Stochastic Optimization of a Biofuel Supply Chain With and Without BCAP Considering Switchgrass Yield Uncertainty and Risk Preference

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MOTIVATION

•Biofuel produced from switchgrass is potentially a socio-economically sustainable renewable energy source.
•However, feedstock yield uncertainty and high production costs are significant barriers to invest in a feedstock supply chain for biofuel production.
•Stochastic supply chain designs have primarily focused on optimizing expected economic performance based on the assumption of risk neutrality.
•Design of a risk efficient supply chain that considers biomass yield uncertainty is key to the commercialization of biofuel industry.

OBJECTIVES

Design a risk efficient switchgrass-based biofuel supply chain for large scale biofuel production under biomass supply uncertainty. Specifically, this study:

•Develops the optimal supply chain incorporating strategic land use decisions based on yield uncertainty and risk preferences of decision makers; and
•Estimates the impact of USDA's Biomass Crop Assistance Program (BCAP) on designing a risk efficient supply chain under different risk preferences.

ANALYTICAL METHODS

Expected cost minimization (Model 1): Risk-neutral preference

- Computation of optimal strategic and operational level variables is driven by the minimization of the first-stage cost ($Cost_{1st\_stage}$) and the expected second-stage random costs ($Cost_{2nd\_stage}(s)$) with the probability associated with each random feedstock yield scenario ($prob\ (s)$).

$$Min:\ E(Cost) = \sum_{s\in S} Cost(s) \times prob\ (s)$$

$$Cost(s) = Cost_{1st\_stage} + Cost_{2nd\_stage}(s)$$

$$Cost_{1st\_stage} = C_{inv}^{fac} + C_{est}^{swi} + C_{opc}^{swi}$$

$$Cost_{2nd\_stage}(s) = C_{pro}^{swi}(s) + C_{stg}^{swi}(s) + C_{trans}^{swi}(s) + C_{conv}^{bio}(s) + C_{trans}^{bio}(s) + C_{short}^{bio}(s)$$

- Scenario independent first-stage costs include annualized costs of conversion facility investment (C_{inv}^{fac}), switchgrass establishment (C_{est}^{swi}), and opportunity cost of switchgrass (C_{opc}^{swi}).
- Scenario dependent second-stage costs 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 inclusive of penalty on biofuel shortage: $C_{short}^{bio}(s)$.

Conditional Value-at-Risk minimization (Model 2): Risk-averse preference

Within a given confidence interval z, Value-at-Risk (VaR_z) of random costs is defined as the lowest value t such that with probability z the cost will not be greater than t (Rockafellar and Uryasev 2000). Conditional Value-at-Risk ($CVaR_z$) is the conditional expectation of the cost above the value t.

$$Min: CVaR_z(Cost, z) = \frac{\sum_{s\in S} \emptyset(s) \times prob(s)}{1-z} + VaR_z(Cost)$$

Subject to:

$$\emptyset(s) \geq Cost(s) - VaR_z(Cost), \emptyset(s) \geq 0, VaR_z(Cost) \geq 0$$

Modeling influence of BCAP subsidies

Introduced subsidy for feedstock establishment and maintenance costs offered in the BCAP. Introduced 50% subsidy in amortized feedstock establishment costs and amortized the total of 5-year annual subsidies corresponding to maintenance costs (equivalent to land rents) offered in the BCAP. Discount rate of 10% for establishment subsidies and 7.5% for maintenance subsidies were used.

KEY DATA AND PARAMETERS

- Spatial data in 5 square-mile for switchgrass production and biorefinery location was used for West Tennessee (Yu et al. 2016).
- Annual demand of 290 million gallons biofuel from blending facility near Memphis.
- Penalty for not fulfilling demand equals $5/gallon and the risk aversion parameter z equals 95th percentile.
- Fifteen yield scenarios were generated from mature switchgrass yield at west Tennessee in 2006-2011 (Boyer et al. 2013) (Table 1).
- Within each scenario, normally distributed yield pattern is mapped following Jager et al. (2010).

Table 1. Simulated Yield Scenarios

Scenario	Yield (ton/acre)	Prob.
S1	$0.9 \leq \delta^* < 1.89$	0.005
S2	$1.89 \leq \delta < 2.88$	0.016
S3	$2.88 \leq \delta < 3.88$	0.067
S4	$3.88 \leq \delta < 4.87$	0.124
S5	$4.87 \leq \delta < 5.86$	0.159
S6	$5.86 \leq \delta < 6.85$	0.220
S7	$6.85 \leq \delta < 7.84$	0.183
S8	$7.84 \leq \delta < 8.84$	0.118
S9	$8.84 \leq \delta < 9.83$	0.063
S10	$9.83 \leq \delta < 10.8$	0.023
S11	$10.8 \leq \delta < 11.8$	0.009
S12	$11.8 \leq \delta < 12.8$	0.007
S13	$12.8 \leq \delta < 13.8$	0.002
S14	$13.8 \leq \delta < 14.8$	0.002
S15	$14.8 \leq \delta \leq 15.8$	0.002

*Denotes spatial yield

RESULTS

Decisions without BCAP subsidies

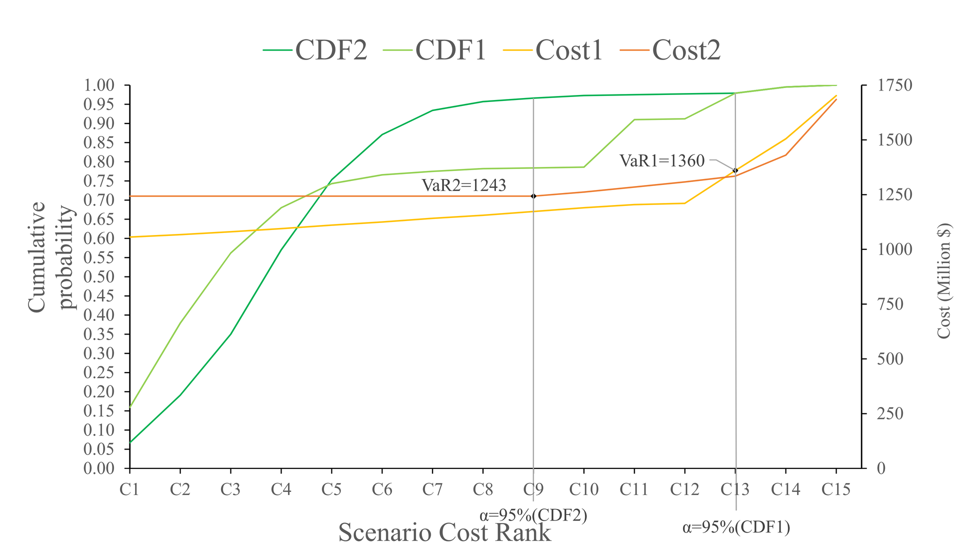

Fig. 1. Cumulative Density Function (CDF) of optimal costs under both models

Note: Cost1 and Cost2 denotes optimal costs associated with yield scenarios for the Model 1 and 2 respectively. CDF1 and CDF2 denotes cumulative density of the optimal costs for the Model 1 and 2 respectively. Cost rank of each scenario under each model is shown in Table 2.

Table 2. Ranked Optimal Scenario Costs

Cost*	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
Model 1	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S4	S15	S3	S2	S1
Model 2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S2	S1

*Ranked in the ascending order

RESULTS (Cont'd)

Table 3. Optimal Objective Values

Objective	Unit	Model 1	Model 2
E(Cost)	Million $	1,124	**1,249**
CVaR(Cost)	Million $	**1,441**	1,358

Numbers in blue and Bold are calculated expost

•Although expected cost increased in Model 2, risk of high costs has been minimized i.e. CVaR decreases by $83 M (Table 3).
•Similarly, risk corresponding to 95th percentile of cost distribution has been reduced significantly in Model 2 i.e. VaR decreases by $117 M (Figure 1).
•Probability of those high costs was effectively reduced in Model 2 (Figure 1) . Low opportunity cost pasture land was primarily selected without BCAP subsidies. Only crop land near the biorefineries was converted (Figs 2 and 3).
•Model 2 selected more acreages under both the pasture and crop lands to reduce high costs of low yield scenarios in Model 1.
•The color indicates the type of land that the feedstock is coming from – pasture or pasture/cropland.
•Reduction of biofuel shortage in Model 2 lowered costs of low yield scenarios (Figure 4).

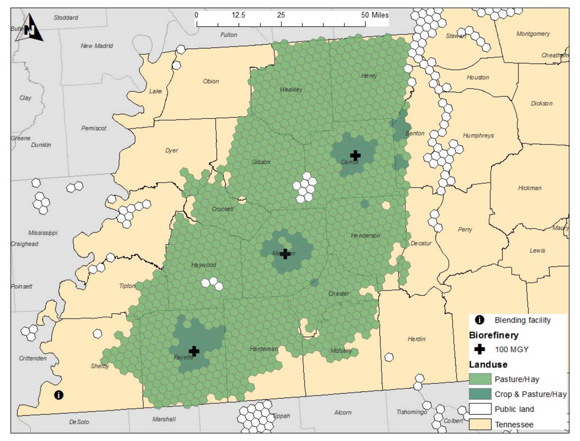

Figure 2. Model 1 without BCAP

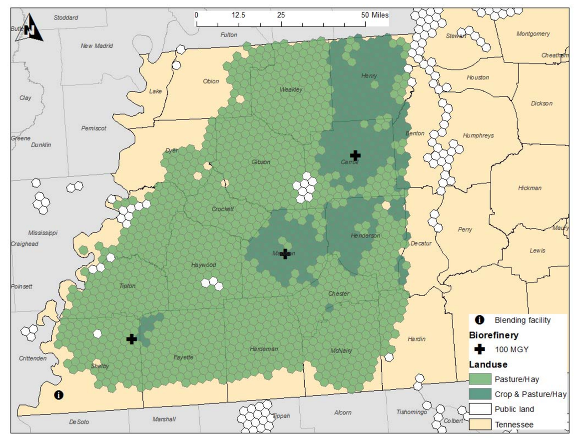

Figure 3. Model 2 without BCAP

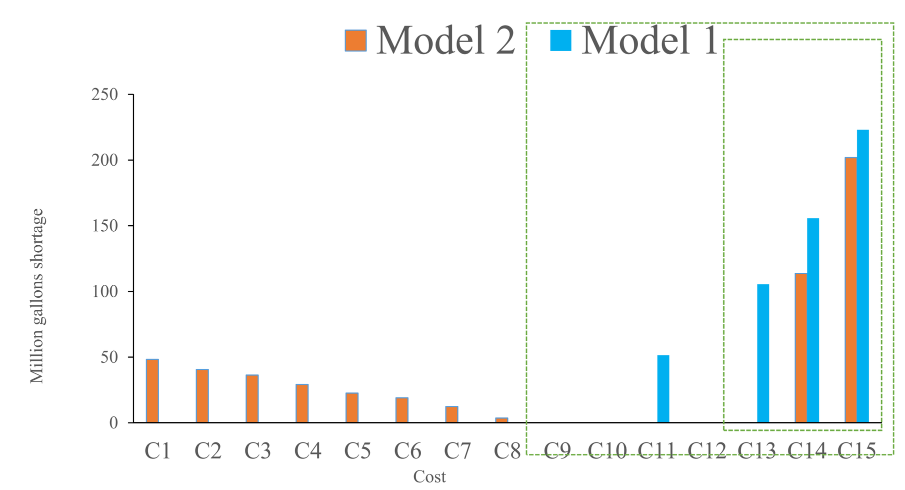

Figure 4. Optimal scenario costs and biofuel shortage

Note: Small and large insets capture 95th percentile and above cost distribution for Model 1 and 2 respectively

RESULTS (Cont'd)

Decisions with BCAP subsidies

With BCAP subsidies, both E(Cost) and CVaR(Cost) reduced but Model 2 achieved larger reduction because of more acreage selection (Fig. 5).

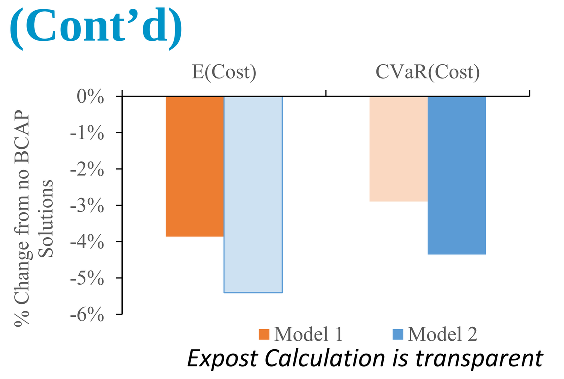

Fig. 5. Changes in objectives with BCAP

•Biorefinery locations shifted with increased crop acreage and less pasture acreage (Figures 6 and 7).
•A greater reduction in opportunity costs due to payments from BCAP for crop lands induced increased crop acreage selection.
•However, changes in land use was higher for Model 2 (Figures 3 and 7) than Model 1 (Figures 2 and 6) with more land with high spatial yields being selected.

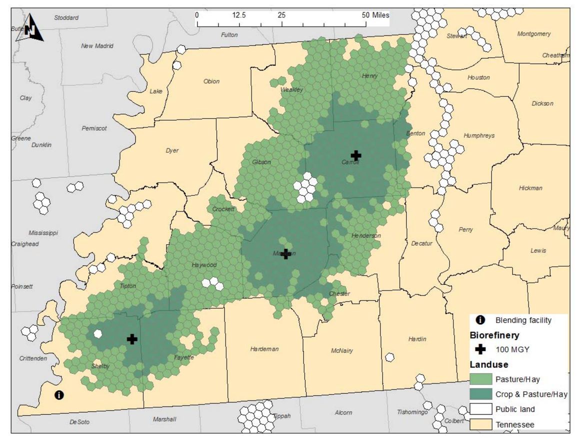

Figure 6. Model 1 with BCAP

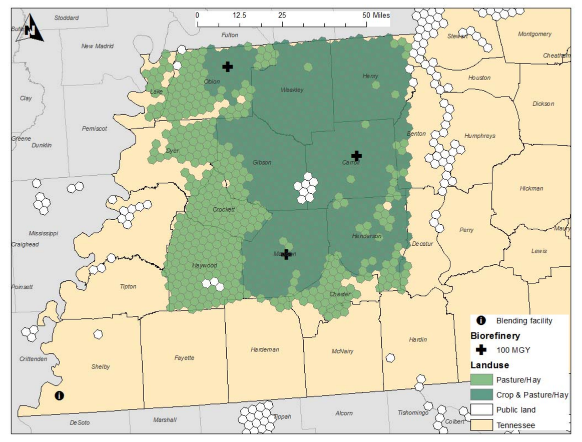

Figure 7. Model 2 with BCAP

CONCLUSION

•More acreage was selected to reduce the cost associated with low yield scenarios in the CVaR minimization model than in the risk-neutral preference model.
•When compared to the no BCAP solution, under the BCAP subsidies, crop land selection increased whereas pasture land use decreased. Biomass transportation costs were also lowered.
•Switchgrass supply uncertainty optimal investment decisions, (i.e. feedstock acreage as well as biorefinery configuration) were more responsive to BCAP subsidies with risk-averse individuals compared to risk-neutral decision makers.

REFERENCES

Boyer, C. N., R. K. Roberts, B. C. English, D. D. Tyler, J. A. Larson, and D. F. Mooney. 2013. Effects of soil type and landscape on yield and profit maximizing nitrogen rates for switchgrass production." *Biomass and Bioenergy* no. 48:33-42.

Jager, H. I., L. M. Baskaran, C. C. Brandt, E. B. Davis, C. A. Gunderson, and S. D. Wullschleger. 2010. "Empirical geographic modeling of switchgrass yields in the United States." *GCB Bioenergy* no. 2 (5):248-257.

Rockafellar, R. T., and S. Uryasev. 2000. "Optimization of conditional value-at-risk." *Journal of risk*, no. 2:21-42.

Yu, T. E., B. C. English, L. He, J. A. Larson, J. Calcagno, J. S. Fu, and B. Wilson. 2016. "Analyzing Economic and Environmental Performance of Switchgrass Biofuel Supply Chains." *BioEnergy Research* no. 9 (2):566-577.

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