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Economic Optimization of a Lignocellulosic Biomass-to-Ethanol Supply Chain

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ABSTRACT

This paper presents an optimization study of the net present value of a biomass-to-ethanol supply chain in a 9-state region in the Midwestern United States. The study involves formulating and solving a mixed integer linear programming (MILP) problem. A biochemical technology is assumed for converting five types of agricultural residues into ethanol utilizing dilute acid pretreatment and enzymatic hydrolysis. Optimal locations and capacities of biorefineries are determined simultaneously with biomass harvest and distribution. Sensitivity analysis is performed to elucidate the impact of price uncertainty on the robustness of the supply chain and whether or not the proposed biorefineries will be built or will fail financially after being built.

1. Introduction

Growth of a biomass-to-biofuel industry has the potential to reduce oil imports, support agriculture and forestry growth, foster a domestic biorefinery industry (Perlack et al., 2005) and reduce greenhouse gas emissions by an estimated 86% over gasoline (Wang et al., 2007). For these reasons, many nations have set biofuels targets. The United States Renewable Fuels Standard program (RFS2), as amended by the Energy Independence and Security Act of 2007, mandates that by 2022, at least 36 billion gallons per year (BGY) of renewable fuel be blended into motor-vehicle fuel, including 16 BGY from cellulosic biofuel (U.S. Environmental Protection Agency, 2010). Using the "Biofuels Deployment Model", researchers at Sandia National Labs determined that 21 BG of cellulosic ethanol could be produced per year by 2022 in the U.S. without displacing current crops (West et al., 2009). Similarly, the European Union has set a minimum target to replace 10% of overall consumption of petrol and diesel in transport with biofuels by 2020 (Commission of the European Communities, 2007).

Cellulosic ethanol is produced from biomass (wood, grasses, non-edible parts of plants, and municipal wastes) and is the only currently demonstrated renewable liquid transportation fuel (Foust et al., 2007). If the 1.3 billion dry tons of forestry and agricultural residues produced annually in the US (Perlack et al., 2005) were collected and converted into ethanol, it would replace over one-third of the current US demand for transportation fuel (West et al., 2009). As of January 2010, there were 187 ethanol refineries operating in the U.S. producing a total of 12.9 BGY ethanol almost exclusively from maize (corn) grain (Renewable Fuels Association, 2010). Cellulosic ethanol production represented only 3 million gallons per year (MGY). Only demonstration cellulosic ethanol biorefineries are operational. DOE-supported project that are currently funded, under construction or operational are shown in Fig. 1.

One of the major hurdles that must be overcome to increase cellulosic biofuel production in the U.S. by three orders of magnitude to meet the 2022 mandates is to collect and transport biomass efficiently, for it is inherently a distributed resource. Many previous studies have addressed various aspects of delivering biomass for further processing. The distribution of available biomass was quantified in (Perlack et al., 2005; Milbrandt, 2005), the environmental and economic impacts of an ethanol economy were examined in (West et al., 2009; Foust et al., 2007), and the cost of delivered biomass was estimated in (Morey et al., 2010; Gallagher et al., 2003).

Also, previous work has used knowledge of the geospatial distribution of feedstocks and biofuel demand to evaluate particular biorefinery locations (Petrolia, 2008) or to determine optimum placements of biorefineries among a set of candidate locations using mixed integer programming. The goals of the latter type of study have included determining the potential of a biorefinery

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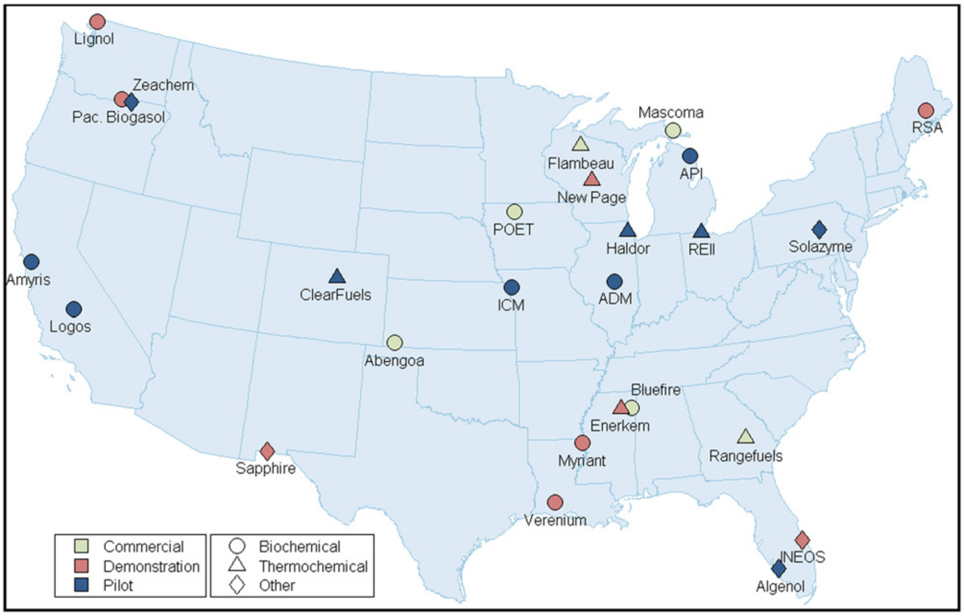

Fig. 1. DOE supported integrated biorefinery projects by capacity and conversion technology. (redrawn from (U.S. DOE Energy Efficiency & Renewable Energy, 2010a)).

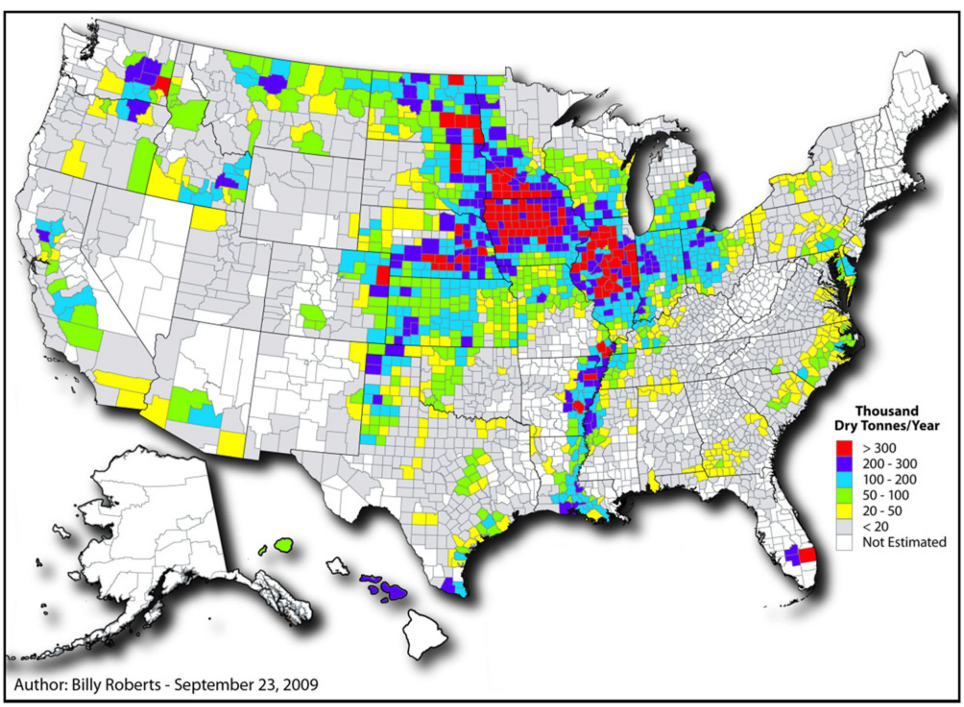

Fig. 2. Crop residue availability in the United States by county. (adapted from (Milbrandt, 2005)).

technology that uses biomass, coal and natural gas to produce a variety of transportation fuels (Elia et al., 2011), meeting geospatial fuel demand economically using biomass (Mapemba, 2005; Mapemba, 2008; Zamboni et al., 2009; Kang et al., 2010; Morrow et al., 2006; Ekşioğlu et al., 2009; Tembo et al., 2003) while also reducing the environmental impact (Zamboni et al., 2009), and providing local heat and electricity with biomass (Leduc et al., 2009). Most previous studies have examined biomass-to-biofuel supply chains at the state-level or within a small region.

The present study presents a mixed-integer linear program (MILP) that can be applied at the regional or national level to optimize a biomass-to-biofuel supply chain when biomass producers and candidate biorefinery locations are specified. A case study of a 9 state region in the Midwestern U.S. (Illinois, Indiana, Iowa, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin) is presented which may be useful as a tool for determining national biofuel policies as most of the agricultural residues in the U.S. are located there, as shown in Fig. 2. The residues of barley, corn, oats and wheat are included with a collection and densification scheme that decouples the biorefinery from the variability of biomass supply. A biochemical technology for biomass-to-ethanol conversion was assumed that is expected to be commercialized in the short-term (within 5 years), allowing for the use of recent agricultural data. The economic parameters for this developing industry are inherently uncertain. Single parameter sensitivity analysis and Monte Carlo simulation are performed to determine the supply chain robustness.

2. Optimization problem formulation

The optimization problem is to determine where to place biorefineries and of what capacity, how much biomass to harvest and to which biorefineries to ship it to maximize the Net Present Value (NPV) of the entire supply chain. NPV is calculated as the sum of a time series of cash flows that have been discounted back to the present. For annual cash flows $\{R_m\}$ that occur over a project lifetime T_L,

$$\mathrm{NPV} = \sum_{m=1}^{T_L} \frac{R_m}{(1+i)^m} \tag{1}$$

where i is the discount rate (or annual rate of return of a competing investment) (Seider et al., 2008).

For the optimization problem, we assume that all capital investment R_{invest} occurs in the present year and that the total of all other cash flows R_{annual} are identical for each year of the project lifetime. This leads to the simplification:

$$\mathrm{NPV} = \theta \cdot R_{\text{annual}} - R_{\text{invest}} \tag{2}$$

where the scaling factor θ arrives from the simplification of the geometric series with constant ratio $(1+i)^{-1} \neq 1$ and is defined as:

$$\theta = \frac{(1+i)^{T_L} - 1}{i(1+i)^{T_L}} \tag{3}$$

Optimizing the NPV ensures that all biorefinery infrastructure investments meet or exceed a rate of return over the project lifetime. In this biomass-to-ethanol supply chain, R_{annual} includes cash flows for product (ethanol) sales, costs of harvest and transportation of biomass. Biorefinery investment and operating costs are included in R_{invest}, so the objective function and the optimization problem can be stated as follows:

$$\text{maximize} \quad \mathrm{NPV} = \theta \cdot \left\{ \sum_{r=1}^{R} \sum_{p=1}^{P} \sigma_p a_{r,p} - \sum_{n=1}^{N} \sum_{b=1}^{B} \rho_b h_{n,b} - \sum_{n=1}^{N} \sum_{r=1}^{R} \sum_{b=1}^{B} \tau_{n,r} y_{n,r,b} \right\} - \left\{ \sum_{r=1}^{R} \sum_{l=1}^{L} \psi_l x_{r,l} \right\} \tag{4}$$

where the notations for the subscripts, parameters and variables are defined in Table 1–3, respectively.

Notice that NPV is a linear function of continuous (a,h,y) and binary (x) variables, making this biomass-to-ethanol supply chain optimization problem a mixed integer linear program (MILP). The MILP is completely defined with the set of linear constraints described below.

The first set of constraints limits the amount of biomass harvested to the amount that is available annually in each biomass producing location n for each type of biomass b:

$$h_{n,b} \le \lambda_{n,b}, \quad \forall n,b \tag{5}$$

Once harvested, the biomass is put into local storage where a fraction is lost due to deterioration. A mass balance around the local storage sites of each biomass producing location can be written to account for shipments of biomass to biorefinery sites:

$$-h_{n,b} + (1+\alpha_b) \sum_{r=1}^{R} y_{n,r,b} \le 0, \quad \forall n,b \tag{6}$$

where losses in local storage due to deterioration are defined such that an additional fraction α_b of biomass b must be collected and put into storage than can be removed and shipped to biorefineries.

Each biorefinery in this formulation utilizes the same technology, thus has an equal yield of ethanol per dry metric ton (dt). Any biomass shipped to a biorefinery location is proportional to the product produced there:

$$a_{r,p} - \sum_{b=1}^{B} \sum_{n=1}^{N} \beta_{b,p} y_{n,r,b} \le 0, \quad \forall r,p \tag{7}$$

where the product yield per dt biomass may depend on the biomass type.

A biorefinery of capacity l is optimally placed at site r if the corresponding binary variable $x_{r,l}$ is one. If the binary variable is zero, that biorefinery size is not constructed there. The binary variables are therefore defined as:

$$x_{r,l} \in \{0,1\}, \quad \forall r,l \tag{8}$$

The amount of biomass that can be processed at a biorefinery site is limited by the total biorefinery capacity there. If a biorefinery of size $l=2$ is installed at candidate biorefinery site $r=3$, then the production of ethanol $p=1$, for example, cannot exceed the nameplate capacity $\xi_{2,1}$. In general,

$$a_{r,p} - \sum_{l=1}^{L} \xi_{l,p} x_{r,l} \le 0, \quad \forall r,p \tag{9}$$

Table 1
Subscripts.

Name	
$n \in \{1,\ldots,N\}$	biomass producing locations
$r \in \{1,\ldots,R\}$	candidate biorefinery locations
$l \in \{1,\ldots,L\}$	allowed biorefinery capacities
$b \in \{1,\ldots,B\}$	biomass feedstocks
$p \in \{1,\ldots,P\}$	products (e.g. ethanol)

Table 2
Parameters.

Name	
i	annual discount rate
T_L	project lifetime (y)
θ	NPV scaling factor
σ_p	unit sale price for product p (\$/gal)
ρ_b	unit feedstock cost for biomass b (\$/dt)
$\tau_{n,r}$	unit biomass transportation cost from n to r (\$/dt)
ψ_l	investment and lifetime operating cost for a biorefinery of size l (\$)
$\lambda_{n,b}$	amount of biomass b harvestable at n annually (dt/y)
α_b	fractional deterioration of biomass b in local storage
$\beta_{b,p}$	biorefinery conversion of biomass b to product p (gal/dt)
$\xi_{l,p}$	annual production capacity of product p for biorefinery of size l (gal/y)

Table 3
Decision variables.

Name	
$a_{r,p}$	amount of product p produced at r annually (gal/y)
$h_{n,b}$	amount of biomass b harvested at n annually (dt/y)
$y_{n,r,b}$	amount of biomass b transported from n to r annually (dt/y)
$x_{r,l}$	biorefinery of size l installed at r (binary variable)

A maximum of one biorefinery can be placed at each candidate biorefinery location:

$$\sum_{l=1}^{L} x_{r,l} \leq 1, \quad \forall r \tag{10}$$

All harvests, shipments and productions must be non-negative quantities:

$$a, h, y \geq 0 \tag{11}$$

This MILP formulation is a Facility Location Problem and is thus NP-Hard (Owen and Daskin, 1998). For relatively small sized problems, it is possible to obtain an optimal solution in a reasonable amount of time using standard algorithms. For large problems, an approximate solution approach might be needed (see, for example, Gen and Cheng, 1997; Jaramillio et al., 2002; Hinojosa et al., 2000). The problems we consider in this paper, including the case study of Section 4, are solvable to optimality using the commercial software IBM ILOG CPLEX Optimization Studio (IBM, 2011).

3. Case study parameters

3.1. Biomass supply

The case study examined the use of agricultural residue as feedstock from the following five grains: barley, corn, oats, spring wheat (including durum), and winter wheat. These crops were chosen for their relative abundance in the Midwestern US region and because agricultural residues of this type can be easily processed in a fermentation biorefinery.

Annual grain production per county was determined as the mean of the 2007 to 2009 figures reported to the U.S. Department of Agriculture and available online on the National Agricultural Statistics Service (NASS) website (U.S. Department of Agriculture, 2010). NASS Quickstats web service was used to collect grain production data for the 779 counties in Illinois, Indiana, Iowa, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin.

A method from (Milbrandt, 2005) was used to convert these total grain production figures to dry tons (dt) of each crop residue available per county. Specifically, bushels of grain were converted to an equivalent volume of residue and then corrected for average moisture content. Conversions used are shown in Table 4. Spring and winter wheat are assumed to have the same properties. The study included the 535 counties highlighted in Fig. 3 that are within 100 miles of any candidate biorefinery location. Harvesting of specific residues in counties producing less than one thousand dry metric tons per year was not allowed.

A number of factors limit the amount of crop residue that can physically be collected. Technical harvest efficiency on the field is never 100%, some residues are required to remain on the field to mitigate soil erosion based on tillage procedure, a portion may be used for grazing or bedding, and there are losses during transportation to central storage. One study assumed that 30% of crop residues are required for soil protection, 20–25% are consumed by grazing animals and 10–15% are used for other purposes, allowing for 35% of available residues to be collected (Milbrandt, 2005). Most studies that propose a round bale collection scheme assume 30–35% collection efficiency (West et al., 2009; Morey et al., 2010; Petrolia, 2008; Wilhelm et al., 2007). The present case study allows for an average collection of 35% of available residues (70% of residues removed every other year to reduce harvest operational costs) for all feedstocks and assumes a round bale technology.

3.2. Biomass producing locations

Counties are modeled as point sources of biomass due to the availability of biomass resource data. Shipments of agricultural residues will originate from local storage sites distributed within each county, but it is a reasonable assumption that an average biomass shipment will originate from the county geographical center. Some studies that model counties as point sources of biomass use county seats as transportation origins (Petrolia, 2008). Others selected a city centered within each county (Mapemba, 2005). In this study, the geographical county center (centroid) was used. The county centroids were calculated in MATLAB from each county's boundary using equal area bins. A shapefile of geospatial vector data describing the 2001 county boundaries was downloaded from the NationalAtlas.gov website (NationalAtlas.gov, 2010) and was originally compiled by the U.S. Geological Survey.

3.3. Biorefinery locations

Candidate biorefinery locations were restricted to cities in Illinois, Indiana, Iowa, Minnesota, Missouri, Nebraska, North Dakota, South Dakota and Wisconsin with U.S. Census 2000 population between three thousand and ten thousand with a maximum of one city per county. Geographic information system (GIS) data for city center coordinates and population was downloaded from the NationalAtlas.gov website (NationalAtlas.gov, 2010). Cities not located near biomass producing counties were removed, namely the urban areas around Chicago and the Twin Cities. See Fig. 3 for the 69 candidate refinery locations.

Many approaches have been taken in similar studies to determine potential refinery locations. Some studies prefer to allow current corn starch ethanol facilities to expand and utilize cellulosic feedstocks (Morrow et al., 2006). Others allow a central city from each county in the model that produces biomass to be a candidate plant location (Mapemba, 2005; Mapemba, 2008; Tursun et al., 2008). Another study allows biorefineries near the centers of biomass production or fuel consumption (Leduc et al., 2009). Some even perform a preliminary study with an evenly spaced coordinate grid of candidate locations over the region of study to determine a smaller set of locations for the full model (Schmidt et al., 2009). The population cutoff was chosen for this study to ensure that the locations have an adequate employment pool, utility and highway infrastructure, and demand for power produced at the biorefinery.

3.4. Biomass transportation distance and cost

In this model roll-press compacted biomass is transported from local county-level storage sites to biorefineries in 22.7 wet metric ton load semi-trucks. A dedicated semi-truck transport is \$800 per day and can drive 260 round-trip miles per day (Morey et al., 2010). So the cost of the transportation scheme is \$0.136 per wet metric ton per round-trip mile or \$0.160 per dry metric ton per round-trip mile for 15% moisture content load.

Table 4
Crop to residue ratio and moisture content of selected crops (Milbrandt, 2005).

Crop	Residue to grain ratio (by volume)	Moisture content (%)	Bushel weight (lb)
Barley	1.2	14.5	48
Corn	1.0	15.5	56
Oats	1.3	14.0	32
Wheat	1.3	13.5	60

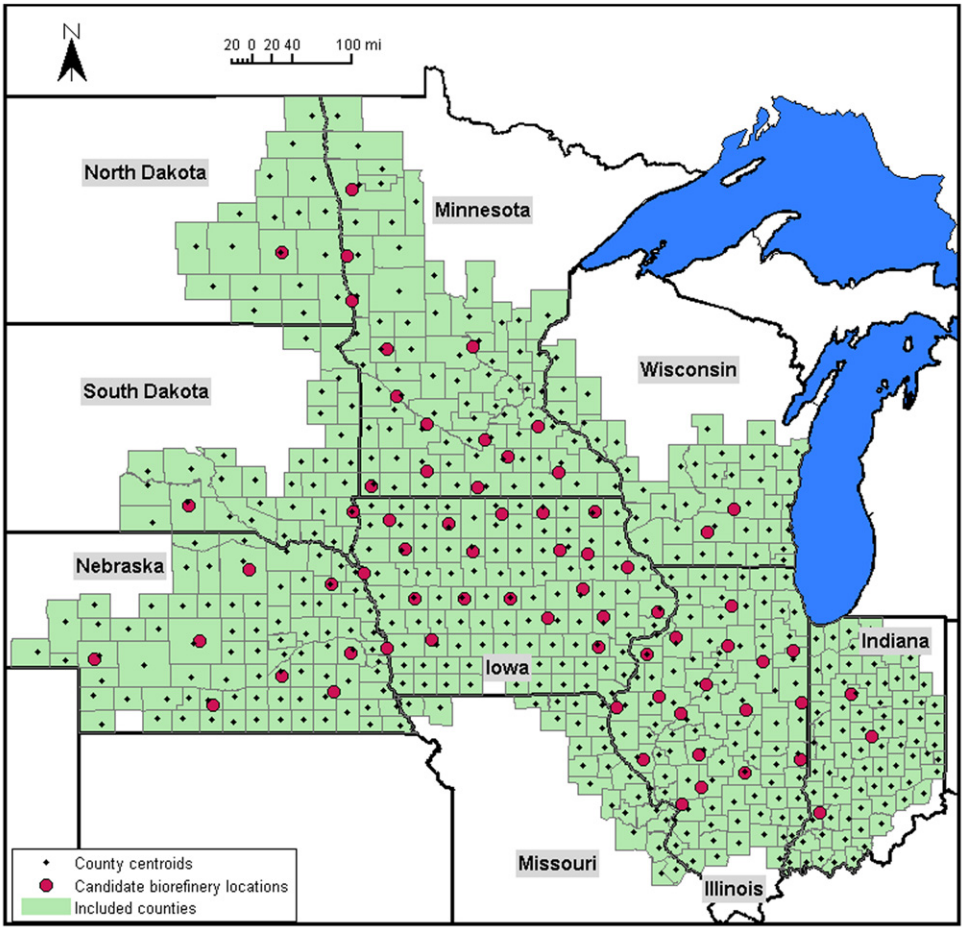

Fig. 3. The 535 biomass producing counties and 69 candidate biorefinery locations included in the case study.

To calculate the matrix of transportation costs $\tau_{n,r}$ from any biomass producing location to any candidate biorefinery location a corresponding matrix of travel distances was determined. Shortest path highway travel distance was found using Google Maps (Google Inc., 2010). For simplicity, each biomass type has equivalent transportation costs. Sourcing of biomass from farther than 100 miles was discouraged in the model.

3.5. Biomass cost

Economists have studied the economic feasibility of utilizing crop residues for fuel production and process heating for decades with attention placed on the delivered cost of biomass. The use of crop residue in Iowa as an auxiliary fuel in coal-fired power plants to reduce sulfur emissions has been examined (English et al., 1981). They found a total delivered cost of \$69/t (converted to 2009 dollars using the Consumer Price Index) that included the costs for farm production, transportation, processing and handling. A number of National Renewable Energy Laboratory reports in recent years have found delivered biomass feedstock costs of \$39/dt (Foust et al., 2007), \$72/dt (Humbird and Aden, 2009), and \$83/dt (Kazi et al., 2010). The variability here is due to differences in collection technology. The present study focuses on more near-term collection methods.

The system of collection and densification of biomass in this study was proposed in (Morey et al., 2010) for corn stover only, but is assumed the same for all feedstocks. This method achieves a bulk density of 15 lb/ft^3 and allows for truck transportation to be limited by weight rather than volume. Crop residues are shredded and spread onto the field following grain harvest, then raked, and net-wrapped into large round bales (1250 lbs) at 15% moisture. The bales are transported from the field to local storages within a 2 mile radius. They are stored uncovered on level ground in lines running north-south to minimize water gain. A land rent charge of \$0.42/dt is incurred annually for crop residue inventory at local storage sites, assuming 15% moisture content. Average fractional deterioration during storage is assumed to be 5% for all feedstocks. Thus the cost of local storage loss is equal to 5% of the sum of the costs incurred to get the biomass to local storage.

Portable 22.7 t/h capacity processing units move around to the local storage sites to grind and densify the residue bales by roll-press compaction into a bulk material transportable by 22.7 metric ton load trucks. Table 5 specifies costs for each of these steps in addition to nutrient replacement and other farmer incentives on a dry metric ton basis. Feedstock cost is \$87.35/dt and does not include the cost of transporting densified biomass from local storage to a biorefinery.

3.6. Ethanol sale price

In October 2010, the average at-the-pump sales price of E85 in the Midwestern U.S. was \$2.42/gal and the average gasoline price was \$2.78/gal (U.S. DOE Energy Efficiency & Renewable Energy, 2010b). Thus, the equivalent average price of 100% ethanol was \$2.36/gal. This is the price observed at the fuel station after tax incentives have been applied and is not the sale price from a biorefinery. We assume our example biorefinery qualifies for the Cellulosic Biofuel Producer Tax Credit of \$0.46 per gallon ethanol (U.S. DOE Energy Efficiency & Renewable Energy, 2010c); and the Volumetric Ethanol Excise Tax Credit which expires December 31,

Table 5
Biomass collection and local storage costs (Morey et al., 2010).

Source	Cost ($/t)	Cost ($/dt) [a]
Nitrogen replacement	$3.68	$4.33
Phosphorous replacement	$2.04	$2.40
Potassium replacement	$13.55	$15.94
Participation payment to farmer	$7.50	$8.82
Stalk shredding	$2.54	$2.99
Raking	$1.54	$1.81
Baling	$21.16	$24.89
Bale transportation to local storage	$5.51	$6.48
Local storage land rent	$0.36	$0.42
Local storage loss	$2.88	$3.38
Tub grinding of bales	$7.26	$8.54
Roll-press compacting	$2.48	$2.92
Payment to aggregator	$3.75	$4.41
Total	$74.25	$87.35

[a] Assuming 15% moisture content for all agricultural residues.

Table 6
Biorefinery capital costs (Humbird and Aden, 2009).

Installed equipment	Investment
Pretreatment	$25,300,000
Neutralization and conditioning	$11,400,000
Saccharification and fermentation	$22,200,000
Distillation and solids recovery	$27,100,000
Wastewater treatment	$5,700,000
Storage	$4,200,000
Boiler and turbogenerator	$55,000,000
Utilities	$6,500,000
Total Installed Equipment cost	$157,300,000
Added costs [a]	$115,200,000
Total Project Investment	$272,500,000

[a] Added costs include indirect costs (engineering and supervision, construction expenses, legal and contractor fees) and contingency.

Table 7
Biorefinery operating costs (Humbird and Aden, 2009).

Source	Cost ($/year)
Corn steep liquor (CSL) nutrient	$8,700,000
Cellulase	$19,600,000
Other raw material	$15,500,000
Waste disposal	$1,200,000
Electricity[a]	−$7,400,000
Total Operating Cost	$37,600,000

[a] Evaporator syrup, lignin, digester solids and biogas are combusted for process heat and to generate excess electricity.

2011 is not renewed. The effective ethanol sale price σ_1 seen at the biorefinery is $2.82/gal. Other incentives such as the Small Ethanol Producer Tax Credit ($0.10/gal discount up to 15MGY production) or programs from the USDA and DOE are not considered.

Ethanol shipment scheduling is not determined by the model as the customer is not necessarily defined and the cost of shipping ethanol is relatively low compared to shipping biomass. Ethanol from a biorefinery is often sold to a central gasoline blending facility that then distributes the common ethanol blends, like E10 and E85, to local fuel stations. To account for the local fuel station demand, (Morrow et al., 2006) modeled cellulosic ethanol production in the U.S. by including ethanol shipments to Metropolitan Statistical Areas. In that study, the cost of delivering biomass to the biorefinery was found to be relatively high compared to the cost to deliver ethanol to the customer.

3.7. Biorefinery costs and capacities

The two main process platforms for cellulosic ethanol production are biochemical (enzymatic hydrolysis and acid hydrolysis) and thermochemical (gasification). National laboratories have focused more on the biochemical platform (West et al., 2009; Humbird and Aden, 2009; Kazi et al., 2010; Aden et al., 2002; Lynd et al., 2005) with the thermochemical platform expected to be demonstrated at the pilot-unit level by 2012 (Phillips et al., 2007). This study utilizes a biochemical platform that is expected to be commercialized first. In particular, a dilute acid pretreatment with enzymatic hydrolysis of cellulose to simple sugars followed by fermentation to ethanol is thought to be a commercialized technology in the short-term (5 years) (Hamelinck et al., 2005). In fact, in a final rulemaking report by the U.S. EPA regarding RFS2 volume requirements for calendar year 2011, four companies are cited in the U.S. with the potential to produce cellulosic alcohol and make it commercially available in 2011. Three of those companies utilize an enzymatic hydrolysis to sugars followed by fermentation to ethanol technology (U.S. Environmental Protection Agency, 2010).

Pretreatment of the lignocellulosic biomass is essential to improve ethanol yield for biochemical platform processes. Solvents, acids and bases, or high temperature can be used to remove hemicelluloses and lignin from cellulose. Common pretreatment processes include dilute-acid pretreatment, hot

Table 9
Feedstock composition by mass fraction and predicted ethanol yield.

Feedstock	Cellulose (glucan)	Xylan	Ethanol yield (gal/dt)
Barley straw (Wilke et al., 1981)	0.375	0.15	66.2
Corn stover (Humbird and Aden, 2009)	0.374	0.211	72.6
Wheat straw (Lee et al., 2007)	0.376	0.195	71.1

Table 8
Sugar conversions by mass fraction (Humbird and Aden, 2009).

Unit operation	Reaction	Conversion (mass fraction)
Pretreatment (1.1% sulfuric acid @ 190 °C, 12.1 atm)	$(\text{Xylan})_n + n\ H_2O \rightarrow n$ Xylose	0.75
Saccharification (5 days with 20 mg cellulase/g cellulose)	$(\text{Glucan})_n + n\ H_2O \rightarrow n$ Glucose	0.90
	sugar loss to contamination	0.07
Conditioning (ammonia loading)	Glucose loss	0.01
	Xylose loss	0.02
Fermentation (2 days)	Glucose → 2 Ethanol + 2 CO_2	0.90
	3 Xylose → 5 Ethanol + 5 CO_2	0.80
	minor sugars → Ethanol	0

water pretreatment, steam explosion, ammonia fiber explosion (AFEX), and treatment with organic solvents (Lynd, 1996). The economic competiveness of different pretreatment and separation techniques for a cellulase enzymatic hydrolysis process were evaluated in (Kazi et al., 2010). The cost analysis was performed assuming *n*th plant (proven) technology and first-of-kind (pioneer plant) economics for processes published in literature. They determined that dilute acid pretreatment with cellulase saccharification, and cofermentation of C5 and C6 sugars with recombinant *Zymomonas mobilis* is most economical with an ethanol product value of \$3.40/gal for the *n*th plant. Added expenses and risks for a pioneer plant increased the ethanol product value to \$5.76/gal.

The National Renewable Energy Laboratory 2008 State of Technology (SOT) Model for biochemical production of ethanol has a similar process design and is used in this study for biorefinery economic parameters, because it contains only experimentally determined data (Humbird and Aden, 2009). No commercial cellulosic ethanol plants exist today, but the SOT is meant to reflect the best estimate of *n*th plant ethanol production costs.

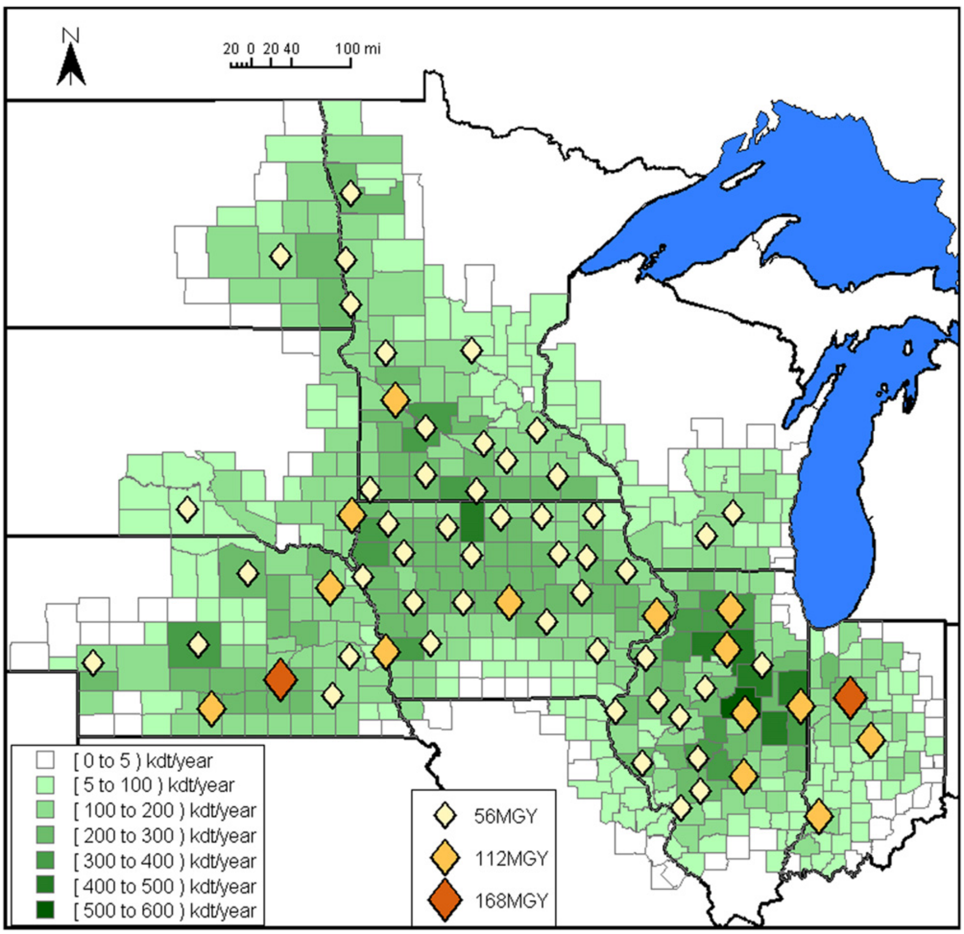

Fig. 4. Base case optimal supply chain with installed biorefinery capacity in million gallons per year (MGY). Total biomass harvest in thousand dry metric tons per year (kdt/year).

Table 10
Base case result breakdown of cost sources.

Cash flow source	Annual cash flow[a]	Sum of discounted cash flows[b]	Percentage[c]
Ethanol sales	+\$13,091 MM	+\$111,451 MM	N/A
Biomass farming[d]	−\$4,118 MM	−\$35,053 MM	33.6%
Biomass local storage[e]	−\$693 MM	−\$5,897 MM	5.7%
Biomass densification	−\$1,068 MM	−\$9,092 MM	8.7%
Biomass transportation	−\$605 MM	−\$5,151 MM	4.9%
Biorefinery investment and operation	N/A	−\$49,187 MM	47.1%
	Net Present Value:	+\$7,070 MM	

[a] Annual cash flow is assumed equal for each year of the 20 year project lifetime.
[b] Determined by discounting each year of the project lifetime.
[c] Contribution to the total production cost of ethanol.
[d] Includes farmer payment, nutrient replacement and baling.
[e] Includes bale transportation, local storage land rent and deterioration losses.

Capital investment and operating costs for a 56 million gallon per year (MGY) biorefinery are shown in Table 6 and 7, respectively. Minimum ethanol selling price for an Internal Rate of Return of 10% was $2.61/gal (Humbird and Aden, 2009).

Ethanol yield in the (Humbird and Aden, 2009) model was 72.6 gallons per dry US ton corn stover with details given in an earlier model (Aden et al., 2002). Important unit operation conversions are summarized in Table 8. These conversions are assumed equal for all feedstocks, allowing for process yields to be calculated from feedstock sugar composition as shown in Table 9. Oat straw is assumed to have the same yield as corn stover.

Biorefinery capacities included in the present model are $\xi_{l,1}$={56 MGY, 112 MGY, 168 MGY, 224 MGY} ethanol ($p=1$). At each candidate biorefinery location there can then be up to four of the benchmark NREL SOT biochemical facilities. Locating five of the facilities at one location for a combined capacity of 280 MGY is not economical at any of the candidate biorefinery locations with base case parameters. Total project investment (TPI) and annual operating costs (AOC) are scaled accordingly to calculate the biorefinery lifetime cost $\psi_l=(\mathrm{TPI})_l+\theta(\mathrm{AOC})_l$.

3.8. Internal Rate of Return (IRR)

Internal Rate of Return (IRR) is the interest rate at which the Net Present Value, calculated in Eq. (2), is zero and is calculated for the optimum supply chain configuration. This gives a measure of the desirability of making all of those supply chain choices together. It does not measure the desirability of choosing each of the candidate biorefinery locations, for example. The estimated project lifetime T_L in Eq. (3) is assumed to be 20 years.

Table 11
Base case model biomass utilization.

Crop	Amount of residue that can be removed (MM dt/year)	Amount of residue harvested (MM dt/year)	Utilization
Barley	0.127	0.040	31.8%
Corn	67.0	64.2	95.7%
Oats	0.113	0.105	92.4%
Wheat (spring)	1.87	1.46	78.5%
Wheat (winter)	2.24	1.52	67.7%
Total	71.4	67.3	94.3%

4. Software

Software used in this project included MATLAB (The MathWorks Inc., 2009) and CPLEX (IBM, 2011). The objective function coefficient vectors, constraint matrix, and constraint bound vector were created in MATLAB following Eqs. (13)–(18). The IBM ILOG CPLEX Connector for MATLAB was used to interface between MATLAB and CPLEX. Optimization results were processed and displayed in MATLAB using the Mapping Toolbox.

Optimization time was reduced by taking advantage of the geography of the problem. Single-state optimization sub-problems with a reduced set of decision variables were solved quickly for each state. The combination of these sub-problem solutions was used as an initial guess for the combined regional problem as it is an integer feasible solution for the entire region problem. The branch and bound algorithm utilized in CPLEX takes advantage of such integer feasible solutions to trim branches of the search tree by bounding. This sub-problem solution strategy reduced the total runtime by about a third compared to having no initial guess. A solution was returned when the gap between lower and upper bounds on the optimal value of the objective function was less than 0.5%.

5. Results

5.1. Base case

The maximum Net Present Value supply chain network for the base case model is shown graphically in Fig. 4. The base case model contains 5557 constraint equations governing 187,595 decision variables, including 276 binary variables that accommodate the possibility of one of four biorefinery capacities at each of

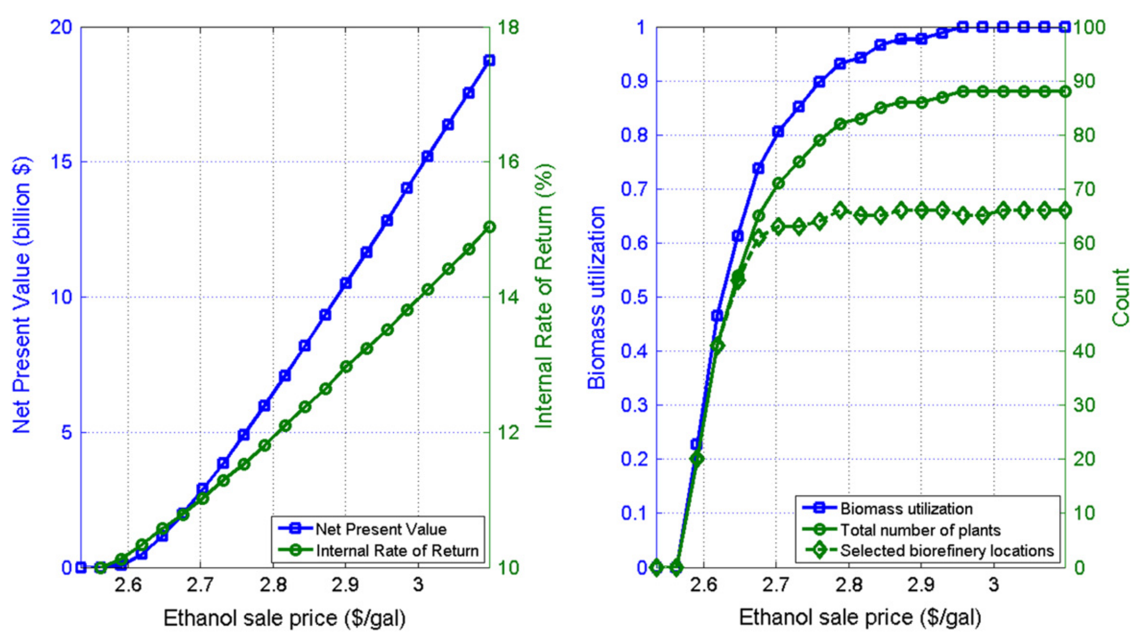

Fig. 5. Effect of varying ethanol sale price with other base case parameters fixed.

the 69 candidate biorefinery locations. The matrix of constraint coefficients contains 375,190 nonzero entries (0.036% nonzero elements). The base case model required about 65.7 s (the 9 subproblems required a combined runtime of 3 s) to solve on a quad core Intel Xeon 3.20 GHz 64-bit processor.

Our analysis identified biorefineries that are optimally located in 65 of the 69 allowed biorefinery locations. Total capacity of the system is 4.7 BGY of ethanol, which is equivalent to 83 of the NREL SOT 2008 biochemical benchmark biorefineries. The expected Net Present Value is $7.07 BB over a 20-year estimated plant life with an annual discount rate of 10%. The Internal Rate of Return is 12.1% annually. Costs by source are described in Table 10.

Agricultural residue biomass is more densely available in Illinois and Iowa. In Iowa, biomass availability is limited almost exclusively to corn stover. Illinois has some winter wheat, but is also dominated by corn stover. Wheat becomes prevalent in the Dakotas and northwestern Minnesota.

Of the 35% of crop residues that can be removed annually, about 94% is harvested for the base case model. Table 11 summarizes the biomass utilization by feedstock. This finding may be misleading in that the model assumed fixed economic and technological parameters. The economic variability inherent in the real world may make certain regions too risky for a biorefinery investment. Thus, parameter sensitivity must be used to determine the biorefinery supply chain robustness.

5.2. Sensitivity analysis

Certain variability exists in the base case economic parameters because they specify volatile prices or characteristics of technology

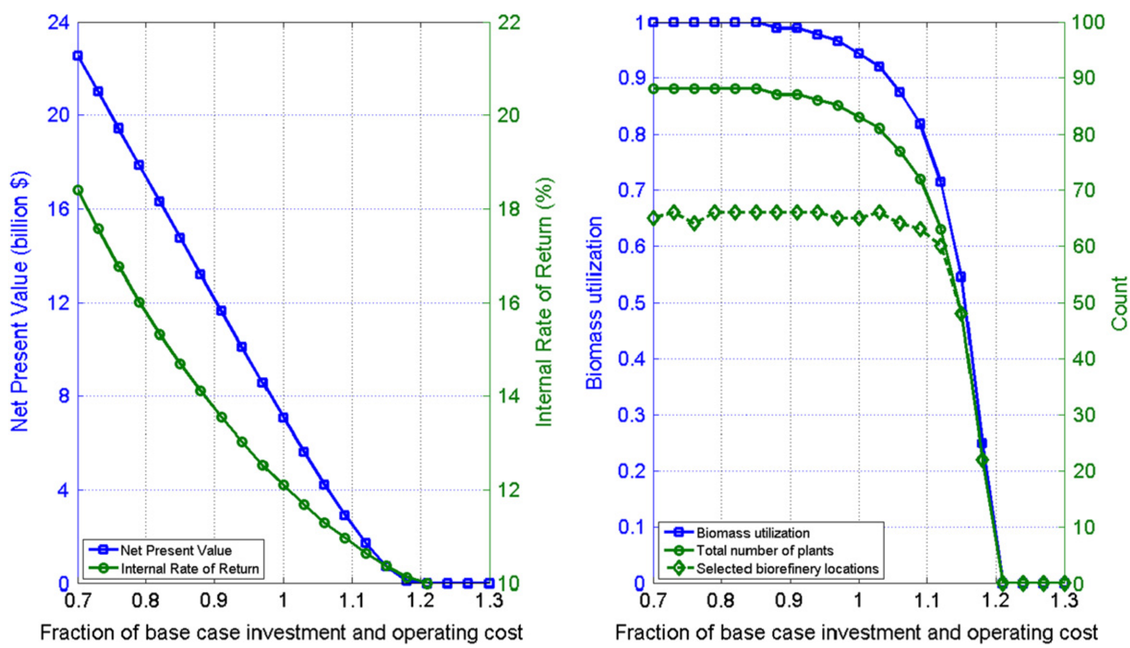

Fig. 6. Effect of varying biorefinery capital investment and operating cost with other base case parameters fixed.

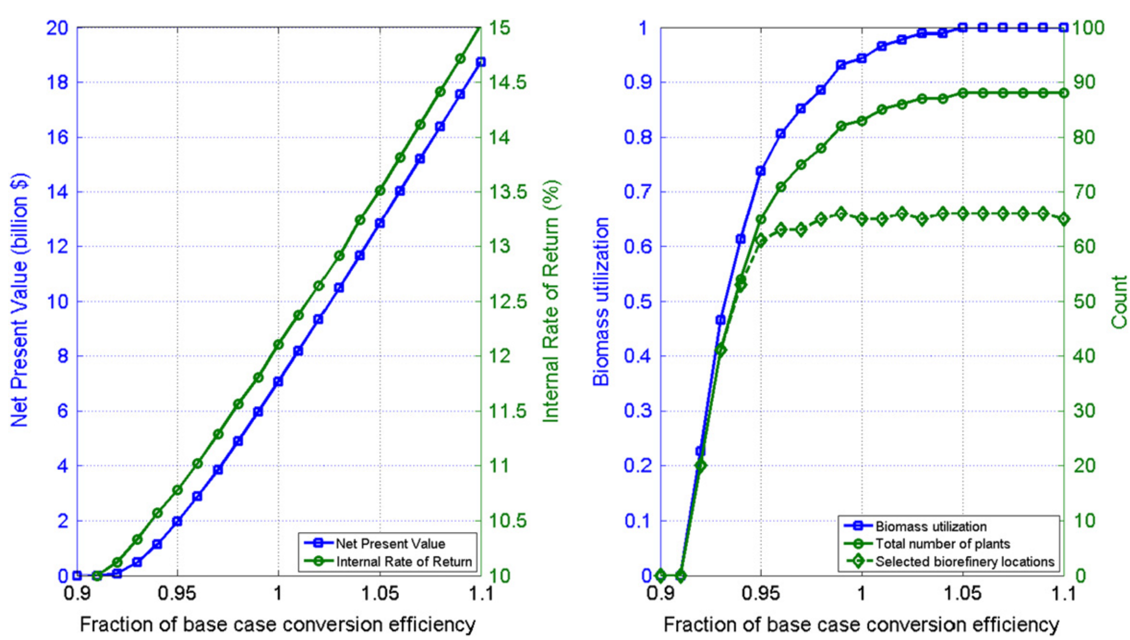

Fig. 7. Effect of varying conversion efficiency with other base case parameters fixed.

Table 12
Variability of model parameters.

Parameter		Variability
σ_p	unit sale price for product p (\$/gal)	$\pm$20%
ρ_b	unit feedstock cost for biomass b (\$/dt)	$\pm$30%
$\tau_{n,r}$	unit biomass transportation cost from n to r (\$/dt)	$\pm$10%
ψ_l	investment and lifetime operating cost for a biorefinery of size l (\$)	$\pm$20%
$\lambda_{n,b}$	amount of biomass b harvestable at n annually (dt/y)	$\pm$15%
$\beta_{b,p}$	biorefinery conversion of biomass b to product p (gal/dt)	$\pm$10%

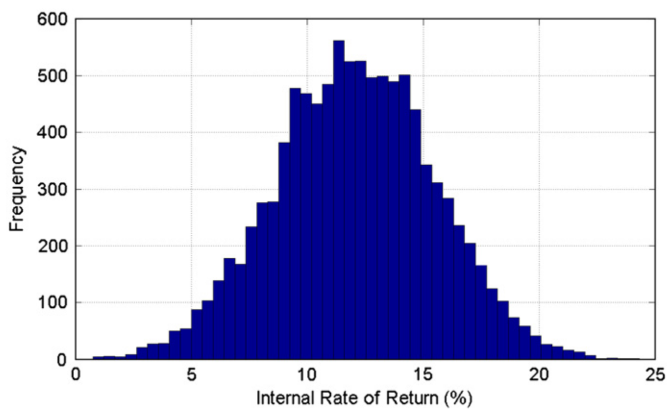

Fig. 8. Monte Carlo method sampling of the parameter space for the base case optimum supply chain configuration.

not demonstrated at this scale. Many studies have examined how biomass utilizing systems can be affected by economic parameter uncertainty. The logistic challenges for fossil fuel substitution with biomass for energy production were explored in (Caputo et al., 2005). The sensitivity of ethanol production cost was compared across multiple technologies in (Hamelinck et al., 2005).

Analyzing the effects of a single parameter change on the model optimum supply chain while the other base case parameters are fixed gives an intuitive understanding of that parameter's effect on profitability. This may be useful to policy makers interested in encouraging this technology. For example, when the ethanol sale price σ_1 seen by the biorefinery is varied as in Fig. 5, we can see that a reduction to \$2.7/gal may not affect the industry. Most biorefineries would still be able to make at least a 10% return on investment to remain open, and biomass would still be utilized. An ethanol sale price below \$2.7/gal could affect the willingness of companies to invest in a biorefinery. Ideally, tax incentives that increase the ethanol sale price seen by the biorefinery would be stable across the facility lifetime as a sudden drop could cause biorefineries to scale down production.

When the biorefinery capital investment and operating costs are varied as shown in Fig. 6, the number of installed biorefineries is unchanged until costs rise about 10%. There is enough economic incentive before that point to utilize almost all the available biomass for a developed cellulosic ethanol industry, but the industry would develop more rapidly if incentives lowered capital costs. Similarly, increasing the conversion efficiency $\beta_{b,1}$ from biomass to ethanol as shown in Fig. 7 greatly increases the IRR.

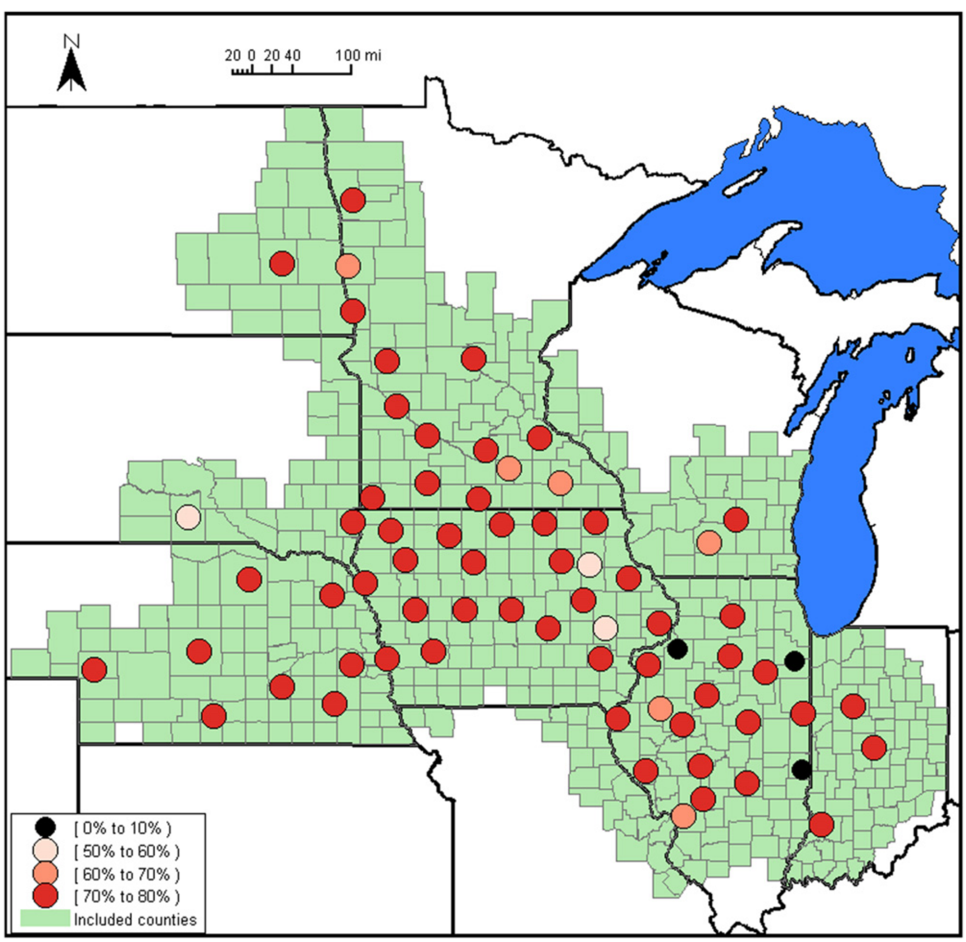

Fig. 9. Percentage of trials in which each candidate biorefinery location was selected in 200 model runs, each using a randomly sampled parameter set. Biomass producing counties are shaded.

5.3. Monte Carlo analysis

Monte Carlo based random sampling of the parameter space can give insights into the system robustness in two ways. After determining the optimum supply chain for the base case, random sampling of the parameter space and recalculation of the economics can determine how good the choice was. If companies had indeed decided to place biorefineries there and create long-term contracts with the local farmers to provide them with agricultural residues, an estimate of the probability of meeting their 10% annual rate of return could be determined. A second analysis of robustness could find the most robust supply chain choices. For each set of randomly sampled parameters, the supply chain would be re-optimized and the results compared.

For the first analysis, each parameter was sampled from a triangle distribution having the variability shown in Table 12. The parameter variability is similar to that used in (Tiffany and Taff, 2009). Fig. 8 shows the variability in IRR for the base case optimum supply chain when the parameter space is sampled for 10,000 parameter sets. With the assumed parameter variability, the biorefinery supply chain investments will fall short of a 10% rate of return, and thus have negative NPV, about 15% of the time.

For the second analysis of robustness, the model was optimized for 200 independently drawn parameter sets. An indication of the favorability of each candidate biorefinery location considering the parameter variability is shown in Fig. 9. The fraction of trials in which a biorefinery of any size was placed at each location was calculated. Locations chosen least frequently are not surrounded by biomass producing counties included in the model. If more biomass producing counties were included in the model, these locations might be able to support a biorefinery economically.

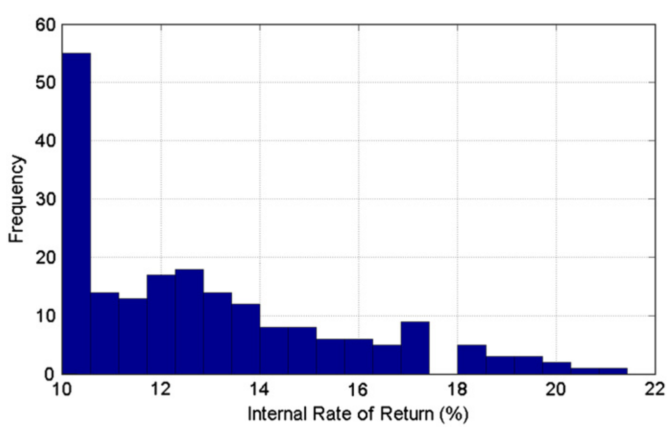

Fig. 10. Internal Rate of Return for 200 model optimization trials sampled from the parameter space.

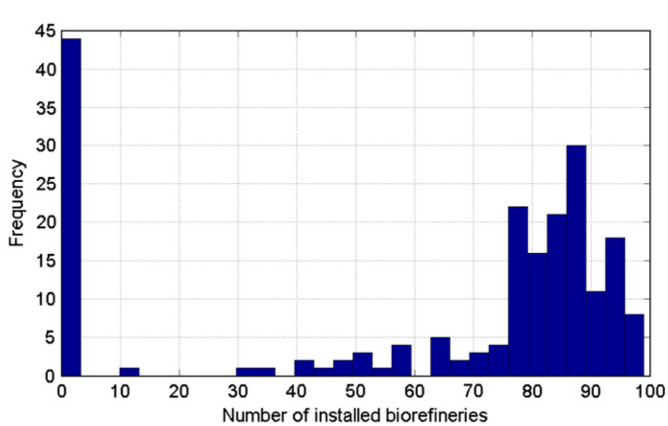

Fig. 11. Total number of installed NREL SOT 2008 biochemical benchmark biorefineries for 200 model optimization trials sampled from the parameter space.

It was not economical to construct any biorefineries in 21.5% of the trials. A large spread of total system IRR is observed as shown in Fig. 10. The number of installed biorefineries (NREL SOT 2008 biochemical benchmark) is high as shown in Fig. 11, such that 53.5% of trials had biomass utilization of 95% or higher.

6. Conclusions

The methodology proposed in this article provides an assessment of the maximum profit supply chain for lignocellulosic biomass-to-ethanol conversion technology systems when accounting for the spatial distribution of biomass. There is considerable potential for cellulosic ethanol production in the Midwest U.S. due to high biomass availability. Once the technology has been proven and *n*th-plant economics evolve, and economic parameters stabilize, there is enough incentive for a 4.7 BGY cellulosic ethanol industry to develop in the region.

With the current estimated parameter variability of the system, there is a 21.5% chance this industry will not develop. If the industry did develop, it could become uneconomical approximately 15% of the time. An ethanol sale price seen by the biorefinery including tax incentives below $2.7/gal could affect the willingness of companies to invest in biorefineries. There are various approaches to curb the risks associated with this non-commercialized technology. The cellulosic ethanol sale price seen by the biorefinery could be stabilized up to at least $2.99 per gallon by continuing the Volumetric Ethanol Excise Tax Credit, or similar incentive. Incentive programs that lower first-of-kind biorefinery capital investment allow for convergence to the *n*th plant economics assumed in this study.

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