'total_cost');
pbcost_liq(plot,%region%)= liq_feedstock_od_table(plot,%region%,'total_cost');
pbdist(plot, %region%) =  feedstock_od_table(plot,%region%,'road_miles') +
feedstock_od_table(plot,%region%,'rail_miles') +
feedstock_od_table(plot,%region%,'water_miles');

*Caluclate diesel use in 0.01 gge per ton-link
diesel_use(plot, brfn, feed) = (feedstock_od_table(plot,brfn,'road_miles')*1084.5 +
feedstock_od_table(plot,brfn,'rail_miles')*341 +
feedstock_od_table(plot,brfn,'water_miles')*510)/(1-feed_MC(feed))/116093;

*Calculate the fuel products and coproducts per ton of cellulosic biomass
conv_eff(herbf(feed), tech, 'herb') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;

conv_eff(mswf(feed), tech, 'msw') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;

conv_eff(woodyf(feed), tech, 'woody') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;

electricity(tech, feed) = elec_eff(tech)*biomass_composition(feed, 'HHV')/1.1023/.0036/1000;

naptha(tech, feed) = naptha_eff(tech)*biomass_composition(feed,
'HHV')/1.1023/0.1216089/1000;
*Existing facility information

Parameters      remaining_cap(brfn, class, tech)        remaining capital for existing facilities
                existing_cap(brfn, class, tech)         existing capacity of ethanol facilities  /
$ondelim
$include existing_ethanol_capacity.csv
$offdelim
/;

*Find the regional supply points by find those supplies with less than $45/wet ton cost to a
biorefinery in the region
%region%_plot(plot)$(smin(%region%, pbcost_dry(plot, %region%)) lt 45 )=yes;

sets spar(plot, %fdstk%f, %region%)  set used to eliminate unnecessary links
    spar1(plot, %fdstk%f, plev)       set used to eliminate unnecessary supplies
      spar2(%fdstk%f, %region%)         set used to define feedstock-brfn combinations that
have a linkage;
spar(%region%_plot, %fdstk%f, %region%)$(sum(plev, supply(%region%_plot, %fdstk%f,
plev)) gt 0 and pbcost_dry(%region%_plot, %region%) gt 0 and pbcost_dry(%region%_plot,
%region%) lt 45 and pbdist(%region%_plot, %region%) lt 1000)=yes;
```

```
spar1(%region%_plot, %fdstk%f,  plev)$(supply(%region%_plot, %fdstk%f, plev))=yes;
spar2(%fdstk%f, %region%)$(sum((%region%_plot, plev), supply(%region%_plot, %fdstk%f,
plev)*pbcost_dry(%region%_plot, %region%)) gt 0) = yes;



*Assign liquid transportation costs to oils and greases and dry bulk cost to cellulosic
feedstocks and corn
pbcost_base(%region%_plot, %region%, %fdstk%f)$(bulk(%fdstk%f)) =
pbcost_dry(%region%_plot, %region%)/(1-feed_MC(%fdstk%f));

pbcost_base(%region%_plot, %region%, %fdstk%f)$(liquid(%fdstk%f)) =
pbcost_liq(%region%_plot, %region%)*feed_density(%fdstk%f);

*pbcost(plot, brfn, feed)$(sum(plev, supply(plot, feed, plev)) lt 106) = pbcostR_dry(plot,
brfn)/(1-feed_MC(feed));



*Assign missing links a very high cost
pbcost_base(%region%_plot, %region%, %fdstk%f)$(pbcost_base(%region%_plot, %region%,
%fdstk%f) lt 0.05) = 200;

*Model scaling - Fix the parameters to have units of $10M, 10M gallons, and 10k tons

pbcost_base(%region%_plot, %region%, %fdstk%f) = pbcost_base(%region%_plot, %region%,
%fdstk%f)/1000;
supply(%region%_plot, %fdstk%f, plev) = supply(%region%_plot, %fdstk%f, plev)/10000;
prices(plev) = prices(plev)/1000;
prices_feed(plev, feed) = prices(plev);

pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;

Positive Variables
        biomass_consumed(%fdstk%f, plot, plev)          annual quantity of feedstock consumed
from plot "i" at price level "plev"
        p2b(%fdstk%f, plot, %region%)           annual quantity of biomass from plot "i" taken to
biorefinery "k"
        Qb(%region%, tech, class)               quantity of fuel "b" produced at biofinery "k"
        x1(%fdstk%f, %region%, tech, class)             linearizing variables for biorefinery
costs;

Variables
        total_cost                      objective variable
        profit;

Binary variable
        xi(%region%, tech, class);

Equations
        annual_cost                     total annual cost for biofuel supply
        annual_profit
```

```
        xi_constraint(%region%, tech, class)       constraint for integer variable xi
        Qb_constraint(%region%, tech, class)       relates Qb to x1's



*Constraints to set up biofuel networks
        supply_constraint(%fdstk%f, plot, plev)     limits biomass leaving a plot at a price level
to what is available
        plot_flow(%fdstk%f, plot)                  constrains feedstock leaving plot to what is
consumed
        brfn_cap(%fdstk%f, %region%)               limits fuel production capcity at biorefinery to
be less than or equal to the feedstock inputs
;

Parameters
        aa(tech, class)                     fixed cost component in linearized biorefinery costs      /
$ondelim
fame      virgin       0.18106
fame      waste        0.09317
fahc      virgin       1.3783
$offdelim
/

        bb(tech, class)                     feed capacity depedent component in linearized biorefinery
costs     /
$ondelim
fame      virgin       0.06032
fame      waste        0.1704
fahc      virgin       0.068699
$offdelim
/

        feed_tech_match(feed, tech)     /
$ondelim
hec             lce           1
ag_res          lce           1
ovw             lce           1
forest          lce           1
pulpwood        lce           1
msw_wood        lce           1
msw_yard        lce           1
msw_paper       lce           1
msw_dirty       lce           1
msw_constr_demo  lce          1
pulpwood        ft_diesel     1
ovw             ft_diesel     1
ag_res          ft_diesel     1
forest          ft_diesel     1
hec             ft_diesel     1
msw_paper       ft_diesel     1
msw_yard        ft_diesel     1
msw_wood        ft_diesel     1
msw_dirty       ft_diesel     1
```

```
msw_constr_demo  ft_diesel       1
msw_food         lce           1
grease          fame          1
grease          fahc          1
seed_oils       fame          1
seed_oils       fahc          1
animal_fats     fame          1
animal_fats     fahc          1
corngrain       dry_mill      1
corngrain       wet_mill      1
$offdelim
/;

Parameters
        ac(tech)                    fixed cost component in linearized biorefinery costs      /
dry_mill        0.7504670
wet_mill        12.4830588
lce           8.0794
ft_diesel       7.9022/
        bc(tech)                    feed capacity depedent component in linearized biorefinery costs
/
dry_mill        0.15337
wet_mill        0.124006
lce           0.3517
ft_diesel       0.55098/

        iir           /0.1/
       lifetime       /20/
        CRF

        ao(tech)                    fixed cost component in linearized biorefinery costs      /
dry_mill        0.0863381
wet_mill        0
lce           0.4476
ft_diesel       0.3477/

        bo(tech)                    tech cap dependent component in linearized biorefinery costs    /
dry_mill        0.01308
wet_mill        -0.079505
lce           0.03548
ft_diesel       0.024243/

        MM(tech)                            big number used in constraints                              /
dry_mill       100
wet_mill       400
lce           131
ft_diesel       172
fame           32
fahc           78.5/

        a(brfn, tech, class)
        b(brfn, tech, class)
        M(brfn, tech, class);
```

```
CRF = iir*(1+iir)**lifetime/((1+iir)**lifetime - 1);

remaining_cap(brfn, class, tech) = 1;
remaining_cap(brfn, class, 'dry_mill') = 0;
remaining_cap(brfn, class, 'wet_mill') = 0;
remaining_cap(brfn, 'new', 'wet_mill') = 1;
remaining_cap(brfn, 'new', 'dry_mill') = 1;

a(brfn, tech, class) = (CRF*ac(tech)*remaining_cap(brfn, class, tech) + ao(tech));
b(brfn, tech, class) = (CRF*bc(tech)*remaining_cap(brfn, class, tech) + bo(tech));
M(brfn, tech, class) = MM(tech);

M(brfn, 'dry_mill', class) = existing_cap(brfn, class, 'dry_mill');
M(brfn, 'wet_mill', class) = existing_cap(brfn, class, 'wet_mill')*1.12;
M(brfn, 'dry_mill', 'new') = MM('dry_mill');
M(brfn, 'wet_mill', 'new') = MM('wet_mill');

a(brfn, tech, 'virgin') = aa(tech, 'virgin');
b(brfn, tech, 'virgin') = bb(tech, 'virgin');
a(brfn, tech, 'waste') = aa(tech, 'waste');
b(brfn, tech, 'waste') = bb(tech, 'waste');

*Objective
annual_cost..          total_cost =e= sum((spar(%region%_plot, %fdstk%f, %region%)),
pbcost(%region%_plot, %region%, %fdstk%f)*p2b(%fdstk%f, %region%_plot, %region%)) +
sum((spar1(%region%_plot, %fdstk%f, plev)), prices_feed(plev,
%fdstk%f)*biomass_consumed(%fdstk%f, %region%_plot, plev)) + sum((%fdstk%f, %region%,
tech, class), b(%region%, tech, class)*x1(%fdstk%f, %region%, tech, class)) + sum((%region%,
tech, class), a(%region%, tech, class)*xi(%region%, tech, class));

annual_profit..        10*profit =e= fuel_price*sum((%region%, tech, class),
gge_conversion(tech)*Qb(%region%, tech, class))+ elec_price*sum((%fdstk%f, %region%, tech,
class), electricity(tech, %fdstk%f)*x1(%fdstk%f, %region%, tech, class)) +
naptha_price*sum((%fdstk%f, %region%, tech, class), naptha(tech, %fdstk%f)*x1(%fdstk%f,
%region%, tech, class)) - total_cost;

*Subject to:
supply_constraint(%fdstk%f, %region%_plot, plev)$spar1(%region%_plot, %fdstk%f, plev)..
biomass_consumed(%fdstk%f, %region%_plot, plev) =l= supply(%region%_plot, %fdstk%f,
plev);

plot_flow(%fdstk%f, %region%_plot)..      sum(spar1(%region%_plot, %fdstk%f, plev),
biomass_consumed(%fdstk%f, %region%_plot, plev)) =g= sum(spar(%region%_plot, %fdstk%f,
%region%), p2b(%fdstk%f, %region%_plot, %region%));

brfn_cap(%fdstk%f, %region%)..      sum(spar(%region%_plot, %fdstk%f, %region%),
p2b(%fdstk%f, %region%_plot, %region%)) =g= sum((tech, class), x1(%fdstk%f, %region%,
tech, class));

xi_constraint(%region%, tech, class)..     sum(%fdstk%f, x1(%fdstk%f, %region%, tech, class))
=l= M(%region%, tech, class)*xi(%region%, tech, class);
```

```
Qb_constraint(%region%, tech, class)..      Qb(%region%, tech, class) =l= sum(%fdstk%f,
x1(%fdstk%f, %region%, tech, class)*conv_eff(%fdstk%f, tech, class));

biomass_consumed('seed_oils', %region%_plot, plev)) =l= 383;

x1.up(%fdstk%f, %region%, tech, class) = feed_tech_match(%fdstk%f, tech)*M(%region%,
tech, class);


Option MIP = cplex;
Option iterlim = 1000000;
Option reslim = 54000;


Model USDA /ALL/;


FILE opt "Cplex option file" / cplex.opt /;
PUT opt;
PUT
'workmem 10000'/
'brdir 1'/
'cuts    2'/
'polishaftertime 36000'/
'probe   3'/
'parallelmode -1'/
'threads=0'/;
PUTCLOSE OPT;

USDA.optfile=1;
USDA.OptCR = 0.005;

*Solve with baseline assumptions
Solve USDA using MIP maximizing profit;


*Define parameters to save the optimally designed system
Parameter        locations(brfn, tech, class)
                 links(feed, plot, brfn);

*Save baseline woody @ $3/gge
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Change fuel price to $6/gge
fuel_price = 6;

*Update parameters
naptha_price = 0.86*fuel_price;
pbcost(plot, brfn, feed) = pbcost(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;
```

```
*Solve using baseline assumptions @ $6/gge
Solve USDA using MIP maximizing profit;

*Save baseline woody @ $6/gge
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Remove cellulosic ethanol from consideration
x1.up(%fdstk%f, %region%, 'lce', class)= 0;

*Resolve @ $6/gge
Solve USDA using MIP maximizing profit;

*Save
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Change fuel price
fuel_price = 3;

*Update parameters
naptha_price = 0.86*fuel_price;
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;

*Resolve @ $3/gge
Solve USDA using MIP maximizing profit;

*Save
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Reinstate cellulosic ethanol and remove FTD from consideration
x1.up(%fdstk%f, %region%, tech, class) = feed_tech_match(%fdstk%f, tech)*M(%region%,
tech, class);
x1.up(%fdstk%f, %region%, 'ft_diesel', class) = 0;

*Solve @ $3/gge
Solve USDA using MIP maximizing profit;

*Save
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Change fuel price
fuel_price = 6;

*Update parameters
naptha_price = 0.86*fuel_price;
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;
```

```
*Solve @ $6/gge
Solve USDA using MIP maximizing profit;

*Save
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Change cellulosic ethanol technology to optimistic case and reinstate FTD
a(brfn, 'lce', class) = 0.73497;
b(brfn, 'lce', class) = 0.0529116;
M(brfn, 'lce', class) = 136;

tech_eff('lce', 'hemicellulose') = 0.765;
tech_eff('lce', 'cellulose') = 0.799;
elec_eff('lce') = 0.0338;

conv_eff(herbf(feed), tech, 'herb') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(mswf(feed), tech, 'msw') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(woodyf(feed), tech, 'woody') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;

electricity(tech, feed) = elec_eff(tech)*biomass_composition(feed, 'HHV')/1.1023/.0036/1000;
naptha(tech, feed) = naptha_eff(tech)*biomass_composition(feed,
'HHV')/1.1023/0.1216089/1000;

x1.up(%fdstk%f, %region%, tech, class) = feed_tech_match(%fdstk%f, tech)*M(%region%,
tech, class);

*Solve @ $6/gge
Solve USDA using MIP maximizing profit;

*Save solution
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Change fuel price
fuel_price = 3;

*Update parameters
naptha_price = 0.86*fuel_price;
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;

*Solve @ $3/gge
Solve USDA using MIP maximizing profit;

*Save solution
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;
```

```
*Convert all technologies to pessimistic scenario
a(brfn, 'lce', class) = 1.60052;
b(brfn, 'lce', class) = 0.0997695;
M(brfn, 'lce', class) = 115;

a(brfn, 'ft_diesel', class) = 3.016148;
b(brfn, 'ft_diesel', class) = 0.15408036;
M(brfn, 'ft_diesel', class) = 136;

tech_eff('lce', 'hemicellulose') = 0.714;
tech_eff('lce', 'cellulose') = 0.7;
elec_eff('lce') = 0.05226;

tech_eff('ft_diesel', 'HHV') = 0.31776;
elec_eff('ft_diesel') = 0.1641;
naptha_eff('ft_diesel') = 0.1254;

conv_eff(herbf(feed), tech, 'herb') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(mswf(feed), tech, 'msw') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(woodyf(feed), tech, 'woody') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
electricity(tech, feed) = elec_eff(tech)*biomass_composition(feed, 'HHV')/1.1023/.0036/1000;
naptha(tech, feed) = naptha_eff(tech)*biomass_composition(feed,
'HHV')/1.1023/0.1216089/1000;

*Change fuel price
fuel_price = 6;

*Update parameters
naptha_price = 0.86*fuel_price;
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed) + (fuel_price -
3.55*gge_conversion('fahc'))*diesel_use(plot, brfn, feed)/1000;

*Solve
Solve USDA using MIP maximizing profit;

*Save solution
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Remove FTD from consideration
x1.up(%fdstk%f, %region%, 'ft_diesel', class) = 0;

*Solve
Solve USDA using MIP maximizing profit;

*Save solution
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;
```

```
*Return to baseline technology characterization
a(brfn, tech, class) = (CRF*ac(tech)*remaining_cap(brfn, class, tech) + ao(tech));
b(brfn, tech, class) = (CRF*bc(tech)*remaining_cap(brfn, class, tech) + bo(tech));
M(brfn, tech, class) = MM(tech);

tech_eff('lce', 'hemicellulose') = 0.765;
tech_eff('lce', 'cellulose') = 0.72;
elec_eff('lce') = 0.0366;

tech_eff('ft_diesel', 'HHV') = 0.387;
elec_eff('ft_diesel') = 0.0366;
naptha_eff('ft_diesel') = 0.072;



conv_eff(herbf(feed), tech, 'herb') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(mswf(feed), tech, 'msw') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;
conv_eff(woodyf(feed), tech, 'woody') = sum(comp, biomass_composition(feed,
comp)*tech_eff(tech, comp)*conv_factor(tech, comp))/1000;

electricity(tech, feed) = elec_eff(tech)*biomass_composition(feed, 'HHV')/1.1023/.0036/1000;
naptha(tech, feed) = naptha_eff(tech)*biomass_composition(feed,
'HHV')/1.1023/0.1216089/1000;

*Increase pulpwood prices by 20%
prices_feed(plev, 'pulpwood') = prices(plev)*1.2;

*Solve
Solve USDA using MIP maximizing profit;

*Save solution
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*Import high forest residue supply data
Parameter high_woody(plot, feed, plev)     /
$ondelim
$include 2017_BTS_forest_all.csv
$offdelim
/;


*Correct units on residues, double woody msw for high scenario and make pulpwood prices
20% less than baseline
supply(plot, 'forest', plev) = high_woody(plot, 'forest', plev)/1000;
supply(plot, 'msw_wood', plev) = supply(plot, 'msw_wood', plev)*2;
supply(plot, 'msw_constr_demo', plev) = supply(plot, 'msw_constr_demo', plev)*2;

prices_feed(plev, 'pulpwood') = prices(plev)*.8;

*Resolve
```

```
Solve USDA using MIP maximizing profit;

*Save choosen links and locations by giving the parameter a value of 1
links(%fdstk%f, plot, %region%)$(p2b.l(%fdstk%f, plot, %region%) gt .1) = 1;
locations(%region%, tech, class)$(Qb.l(%region%, tech, class)) =1;

*correct cost to native units ($/wet ton)
pbcost(plot, brfn, feed) = pbcost_base(plot, brfn, feed)*1000;

$onend

file locations_%fdstk%_%region%;
file links_%fdstk%_%region%;

locations_%fdstk%_%region%.pc=5;
links_%fdstk%_%region%.pc=5;

*Output file giving the biorefineries that were choosen
put locations_%fdstk%_%region%;
loop (brfn, tech, class)$(locations(brfn, tech, class) gt 0.5) do
        put brfn.tl, tech.tl, class.tl, 1/
        endloop;

*Output feedstock transport costs for the choosen systems
put links_%fdstk%_%region%;
put     "dummy", "dummy", "dummy", "total_cost", "diesel_use" /;
loop (plot, brfn, feed)$(links(feed, plot, brfn) gt 0.1) do
        put plot.tl, feed.tl, brfn.tl, pbcost(plot, brfn, feed), diesel_use(plot, brfn, feed)/
        endloop;
```