Optimizing fermentation process 

miscanthus-to-ethanol biorefinery scale 

under uncertain conditions

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Abstract
Ethanol produced from cellulosic feedstocks has garnered significant interest for greenhouse gas abatement and energy security promotion. One outstanding question in the development of a mature cellulosic ethanol industry is the optimal scale of biorefining activities. This question is important for companies and entrepreneurs seeking to construct and operate cellulosic ethanol biorefineries as it determines the size of investment needed and the amount of feedstock for which they must contract. The question also has important implications for the nature and location of lifecycle environmental impacts from cellulosic ethanol. We use an optimization framework similar to previous studies, but add richer details by treating many of these critical parameters as random variables and incorporating a stochastic sub-model for land conversion. We then use Monte Carlo simulation to obtain a probability distribution for the optimal scale of a biorefinery using a fermentation process and miscanthus feedstock. We find a bimodal distribution with a high peak at around 10–30 MMgal yr\textsuperscript{-1} (representing circumstances where a relatively low percentage of farmers elect to participate in miscanthus cultivation) and a lower and flatter peak between 150 and 250 MMgal yr\textsuperscript{-1} (representing more typically assumed land-conversion conditions). This distribution leads to useful insights; in particular, the asymmetry of the distribution—with significantly more mass on the low side—indicates that developers of cellulosic ethanol biorefineries may wish to exercise caution in scale-up.

Keywords: cellulosic ethanol, optimal size, fermentation pathway, Monte Carlo analysis

1. Introduction
Ethanol produced from cellulosic feedstocks has garnered significant interest as a greenhouse gas abating and energy security promoting strategy [1–3]. An outstanding question in the development of a cellulosic ethanol industry is the optimal scale of biorefining activities. The optimal scale of a biorefinery determines the size of investment and amount of feedstock needed; as such, it is an important consideration for companies and entrepreneurs seeking to construct and operate cellulosic ethanol biorefineries. The question also has important environmental implications, as the size of biorefineries will affect the nature and location of lifecycle impacts from cellulosic ethanol (for instance, several small biorefineries producing an equivalent amount of fuel as one...
large biorefinery may result in lower feedstock transport impacts, but may also increase impacts from the construction phase of the biorefinery).

Optimization of biorefinery scale seeks to minimize ethanol selling price by evaluating tradeoffs between feedstock transport costs and biorefinery capital costs. In general, unit capital costs decline with increasing biorefinery capacity, while unit transport costs increase as the biorefinery is scaled-up. Other costs tend to scale linearly as refinery capacity increases. Capital cost economies of scale are quite common in chemical process industries. The intuition behind this trend is that the capacity of different refinery components (e.g., reactors and the building itself) is a function of volume, while the cost of these components is a function of the material involved, or their surface area. Volume grows as a cubic function while surface area grows as a square function (times the number of ‘sides’ of the cube or cylinder), so facilities exhibit economies of scale [4]. In contrast, transport costs exhibit diseconomies of scale because as refinery capacity increases, feedstock must be hauled from longer distances. Finally, other inputs (e.g. enzymes, process chemicals) scale linearly in terms of impacts because most are needed in ratios that are fixed closely to feedstock inputs.

As described below, several studies have considered the optimal scale for cellulosic ethanol production from an economics perspective. Many of these studies have found an optimal scale for biorefineries that is at least ten times greater than the largest project currently constructed or planned. A critical shortcoming of these efforts is that all assume average values for parameters such as scaling exponents, crop yields, land conversion to energy crop production, and prices. In reality, these parameters will tend to vary in time, location, and from project to project. We use an optimization framework similar to previous studies, but add richer detail by treating many of these parameters as random variables and incorporating a stochastic sub-model for land conversion. We then use Monte Carlo simulation to obtain a probability distribution for the optimal scale of a biorefinery using a fermentation process and miscanthus feedstock. This distribution leads to useful insights; in particular, the asymmetry of the distribution—with significantly more mass on the low side—indicates that developers of cellulosic ethanol biorefineries may wish to exercise caution in scale-up.

2. Literature review

Here, we provide a brief overview of existing and planned cellulosic ethanol facility scales, previous work examining optimal sizing of biorefineries, and methods for dealing with uncertainty in biorefinery scale optimization. While some literature has used scenario analysis or stochastic programming to address uncertainty, or Monte Carlo simulation for lifecycle analysis, we find no prior work employing Monte Carlo analysis or simulation for optimal sizing of biorefineries [5–7].

The International Energy Agency produced a status report in 2013 [8] on second-generation ethanol facilities. The report found that the largest biochemical ethanol demonstration or commercial project currently online or planned to start-up before 2018 will have a capacity of 75 000 ton fuel yr$^{-1}$ (roughly 25 MMgal yr$^{-1}$) ethanol. Of the 43 biochemical pathway projects reviewed, only six will have a capacity greater than 50 000 ton fuel yr$^{-1}$ (17 MMgal yr$^{-1}$).

Nguyen and Prince establish a framework for optimizing the tradeoff between increasing transport costs and declining capital costs using scaling exponents [9]. The fraction of land available for energy crop cultivation is asserted (no attempt is made to model the underlying decision farmers must make to convert to growing biofuel feedstocks). The study finds an ethanol product cost minimizing biorefinery capacity of 174 MI yr$^{-1}$ (46 MMgal yr$^{-1}$) for ethanol produced from sugarcane and sweet sorghum via a fermentation process in Australia.

Wright and Brown use the methodology established in Nguyen and Prince to produce updated projections of the optimal plant scale for five different fuel pathways [10]. The authors find an optimal size for a biorefinery producing ethanol from lignocellulosics via fermentation of 350 MMgal yr$^{-1}$, at which the unit production cost is $1.78\,\text{gal}^{-1}$. The authors find that scale can vary by as much as 150 MMgal yr$^{-1}$ without greatly impacting unit production cost.

Jack explains three potential strategies for reducing production costs of biofuels and bioenergy in a theoretical work using scaling laws [11]. The study is intended as generic and does not assume a feedstock, final product, or conversion technology. Cost-reduction strategies outlined include reducing the ratio of scale-dependent feedstock costs to transport costs in base technology, reducing the feedstock scaling exponent, and increasing the capital scaling exponent.

Huang et al perform a techno-economic analysis of ethanol production from several feedstocks (aspen wood, hybrid poplar, switchgrass, and corn stover) using a fermentation process [12] (adapting the process model developed by National Renewable Energy Lab modelers [13]). The study includes sensitivity analysis of refinery scale. The authors find that a hybrid poplar refinery minimizes ethanol cost at a scale of 4000 dry ton day$^{-1}$ (about 480 MMgal yr$^{-1}$), while all other feedstocks have optimal scales in excess of 5000 dry ton day$^{-1}$ (though it is not clear what percentage of available land the authors have assumed in this calculation).

Leboreiro and Hilaly employ sensitivity analysis in understanding optimal biorefinery scale [14]. In particular, they develop a detailed model of transportation and storage of biomass then use this model to determine the optimal size of a biorefinery producing ethanol from corn stover via a biochemical pathway. The authors use an individual farm-level model to determine average transport distance and consider three different feedstock transport distance schemes (straight-line distance, right angle distance, and straight line adjusted by a winding (tortuosity) factor). The study finds an optimal plant size of 3450 ton (dry) day$^{-1}$ (about 420 MMgal yr$^{-1}$) feedstock processed for the more realistic transport distance schemes (the right angle distance and winding factor distance). The optimal scale is sensitive to farmer participation.
and tortuosity of the road network. The study assumes a farmer participation of 20%; if increased to 50%, the optimal scale increases to 5800 ton day\(^{-1}\) (about 700 MMgal yr\(^{-1}\)). Finally, if a capital scaling exponent of 0.6 or 0.8 is used, the resulting optimal refinery scale is 4250 ton day\(^{-1}\) or 2450 ton day\(^{-1}\), respectively.

Several other studies employ sensitivity analysis or stochastic optimization to understand uncertainty in ethanol pricing or supply chain investment. Haque and Epplin calculate the minimum ethanol selling price from switchgrass at several biorefinery costs and ethanol conversion rates in Oklahoma, while choosing between three candidate biorefinery scales [15]. Fan et al model optimal biofuel supply chains, employing a stochastic programming framework that takes into account supply uncertainty and seasonality [16]. Applying their framework to California, they find optimal facility sizes between 75 and 100 MMgal yr\(^{-1}\). Similarly, Dal-Mas et al consider biomass production cost and selling price uncertainty in understanding optimal biofuel supply chains. Applying their model to Northern Italy, they find a range of optimal plant sizes under both profit maximization and risk minimization frameworks [17]. Tay et al and Tong et al employ similar methods to study supply chain uncertainty, including robust optimization and fuzzy possibilistic programming [18, 19].

### 3. Modeling framework

The model used in this study seeks to minimize the unit cost of producing ethanol by varying refinery capacity. As a starting point, total production costs are decomposed into capital costs, feedstock (farm-to-refinery) transport costs, and all other factor costs:

\[
TC = C_C + C_T + C_F. \tag{1}
\]

These sub-costs are then expressed in terms of scaling relationships. Specifically, the scaled-up component cost is given by the product of a base (known) component cost and the ratio of the scaled-up capacity to the base (known) capacity, raised to a scaling exponent:

\[
TC(X) = C_C X_0 \left( \frac{X}{X_0} \right)^\alpha + C_T X_0 \left( \frac{X}{X_0} \right)^\beta + C_F X_0 \left( \frac{X}{X_0} \right)^\gamma, \tag{2}
\]

where C represents cost ($), \(X\) represents refinery capacity (MMgal yr\(^{-1}\)), and the subscripts 0, C, T, and F denote base (present technology) conditions, capital costs, feedstock transport costs, and all other factor costs.

The factor cost scaling exponent captures how the costs of inputs like process chemicals vary with refinery size. Because most inputs are needed in fixed ratios with the feedstock throughput, this exponent is set at \(\gamma = 1\). Incorporating this assumption and dividing through by capacity to work with average (unit) cost yields the equation:

\[
AC(X) = \frac{TC(X)}{X} = \frac{C_{C,0}}{X_0} X^{\alpha-1} \cdot \frac{C_{T,0}}{X_0} X^{\beta-1} + \frac{C_{F,0}}{X_0}. \tag{3}
\]

The optimal refinery size occurs when average product cost is at a minimum. Differentiating the average cost equation with respect to capacity, and solving for capacity gives:

\[
X^* = X_0 \left[ \frac{(1 - \alpha)C_{C,0}}{(\beta - \alpha) C_{T,0}} \right]^{\frac{1}{\alpha - \beta}}. \tag{4}
\]

If the capital cost scaling exponent is less than 1 and if the transport cost scaling exponent is greater than 1 (i.e. if there are economies of scale in capital costs and diseconomies of scale in transport costs, as hypothesized), then \(X^*\) will be a global minimum.

#### 3.1. Capital cost scaling law

The capital cost scaling exponent captures economies of scale that can be realized when increasing biorefinery capacity causes the unit capital cost to decline. For values of \(\alpha\) less than 1, economies of scale are present (doubling refinery capacity will not double capital costs). A strong theoretical argument can be made for the existence of economies of scale in capital-intensive chemical processing, as capacity tends to track the volume of reactors while cost tends to track the surface area of reactors (how much material is needed to build the reactor). Since volume grows as a cubic function while surface area grows as a square function, capital cost tend to scale with capacity to approximately the 2/3 power. A reasonable estimate for the capital cost scaling exponent is thus \(\alpha = 0.6\).

Empirical analysis of scale-up in different processes somewhat confirms a 0.6 scaling capital cost hypothesis. Studies have looked at scaling in chemical processing by plotting a log-log scatterplot of capital cost vs capacity for different projects. The slope of such a plot gives an estimate of the scaling exponent. Estimated scaling exponents are as low as 0.4 and as high as 1, but illustrate a central tendency around 0.6 [20, 21]. Such an estimate, however, may not hold for the cellulosic ethanol industry, Gallagher et al for example, report a capital cost scaling factor of 0.86 for the US dry mill ethanol industry, while others report values between 0.7 and 0.9 [14–22]. As there is significant uncertainty about the applicability of the ‘six-tenths’ rule under fermentation pathways, we treat our scaling exponent as uncertain in our simulation.

#### 3.2. Transport cost scaling law

Transport cost can be expressed as:

\[
C_T = FC_T F + VC_T FD, \tag{5}
\]

where \(F\) is the amount of feedstock hauled (tons), \(D\) is the...
average transport distance (mi), and FC \(_T\) and VC \(_T\) are the fixed and variable costs (distance-independent and distance-dependent) to transport a ton of feedstock ($\text{ton}^{-1}$ and $\text{ton}^{-1}\cdot\text{mi}$). Average transport distance can be derived from the feedstock collection area. Assuming a circular collection area, the area needed to support a biorefinery is given by:

\[
F = Y_{\text{Crop}} f_{\text{Crop}} \pi R^2
\]  

(6)

where \(Y\) is the feedstock yield (ton ha\(^{-1}\)), \(f_{\text{Crop}}\) is the fraction of land that is cropland, \(f_{\text{Conv}}\) is the fraction of cropland converted to energy crop production, and \(R\) is the maximum radius of the collection area. Because the average radius of a circular area is \(2/3R\), an expression for the average transport distance can be obtained as:

\[
D = \frac{2}{3} \tau \sqrt{\frac{F}{\pi Y_{\text{Crop}} f_{\text{Conv}}}},
\]

(7)

where \(\tau\) is a factor representing the difference between network distance and straight-line distance. Finally, substituting the expression for average distance into the initial equation, transport cost is:

\[
C_T = FC_T F + VC_T \frac{2\tau}{3} \sqrt{\frac{\pi Y_{\text{Crop}} f_{\text{Conv}}}{F}}\frac{3}{2}.
\]

(8)

This final expression permits insights about the scaling of transport costs. Assuming that the refinery capacity (MMgal yr\(^{-1}\)) is related to a feedstock inputs (ton yr\(^{-1}\)) in a fixed, scale-independent ratio, and assuming that the variable cost term dominates the expression, we can conclude that transport costs scale with capacity to the 3/2 power. In fact, this first assumption is quite reasonable as a first approximation, as the ratio of fuel produced to feedstock input depends on internal process conversion efficiencies, most of which are fixed by reaction stoichiometry and/or not scale dependent\(^5\). Thus, a reasonable estimate for the transport cost scaling exponent in equation (4) is \(\beta = 1.5\).

3.3. Cropland conversion sub-model

The cropland conversion sub-model simulates the decision of whether to convert to energy crop production for 500 farms then calculates the resulting fraction of land converted (the \(f_{\text{Conv}}\) variable in (8)). The decision to convert is based on a profit-maximizing choice between production of an incumbent crop rotation (corn and soy in alternating years) and production of miscanthus.

The fraction of land converted is given by:

\[
f_{\text{Conv}} = \frac{\sum_{i=1}^{500} S_i \delta_i}{\sum_{i=1}^{500} S_i},
\]

(9)

where \(S_i\) is the size of farm \(i\) (ha) and \(\delta_i\) is a binary variable taking a value of 1 if a farm chooses to convert. More specifically, \(\delta_i\) is 1 if the profits from producing miscanthus are greater than corn and soy:

\[
\delta_i = \begin{cases} 
1 & \text{if } \Pi_{\text{Misc},i} > \Pi_{\text{Conv/soy},i} \\
0 & \text{if } \Pi_{\text{Conv/soy},i} \geq \Pi_{\text{Misc},i}
\end{cases}
\]

(10)

The profit from the two crop planting regimes are in turn given by:

\[
\Pi_{\text{Conv/soy},i} = S_i Y_{\text{Crop},i} \left( P_{\text{Conv}} - C_{\text{Conv},i} \right)
\]

and:

\[
\Pi_{\text{Misc},i} = S_i Y_{\text{Misc},i} \left( P_{\text{Misc}} - C_{\text{Misc},i} \right)
\]

(11)

where \(Y_i\) represents the yield for farm \(i\) for the respective crop (ton ha\(^{-1}\) or bushel ha\(^{-1}\)) and \(P\) represents the sale price for the respective crop ($\text{ton}^{-1}$ or $\text{bushel}^{-1}$) and \(C_i\) represents the production cost to grow the respective crop for farm \(i\) ($\text{ton}^{-1}$ or $\text{bushel}^{-1}$).

A farmer’s decision to convert to cultivation of an energy crop such as miscanthus depends on a host of factors beyond expected profits. Most farmers are likely to exhibit risk aversion such that the point of indifference between growing a corn/soy rotation and growing miscanthus is not merely where the expected profits are equal. Further barriers could include time constraints, equipment constraints, land ownership, debt structure, farm size, production activities (i.e., crop, livestock), soil type and topography, and farm program participation [23]. Sherrington et al identify a lack of insurance, contract security, and upfront investment costs as key barriers to energy crop adoption in the United Kingdom [24]. To compensate, a biorefinery could, for instance, guarantee that farmers will receive at least the county average profit per acre of corn, such that farmers would do no worse by growing miscanthus [25].

There are several shortcomings in our treatment of crop adoption in this study. Miscanthus is a perennial crop, which persists for several growing seasons, while corn and soy are annual crops, which perform their entire life cycle in a single growing season. Early miscanthus yields may be lower than annual crops, which perform their entire life cycle in a single growing season. Early miscanthus yields may be lower than later years, and a farmer adopting miscanthus would be required to commit to several years of cultivation. This may increase a farmer’s risk aversion. Future studies of uncertainty in crop adoption should better incorporate risk and temporal issues.

3.4. Integration of model components

Figure 1 illustrates the overall structure of the scale optimization model used in this study. This figure shows the structure of a single model run; we simulate the model 10,000 times to obtain a distribution for optimal refinery scale. Bold-faced parameters are simulated random variables. We simulate prices at the market level, while we simulate production costs and crop yields at the farm level. We combine market prices with yields and costs to determine the optimal crop planting regime for a farm. We perform this calculation for 500 farms (of simulated sizes) to obtain a land conversion
fraction (according to (9)). We then combine the land conversion fraction with transport unit costs (distance-fixed and distance-variable), and a simulated miscanthus yield, cropland fraction, and tortuosity factor to obtain a base annual feedstock transport expenditure (according to (8)). Similarly, we amortize a base capital cost (at 20 yr project life and 7.5% real discount rate) to obtain a base annual capital expenditure. Finally, we use base transport and capital costs, a base scale, and simulated scaling exponents to obtain an optimal scale (according to (4)). Our framework can be applied to other types of biorefineries or feedstocks.

4. Data sources

We obtained the necessary data to implement the model from a variety of sources. A miscanthus yield distribution was constructed from county-level productivity data from MISCANMOD, a GIS based tool for assessing regional miscanthus yields based on soil type, precipitation and other variables [26]. Since corn and soy are the incumbent crops in this analysis, we constrained the geographic area to cornbelt states including Iowa, Illinois, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. Figure 2 shows a histogram of miscanthus productivities for counties in this area. We use this frequency distribution as a probability distribution for miscanthus yield.

Ideally, the distribution for miscanthus yield would vary temporally (reflecting how yields may differ across years with weather or economic conditions). Given the lack of historical data for miscanthus, this analysis relies solely upon a distribution that reflects spatial variation. An analysis based on spatial variation in miscanthus yield represents a scenario in which a company is considering several sites within the Midwest for a cellulosic ethanol refinery, and wishes to bound the range of refinery capacities that it should consider prior to

![Figure 1. Optimal scale model structure. Bold-faced parameters are simulated as random variables. This figure shows the structure of a single model run. We simulate the model 10 000 times to obtain a distribution for optimal refinery scale.](image)

![Figure 2. Frequency distribution of miscanthus yield in study area. Average yield is 19 dry ton (ha yr)$^{-1}$. Study area includes 777 counties in Iowa, Illinois, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.](image)
choosing a site. Moreover, since the refinery will likely exist for many years, the temporal effects may be negligible over the long run (high yield years may cancel out low yield years).

The capital cost and transport cost scaling exponents are both given beta distributions. The beta distribution is a continuous probability distribution that permits skew on a bounded interval. Unlike a normal or lognormal distribution, this distribution allows bounded intervals, which adequately constrain the parameter distribution for these exponents. The capital cost scaling exponent distribution is \( \alpha \sim \text{Beta}(\alpha = 3.75, \beta = 2.15, \text{min} = 0.3, \text{max} = 0.9) \). This distribution has a mode of 0.7 and a significant positive skew, such that the greatest probability density is in the 0.5 to 0.85 range. A distribution of this sort will give a conservative estimate of the optimal biorefinery scale that might match previous dry mill ethanol experiences [22]. If, as discussed above, a good estimate for \( \alpha = 0.6 \), then choosing a distribution where the mode is higher and the greatest density of values is in the high end of the distribution ensures that in most simulations a high scaling exponent will be drawn. This distribution does not permit diseconomies of scale in capital costs (which would correspond to \( \alpha \) greater than 1).

The transport cost scaling exponent distribution is \( \beta \sim \text{Beta}(\alpha = 1.5, \beta = 5, \text{min} = 1.5, \text{max} = 2) \). An exponent of 1.5 is the minimum possible value since transport cost is the product of amount of feedstock hauled (which scales linearly with refinery capacity) and average transport distance (which scales with the square root of refinery capacity). If, however, available land for miscanthus production becomes more sparse with increasing distance from the refinery, the scaling exponent value could be larger (representing greater diseconomy of scale). This could be the case because agricultural uses become less predominant further from the refinery, or because farmers further away feel less compelled to convert to miscanthus production. The distribution selected here permits high diseconomies of scale for transport costs in some simulation trials.

We assume the base capital cost to be normally distributed with a mean of $200 million and a standard deviation of $20 million, scaled to a facility size of 25 MMgal yr\(^{-1}\). We set the base plant capacity at 25 MMgal yr\(^{-1}\) (represented as \( X_b \) in equations (2)–(4)), which represents a midpoint value of the largest size class of operational or planned biochemical cellulosic ethanol refineries [8]. Basic capital costs are representative of early cellulosic ethanol plants that received federal funding [27]. Normal distributions are commonly occurring continuous probability distributions that are symmetric, unimodal, and continuous. This value is intended to incorporate both the costs of building the physical plant and maintenance, insurance, taxes, and labor.

The tortuosity factor is assumed to be triangularly distributed with a mode of 1.6 and min and max values of 1.2 and 3. Tortuosity can vary from 1.2 in areas with a rectangular road grid and flat terrain to 3 or greater in less developed or geographically complex regions [28]. Triangular distributions provide both upper and lower bounds on the distribution and allow for a non-symmetric modal value. Given the relatively square, uniform county-line boundaries in Midwest and Plains counties, a mode tortuosity factor tending more towards an orthogonal road network (1.2–1.6) is appropriate.

A probability distribution for farm size is constructed from the Agricultural Census [29]. The fraction of agricultural land surrounding the refinery that is available for cropland production is assumed to be normally distributed with a mean of 0.535 and a standard deviation of 0.097. This mean is the area-weighted average of the fraction of cropland from the nine states considered in this study. The standard deviation is the standard deviation of these nine values. The fraction of cropland in these nine states is taken from a GIS export of MISCANMOD productivity data.

Miscanthus production cost is assumed to be normally distributed with a mean of $41.67 ton\(^{-1}\) and a standard deviation of $4.17 ton\(^{-1}\). This mean is the breakeven farmgate price excluding land rent [30]; the standard deviation is set at 10% of the mean. Given the normal shape of the miscanthus yield distribution (figure 2), we believe a production cost distribution might have a similar form.

Corn and soy prices, production costs, and yields are all taken from national data for 2001 to 2009 [31]. All are assumed to be normally distributed with means and standard deviations computed from this time-series data (in other words, the mean and standard deviation for each variable are computed based on the nine national average observations over this period). While the use of national average data is a limitation given the more narrow geographic focus of this paper, this limitation is not expected to be significant because the states considered in this paper account for a considerable amount of the nation’s corn and soy production and would therefore see prices, costs, and yields close to the national averages for these crops. A more significant limitation is the fact that the years considered include several years in which corn prices fluctuated significantly due to the introduction and expansion of a national Renewable Fuel Standard. Future studies of uncertainty in crop adoption could attempt to control for this policy-driven price fluctuation and could also attempt to capture how prices, yields, and costs related to incumbent crops may vary spatially (e.g. from county to county) in addition to temporally.

The miscanthus sale price is particularly difficult to project as no mature market exists for this feedstock. For this analysis, we assume a triangular distribution with a mode of $45 ton\(^{-1}\), and min and max values of $40 ton\(^{-1}\) and $60 ton\(^{-1}\). For our analysis, we treat miscanthus production cost and sale price as independent variables; however, they are more likely correlated. While some estimates for miscanthus sale price are much higher than our distribution [32], we set our sale prices closer to miscanthus production costs to reflect common margins in our study area for mature agricultural markets\(^6\). Lower margins also reflect a more mature market with enhanced competition.

\(^6\) For example, corn and soybean returns (revenue less variable costs) have been projected to be $304–364/acre in 2014 in Central Illinois. Using our median productivity assumptions, miscanthus would require a price of $16–19 ton\(^{-1}\) above cost for equivalent returns (at a yield of 19 tons miscanthus per acre). For cost estimates, see: http://farmsdcedaily.illinois.edu/2013/10/corn-soybean-returns-stable-Illinois-acreages.html.
Figure 3. Probability distribution for optimal scaled-up biorefinery size. The distribution is bimodal (mean = 174.15 MMgal yr⁻¹), with a peak in the 100–200 MMgal yr⁻¹ range, and another higher peak in the 10–30 MMgal yr⁻¹ range.

The fixed transport unit costs and variable transport unit costs are treated as uniform distributions. We set our bounds for fixed transportation costs between $3 ton⁻¹ and $5 ton⁻¹, and variable transportation costs between $.07 (ton km)⁻¹ and $.20 (ton km)⁻¹, based on ranges for similar feedstocks cited in previous studies [33, 34]. A uniform distribution is appropriate when there is little reason to suspect a more sophisticated functional form.

Biorefining miscanthus-to-ethanol yield is fixed at 90 gal ethanol per ton (dry) feedstock [13]. Finally, we assume that the refinery will have a lifetime of 20 years, as in [13], and that capital costs are amortized with straight-line depreciation at 7.5% in real terms.

5. Results and discussion

Figure 3 below shows a probability distribution for the optimal scaled-up size for a miscanthus-to-ethanol biorefinery. The distribution is bimodal, with a peak in the 150–250 MMgal yr⁻¹ range, and another higher peak in the 10–30 MMgal yr⁻¹ range. The distribution has a mean value of 193.4 MMgal yr⁻¹ and a standard deviation of 117.8. The mean value is within an order of magnitude of previous analyses; Wright and Brown (2007) find an optimal plant size for biochemical cellulosic ethanol of 240 million gallons of gasoline-equivalent annually (or 360 MMgal yr⁻¹ of ethanol) [10]. The smaller scale is explained by the considerable density at the low end of the distribution.

The low mode optimal size corresponds to scenarios in which a low fraction of farmers elect to convert to miscanthus cultivation. Such scenarios could be driven by high corn or soy prices, by low miscanthus prices, or by a combination of these. In such scenarios, the density of biomass resource available near the plant drops, and transport distances grow. Longer transport distances increase this component of the overall cost, resulting in a lower optimal biorefinery size.

Figure 4 below demonstrates that it is market prices that lead to the considerable dispersion and low mode of the optimum plant size distribution. Corn and soy prices are the greatest drivers of variance, and have a greater influence on optimal plant size than even the scaling exponents. With other parameters held constant at their median, corn prices drive optimal facility sizes near zero at (at $3.80 bushel⁻¹) or up to 304 MMgal yr⁻¹ (at $1.50 bushel⁻¹). Similarly, low soy prices or high miscanthus prices lead to a 302 MMgal yr⁻¹ optimal scale at $4.50 bushel⁻¹ (for soy) or $54 ton⁻¹ (for miscanthus), but decrease scale to 63 MMgal yr⁻¹ at $9.60 bushel⁻¹ (for soy) or $43 ton⁻¹ (for miscanthus). High capital cost exponents (>75) or transport cost scaling exponents (>1.6) lead to an optimal scale at less than 150 MMgal yr⁻¹. The effect of parameter variation varies with plant size; for example, capital cost economies of scale have greatest impact at small plant sizes.

Practically speaking, these results imply that companies and entrepreneurs should exercise caution in the scale-up of biorefineries. While the mean optimal plant size is greater than the largest plant built or planned by a factor of seven, there is a considerable probability that the optimal plant size could be much lower; almost 30% of the distribution lies below 100 MMgal yr⁻¹, and there is a 12% chance that the optimal size is less than 30 MMgal yr⁻¹. By comparison, only 6% of our distribution lies above the 360 MMgal yr⁻¹ value found by Wright and Brown [10]. Wright and Brown assume 60% of acreage surrounding a plant is available for feedstock production, which is higher than most simulated cases in our study; on average, we find 34% (figure 5). Moreover, the cost of building the wrong size plant is likely asymmetric if the miscanthus fermentation pathway is profitable as a gasoline replacement: it is likely more costly to build a plant too large (such that biomass to fully utilize plant capacity cannot be economically obtained) than to build a plant too small (such that all available biomass cannot be utilized and some profits are foregone).

Given this cost asymmetry and the considerable probability that the optimal refinery size could be below the mean, companies or entrepreneurs will benefit from pursuing incremental scale-up, if the resulting fuel is competitive at market prices. Companies would also benefit from seeking to minimize drivers of variability when possible. Much of the variability lies with the decision of farmers to convert to energy crop growing. As figure 5 shows, the distribution of crop conversion fraction emerging from the crop conversion sub-model has a mode in the 0 to 5% range. To the extent that refineries can offer long-term contracts to farmers that minimize the risk of choosing the less profitable crop, refineries can ‘lock in’ a certain percentage of cropland for miscanthus cultivation. Such certainty will minimize the probability of scenarios with extremely high transport costs (i.e. low optimal size plants) and reduce the overall dispersion in the distribution of optimal scale.
6. Conclusions

This study employs an optimization framework including a stochastic sub-model for land conversion to estimate the optimal scale for potential cellulosic biorefineries in the Midwest US. We then use simulation to obtain a probability distribution for the optimal scale of an example biorefinery using a fermentation process and miscanthus feedstock. We find a bimodal distribution for biorefinery scale with a low peak at around 10–30 MMgal yr\(^{-1}\) (representing circumstances where a relatively low percentage of farmers elect to participate in miscanthus cultivation) and a higher and flatter peak between 100 and 200 MMgal yr\(^{-1}\), representing more typically assumed land-conversion conditions.

This distribution leads to useful insights; in particular, the asymmetry of the distribution—with significantly more mass on the low side—indicates that developers of cellulosic ethanol biorefineries may wish to exercise caution in scale-up. We suggest that it is likely more costly to oversize cellulosic

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**Figure 4.** Tornado plot for optimal scaled-up biorefinery size. Bar labels show the test range for each input variable (10th and 90th percentile). Corn price, soy price, and miscanthus price account for 87% of variation.

**Figure 5.** Probability distribution of cropland conversion fraction. The distribution of crop conversion fraction emerging from the crop conversion sub-model has a mode in the 0 to 5% range, leading to low values for optimal scale. Average crop fraction is 34%.
biorefineries and risk under-utilization of capacity than to
undersize them and forego the maximum amount of profit
possible.

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