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# Stochastic optimization of cellulosic biofuel supply chain incorporating feedstock yield uncertainty

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**Abstract**

The global goal to reduce dependence on fossil fuels and to mitigate greenhouse gas emissions has resulted in research focused on environment friendly and socio-economically sustainable renewable energy sources. However, commercial production of bio-energy is constrained by biomass supply uncertainty and associated costs. This study presents an integrated approach to determining the optimal biofuel supply chain considering biomass yield uncertainty. A two-stage stochastic mixed integer linear programming is utilized to minimize the expected system cost while incorporating yield uncertainty in the strategic level decisions related to biomass production and biorefinery investment. Applicability of the stochastic model is illustrated through a case study of switchgrass-based biofuel in west Tennessee.



*Keywords:* switchgrass; stochastic; strategic decision; land use; uncertainty

## 1. Introduction

Growing concerns over future energy security and the need for sustainable renewable energy have encouraged government policies to stimulate biofuel production and use from various sources. Lignocellulosic biomass (LCB) has potential to be the socio-economically sustainable renewable energy source to address these concerns [1]. There has been considerable research on the effects of energy-crop based (second-generation) biofuels on mitigating negative

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consequences associated with food-crop based (first-generation) biofuels. Currently, commercial production of second-generation biofuels that is expected to be mainly produced from LCB, such as switchgrass, remains negligible. One challenge with switchgrass is the strategic uncertainty associated with designing and implementing an efficient switchgrass-based biofuel (SB) supply chain. Variation in biomass availability due to diverse climatic conditions not only hinders the operations of the biofuel industry but also creates difficulties in the assessment of strategic investment decisions. For example, Morrow et al. [2] stated drought induced yield reduction could bring economic disruption to many biorefineries planned in the United States (U.S.) following the climate models. It is crucial to design an optimal SB supply chain for large scale biofuel production while addressing feedstock supply uncertainty.

Driven by the impacts of variation in biomass feedstock availability on the investment and operations of the biofuel industry, a growing number of studies have examined the optimization of biomass to biofuel supply chain considering the uncertainty related to feedstock supply [e.g. 3, 4, 5]. These studies, however, do not address land use decision for feedstock production in the strategic decision level, which needs certain attention because of the absence of markets for large scale supply of biomass currently. In addition, when taking into account feedstock yield variation in the previous studies, a uniform distribution of arbitrary yields was typically assumed without considering spatial characteristics of feedstock. Thus, this study aimed to complement the related literature by developing an optimal supply chain of switchgrass that includes the feedstock establishment along with biorefinery location in the investment decision accounting for switchgrass yield variation from a field experiment data in west Tennessee.

## 2. Analytical Method

A mixed integer linear programming (MILP) was developed incorporating feedstock yield uncertainty, with the optimal supply-chain decisions driven by the expected system cost minimization. When making supply chain design decisions prior to the realization of uncertain parameters, a two-stage stochastic model is often employed [6]. First-stage (strategic/investment) decisions must be made before the realization of uncertain parameters, whereas the second-stage (operational) decisions maintain the flexibility of recourse. Optimal strategic and operational level variables are derived by minimizing the first-stage cost ($Cost_{1st\text{-}stage}$) and the expected second-stage random costs ($Cost_{2nd\text{-}stage}(s)$) with the probability ($prob$) associated with each random feedstock yield scenario ($s$) in equation (1). This model can be generally expressed as

$$Minimize{:}\ E\,(Cost) = \textstyle\sum_{s \in S} Cost\,(s) \times prob\,(s) \tag{1}$$

$$Cost\,(s) = Cost_{1st\text{-}stage} + Cost_{2nd\text{-}stage}\,(s) \tag{2}$$

$$Cost_{1st\text{-}stage} = C_{inv}^{fac} + C_{est}^{swi} + C_{opc}^{swi} \tag{3}$$

$$Cost_{2nd\text{-}stage}\,(s) = C_{pro}^{swi}\,(s) + C_{stg}^{swi}\,(s) + C_{trans}^{swi}\,(s) + C_{conv}^{bio}\,(s) + C_{trans}^{bio}\,(s) + C_{short}^{bio}\,(s) \tag{4}$$

where scenario-independent $Cost_{1st\text{-}stage}$ includes annualized costs of conversion facility investment ($C_{inv}^{fac}$), switchgrass establishment ( $C_{est}^{swi}$), and opportunity cost of producing switchgrass ($C_{opc}^{swi}$); and $Cost_{2nd\text{-}stage}(s)$ include costs of switchgrass production $C_{pro}^{swi}$ ($s$), switchgrass storage $C_{stg}^{swi}$ ($s$), switchgrass transportation $C_{trans}^{swi}$ ($s$), biofuel conversion $C_{conv}^{bio}$ ($s$), biofuel transportation $C_{trans}^{bio}$ ($s$), and biofuel shortage $C_{short}^{bio}$ ($s$).

The cultivation area for feedstock needs to be determined before biofuel production because switchgrass may require three years to reach the matured yield of switchgrass. Similarly, conversion facility (biorefinery) establishment is a long-term capital-intensive decision. Thus, the land use for feedstock cultivation and biorefinery investment decisions should be decided before the realization of feedstock production. Total opportunity cost of switchgrass production ($C_{opc}^{swi}$) is the summation of land use opportunity costs which differ across existing land uses in addition to spatial variations. Land use opportunity cost is defined as either net return from existing land use, or land rent, whichever is higher. The production, storage, processing, transportation, and inventory management operations are influenced by parametric uncertainty and can be adjusted for a particular realization of the feedstock yield. The two-stage model was solved subject to land availability, harvesting capacity, feedstock inventory balance, biorefinery capacity, and biomass conversion constraints given spatial distribution and seasonality of feedstock production.

## 3. Data

Cost and production data for establishing switchgrass-based ethanol industry in west Tennessee was obtained from Yu et al. [7]. Data from field trials between 2006 and 2011 at west Tennessee [8, 9] was utilized to generate yield uncertainty scenarios across existing agricultural lands on 5 square mile spatial units. Fifteen yield intervals were created in which each interval was assumed a scenario with probability obtained from the frequency distribution of yield under each scenario (Table 1). Within each scenario, normally distributed yield pattern was mapped, accounting for spatial yield variation per the simulated switchgrass yields across the U.S. [10].

A total of 18 industrial parks were identified as candidates for establishing biorefinery. Each location can locate at most one biorefinery with either 189 million liters per year (MLY) or 378 MLY capacity. Similarly, a total of 1936 spatial units were eligible for switchgrass cultivation replacing existing crops. An annual demand of 1.1 billion liter (L) ethanol for west Tennessee was assumed [7]. A biomass-to-ethanol conversion efficiency of 304 L/Mg for switchgrass was used in the analysis.

Table 1. Yield scenarios

| Scenario | Yield range (Mg/ha) | Prob. |
|---|---|---|
| S1 | $2.22 \leq \psi^{*} < 4.67$ | 0.005 |
| S2 | $4.67 \leq \psi < 7.12$ | 0.016 |
| S3 | $7.12 \leq \psi < 9.59$ | 0.067 |
| S4 | $9.59 \leq \psi < 12.03$ | 0.124 |
| S5 | $12.03 \leq \psi < 14.48$ | 0.159 |
| S6 | $14.48 \leq \psi < 16.93$ | 0.220 |
| S7 | $16.93 \leq \psi < 19.37$ | 0.183 |
| S8 | $19.37 \leq \psi < 21.84$ | 0.118 |
| S9 | $21.84 \leq \psi < 24.29$ | 0.063 |
| S10 | $24.29 \leq \psi < 26.69$ | 0.023 |
| S11 | $26.69 \leq \psi < 29.16$ | 0.009 |
| S12 | $29.16 \leq \psi < 31.63$ | 0.007 |
| S13 | $31.63 \leq \psi < 34.10$ | 0.002 |
| S14 | $34.10 \leq \psi < 36.57$ | 0.002 |
| S15 | $36.57 \leq \psi \leq 39.04$ | 0.002 |

*Denotes spatial yield

## 4. Results and Discussion

Table 2 presents the annualized cost or expected cost by operation in the supply chain from the two-stage stochastic model, totaled $1,124 million for the whole biofuel supply system. The major supply-chain cost was the expected operation (conversion) cost of biorefineries of $350 million, followed by annualized investment in biorefineries of $326 million. The expected cost on shortage was $85 million, based on a penalty parameter of $1.32/L for not meeting the demand from the blending facility. This amount can be interpreted as the cost incurred at the biofuel industry to procure the quantity of biofuel from alternative sources to meet the contractual demand of the blending facility in the low yield scenarios. The expected cost of delivering biomass to the biorefinery (plant-gate cost) for the harvest season factoring dry matter loss during transportation was around $74/Mg. Considering storage costs and the dry matter loss during storage and transportation, the expected facility-gate cost for the off-harvest season ranged from $109 to

112/Mg based on facility locations. From the biofuel supply perspective, the overall cost of delivering 1.1 billion L of ethanol to the blending facility is $1.02/L.

Table 2. Annualized cost components for investment and production of switchgrass in Tennessee

| Annualized variables | Unit | Level |
|---|---|---|
| Biorefinery investment cost | Million $ | 326 |
| Feedstock establishment cost | Million $ | 49 |
| Land use opportunity cost | Million $ | 20 |
| Feedstock maintenance cost | Million $ | 36 |
| E*(Feedstock harvest cost) | Million $ | 101 |
| E(Feedstock storage cost) | Million $ | 22 |
| E(Feedstock grinding cost) | Million $ | 49 |
| E(Feedstock transportation cost) | Million $ | 62 |
| E(Biofuel transportation cost) | Million $ | 25 |
| E(Biorefinery operation cost) | Million $ | 350 |
| E(Shortage penalty cost) | Million $ | 85 |

*E refers the expectation operator

Optimal land allocation for switchgrass production and biorefinery location under minimization of expected cost is shown in Fig. 1. Three biorefineries, each with the capacity of 378 MLY, were selected to meet the 1.1 billion L ethanol demand. A considerable spatial variation in switchgrass yield across potential cultivation sites was identified under all scenarios. Locating biorefineries near the high yield sites reduced the biomass transportation cost but increased the biofuel transportation cost to blending facility (northern region had higher yields while the blending facility was in the southwest), which mostly explains the observed optimal locations for the biorefineries.

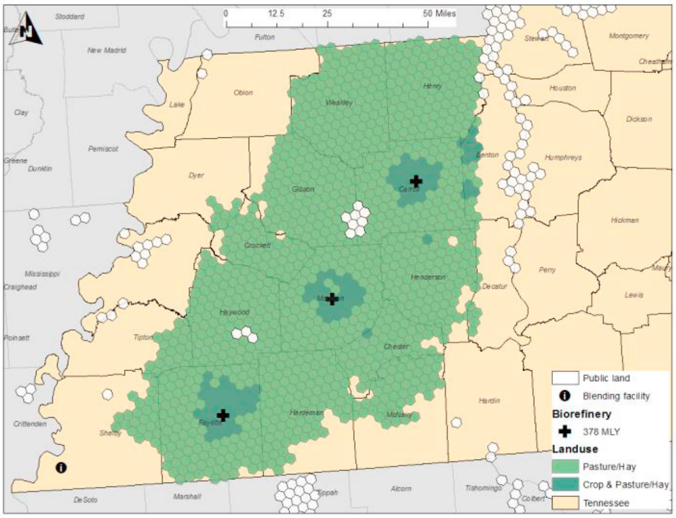


Fig. 1. Optimal land use and biorefinery location

An important consideration in particular land selection is the opportunity cost of land use change. Selection of land under food crops entailed higher opportunity costs compared to pasture which explains the reason behind selecting more pasture land, i.e. 265 thousand hectares, compared to 14 thousand hectares of crop land. Crop land was selected only when the difference in biomass transportation costs between distant pasture fields and proximal crop land exceeded the difference in opportunity costs between the crop land and pasture land.

Such differentiations provide insights into which yield scenarios were more influential in expected system cost minimization, as shown in the Figs. 2 and 3. Yield scenarios with higher probabilities resulted in smaller costs since optimal land allocation for feedstock cultivation was driven by higher probability scenarios while minimizing the expected supply-chain cost (Fig. 2). As expected, biomass surplus and biofuel shortage under each scenario were mutually exclusive (Fig. 3). Also, the lowest cost scenario (S5) with the yield ranging between 12.03 and 14.48 Mg/ha (see Table 1) did not incur penalty cost on shortage nor the inventory cost on surplus.

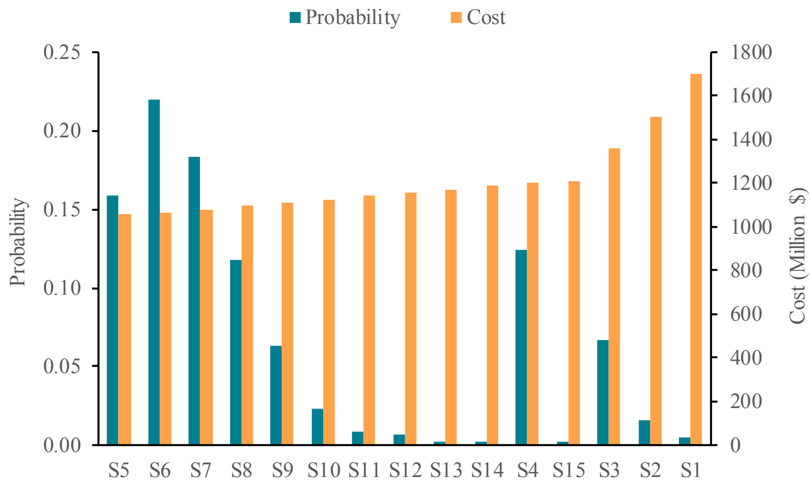


Fig. 2. Probability distribution of optimal costs
Note: Scenarios presented in the ascending order of costs

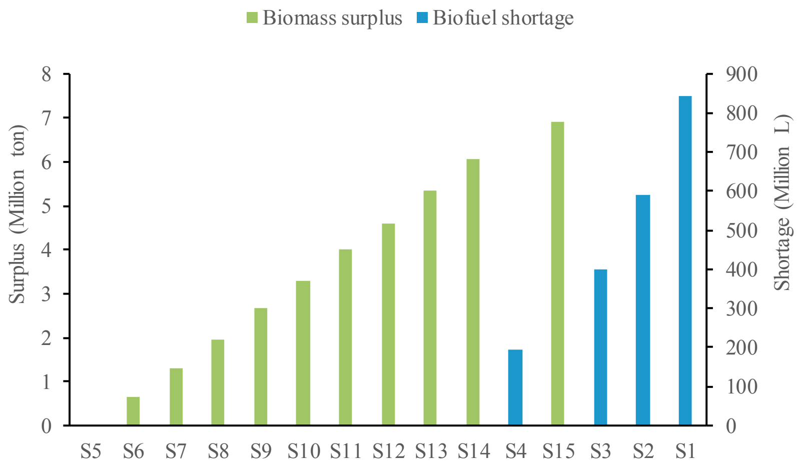


Fig. 3. Biomass surplus and biofuel shortage
Note: Scenarios presented in the ascending order of costs

## 5. Conclusion and recommendations

Designing a cost-efficient supply chain that considers biomass yield uncertainty is vital to the commercialization of biofuel industry. This study developed an optimal supply chain incorporating biomass supply uncertainty in terms of expected cost of supplying commercial-scale cellulosic ethanol. A two-stage stochastic MILP was employed considering allocation of land for switchgrass cultivation in investment decision together with biorefinery configuration under strategic uncertainty of feedstock yields. Applicability of the stochastic model was illustrated through a case study in west Tennessee. Biorefinery location was influenced by the transportation costs and the spatial yield variability whereas the land use decisions were dictated by yield scenarios with higher probabilities along with land use opportunity costs.

The cost-efficient design emerged from integrated supply-chain optimization can serve as an important guideline in decision-making process for large-scale biofuel production under strategic uncertainties. This study is unique because of the use of experimental data collected from field trials in west Tennessee for generating probabilistic yield scenarios rather than assuming a random uniform distribution. Instead of expected economic performance, which assumes risk-neutrality, implementing and optimizing risk measures which provides effective risk mitigating strategies under uncertainties, could be an important extension of this work. Furthermore, future research can incorporate policy supports, which are considered vital for commercial success of perennial energy crops-based biofuel, under uncertain environment.

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