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Impact of government subsidies on a cellulosic biofuel sector with diverse risk preferences toward feedstock uncertainty

Bijay P. Sharma [1], T. Edward Yu [*], Burton C. English, Christopher N. Boyer, James A. Larson

Department of Agricultural and Resource Economics, University of Tennessee, Knoxville, TN, 37996-4518, USA

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ABSTRACT

Investment risk and uncertainty about the availability of biomass feedstock hinders the development of a mature cellulosic biofuel sector. The Biomass Crop Assistance Program (BCAP) is a federal program designed to subsidize farmers to establish, produce and deliver biomass feedstock to biorefineries. This study evaluated the impacts of BCAP on the optimal biofuel supply chain decisions considering feedstock yield uncertainty and associated investment risk given diverse risk preferences of the biofuel sector. The expected cost for a risk-neutral biofuel sector was minimized using a two-stage stochastic mixed integer linear program, whereas the Conditional Value-at-Risk of the supply chain was optimized for a risk-averse sector. *Ex-ante* analysis of a switchgrass-based biofuel sector in west Tennessee indicates BCAP payments could lower expected cost and investment risk for both risk-averse and risk-neutral biofuel sectors. However, the cost saving and risk reduction resulting from BCAP incentives for the risk-averse biofuel sector were higher than the risk-neutral biofuel sector. In addition, BCAP payments may drive more cropland to be converted for switchgrass, which potentially mitigates water-induced soil erosion and reduces greenhouse gas emissions associated with net carbon sequestration, but may also create unintended consequence of competition for land between food and fuel use.

1. Introduction

Growing concerns over greenhouse gas (GHG) emissions from fossil fuel consumption have driven the formulation of government policies to promote the production and consumption of sustainable renewable energy. Biofuel produced from lignocellulosic biomass (LCB) has been suggested as a socio-economically sustainable source of renewable energy (Dale et al., 2011; Field et al., 2018). Perennial switchgrass is a promising LCB crop given its net negative life cycle GHG emissions as a biofuel feedstock compared to gasoline (Wright and Turhollow, 2010). In addition, switchgrass' adaptability on less fertile lands could reduce land competition among food crops (Naik et al., 2010; Carriquiry et al., 2011).

There has been considerable research exploring the potential of producing biofuels derived from switchgrass on a commercial scale (Schmer et al., 2008; Wang et al., 2012; Field et al., 2018). However, the production of switchgrass-based biofuel remains moderate. One of the main challenges to developing an efficient switchgrass supply chain is the uncertainty associated with strategic and operational decisions of the biofuel industry. Variability in biomass production due to weather makes the assessment of strategic investment decisions complex. Morrow et al. (2014) simulated the impact of droughts using climate models and suggest that yield reduction from drought could bring economic disruption to many biorefineries planned in the United States (US). Thus, addressing feedstock supply uncertainty and associated risks is crucial in designing a switchgrass supply chain for large scale biofuel production.

To mitigate the adverse impact of feedstock supply uncertainty on development of a biofuel industry, the United States Congress initiated the Biomass Crop Assistance Program (BCAP) in the Conservation and Energy Act of 2008 (US Department of Agriculture (USDA), 2015), and has reauthorized the program in the 2014 and 2018 Farm Bills. The BCAP provides three types of payments to producers of dedicated energy crops. First, feedstock establishment payments lower farmers' cost of planting dedicated energy crops by 50 percent under the cap of $1236 per hectare. Second, annual rental payments cover farmers' land rental

* Corresponding author. 317A Morgan Hall, 2621 Morgan Circle, University of Tennessee, Knoxville, TN, 37996-4518, USA.
E-mail addresses: bijaypdsharma@gmail.com (B.P. Sharma), tyu1@utk.edu (T.E. Yu), benglish@utk.edu (B.C. English), cboyer3@utk.edu (C.N. Boyer), jlarson2@utk.edu (J.A. Larson).

[1] Sharma was a Ph.D. student at the University of Tennessee when the study was completed. He is currently a postdoctoral research associate at the Institute for Sustainability, Energy and Environment in the University of Illinois, Urbana-Champaign.

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up to five years. Finally, matching payments of up to \$45 Mg^{-1} of feedstock partially covers the cost of collecting, harvesting, storing and transporting biomass to a biorefinery for no more than two years. The three types of payments may lower farmers' cost and risk of producing LCB crops, hence increasing feedstock supply and, ultimately, biofuel production.

A number of studies have assessed the economics of the BCAP through stochastic modeling of crop-enterpise level feedstock yields, prices, and profit and the determination of mean break-even prices of biofuels (Dolginow et al., 2014; Skevas et al., 2016). These studies indicate that the BCAP positively impacted the risk and return profile for LCB crops. Another thread of the literature has evaluated farmers' willingness to produce LCB crops given BCAP payments and found the incentives positively influenced farmers' decisions to adopt dedicated energy crops (Fewell et al., 2016; Eaton et al., 2018; Jiang et al., 2018). Several studies have also analyzed the impacts of BCAP with other biofuel policies on the environmental and economic metrics of biomass/biofuel network design with the goal of helping policymakers to broaden the scope of biofuel incentive programs (Chen and Önal, 2016; Ghani et al., 2018). However, the impact of BCAP subsidies on the design of a stochastic biofuel supply chain considering feedstock yields variation and decision makers' risk preference has not been evaluated.

Uncertainty of feedstock supply has been one of the major issues to address while optimizing the economics of a stochastic biofuel supply chain in the literature. A key assumption made in most studies is that the LCB feedstock is available from markets when local production is scarce (Chen and Fan, 2012; Tay et al., 2013; Huang et al., 2014; Tong et al., 2014; Fattahi and Govindan, 2018). However, large-scale markets for LCB feedstock do not presently exist so additional biomass for biofuel production cannot be easily located in years when there is a shortfall in production due to weather and other stochastic events. In addition, mature yields for perennial LCB crops do not occur until several years after feedstock establishment. Thus, land use choice for LCB production should be included in the strategic decision when addressing variation in the LCB yields. Except for Osmani and Zhang (2013), land selection for feedstock has been neglected in the previous studies of the stochastic biomass feedstock supply chain.

Another assumption embedded in supply chain analyses is risk neutral preferences of decision makers in the biofuel sector. However, the development of a commercial-sized switchgrass supply chain may be impeded by risk-aversion behavior of decision makers concerned about feedstock supply uncertainty. Financial risks associated with the operational level decisions in biofuel supply chain optimization have been addressed in several studies (Kostin et al., 2012; Giarola et al., 2013; Kazemzadeh and Hu, 2013; Sawik, 2013). However, production risk related to uncertainty of feedstock supply and associated land use at the *strategic level* for risk-averse decision makers trading off risk and return is still lacking in the literature.

Thus, the objectives of the present study are three-folded. First, we determined the impacts of BCAP on expected costs and the risk profile of a switchgrass-based supply chain in the presence of feedstock yield uncertainty. Presumably, BCAP subsidies should improve the risk profile of the supply chain. Second, we assessed the influence of land selection in the strategic decision stage on the cost and risk profile of the supply chain, which was typically omitted in stochastic biofuel supply chain studies. In contrast to previous studies that assumed additional feedstock available from markets to handle feedstock supply uncertainty, the present study included land use choice, along with biorefinery facility location, in the investment decisions to better capture feedstock yield uncertainty. Finally, our study aimed to provide a more comprehensive assessment of the biofuel sector's decisions in response to the incentives by including both risk-neutral and risk-averse decision makers in our analysis of BCAP.

2. Analytical methods

To address our study objectives, a two-stage stochastic program was employed to minimize expected cost for risk-neutral decision makers. The corresponding risk metrics, Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), were then calculated after optimization. Similarly, we minimized CVaR (and VaR simultaneously) for risk-averse decision makers of the biofuel sector using the stochastic model and calculated its associated expected cost. Selection of biorefineries location and capacity along with the amount of land required for switchgrass cultivation were the first-stage decisions. All of the first-stage (strategic) and second-stage (operational) decisions were driven by biofuel demand constrained by yield uncertainty. BCAP subsidies were introduced in both cases to illustrate the changes in cost and risk for both types of decision makers.

2.1. *Expected cost minimization model (model 1: risk-neutral decision makers)*

Minimizing the cost of a biofuel supply network system under yield uncertainty results in a two-stage program that optimizes the sum of the first-stage investment costs and the expected cost of the stochastic operations in the second-stage (Ahmed, 2010). It is a recourse model that requires decision makers to make the investment decision prior to operations and then minimize the expected cost of the resulting outcomes associated with the decision. To better capture the impact of stochastic switchgrass yields on the investment decision, our augmented two-stage stochastic mixed integer linear program (MILP) incorporated land use choice and feedstock establishment activities under the investment decisions in the first-stage. The cost associated with feedstock shortage in fulfilling the final demand was included since alternative feedstock availability was not considered. Similarly, feedstock production surplus, if any, was managed as an inventory with a storage cost.

Eq. (1) represents the objective function of the expected cost minimization model (referred as model 1 hereafter).

$$Minimize : E(Cost) = Cost_{1st-stage} + E\left(Cost_{2nd-stage}\right) \quad (1)$$

where all the identifiers, parameters and variables used in the stochastic model are defined in Table 1. Eq. (2) presents the investment related costs which includes annualized investment cost of biorefineries (C^{fac}_{inv}) and annualized establishment cost of switchgrass (C^{swi}_{est}). Similarly, opportunity cost of switchgrass (C^{swi}_{opp}) and maintenance cost of switchgrass (C^{swi}_{mnt}) are included in the first-stage as they were proportional to established switchgrass area (hectares). Computation of these investment cost components is expressed in Eqns. (3)–(6).

$$Cost_{1st-stage} = C^{fac}_{inv} + C^{swi}_{est} + C^{swi}_{opp} + C^{swi}_{mnt} \quad (2)$$

$$C^{fac}_{inv} = \sum_{j\in J}\sum_{g\in G}\left(\mu_g \times z_{jg}\right) \quad (3)$$

$$C^{swi}_{est} = \sum_{i\in I}\sum_{h\in H}\left(\alpha \times X_{ih}\right) \quad (4)$$

$$C^{swi}_{opp} = \sum_{i\in I}\sum_{h\in H}\left(\beta_{ih} \times X_{ih}\right) \quad (5)$$

$$C^{swi}_{mnt} = \sum_{i\in I}\sum_{h\in H}\left(AM \times X_{ih}\right) \quad (6)$$

where

$$\beta_{ih} = \left\{ \begin{array}{ll} P_{ih} \times Y_{ih} - C_{ih} & if \ \ (P_{ih} \times Y_{ih} - C_{ih}) \geq R_{ih} \\ R_{ih} & if \ \ (P_{ih} \times Y_{ih} - C_{ih}) < R_{ih} \end{array} \right\}$$

The establishment cost (α) is a one-time upfront cost that included the cost of seed, labor, and equipment for planting perennial switchgrass

Table 1
Definitions of identifiers, parameters and variables.

Category	Unit	Definition
Identifiers		
$i\ \varepsilon\ I$		location of switchgrass production field
$j\ \varepsilon\ J$		location of the biorefinery facility
$b\ \varepsilon\ B$		location of the blending facility
$g\ \varepsilon\ G$		annual capacity of conversion facility
$m\ \varepsilon\ M$		season of the year
$M_{on}\ \varepsilon\ M$		harvest season of the year
$M_{off}\ \varepsilon\ M$		off-harvest season of the year
$h\ \varepsilon\ H$		crop (pasture, corn, soybean, wheat, sorghum, cotton)
$s\ \varepsilon\ S$		uncertainty scenario for switchgrass yield
x		switchgrass
Parameters		
P_{ih}	\$/Mg	price of crop h at field i
Y_{ih}	Mg/ha	yield of crop h at field i
C_{ih}	\$/ha	production cost of crop h at filed i
Y_{ixs}	Mg/ha	yield of switchgrass under scenario s at file i
R_{ih}	\$/ha	land rent of crop h at field i
α	\$/ha	amortized establishment cost of switchgrass field
β_{ih}	\$/ha	opportunity cost of switchgrass to replace crop h at field i
AM	\$/ha	annual maintenance cost of switchgrass field
μ_g	\$/plant	amortized investment cost of conversion facility g
ω	\$/Mg	per unit harvest cost for switchgrass
γ	\$/Mg	cost per unit of storing switchgrass
Θ	\$/Mg	cost per unit of transporting switchgrass
ρ	\$/L	biorefinery operation cost
δ	\$/L	biofuel transportation cost
DT	%	dry matter loss during transportation
A_{ih}	Ha	available cropland for crop h at field i
DS	%	dry matter loss during storage
σ	L/Mg	switchgrass-ethanol conversion rate
Δ_{mjg}	L/ season	biofuel production capacity g of biorefinery j in season m
D_m	L/ season	demand for ethanol in season m
Ω	\$/L	penalty on biofuel shortage
$Prob(s)$		probability associated with scenario s
Variables		
z_{jg}		1 for selecting biorefinery capacity g at field j, 0 otherwise
X_{ih}	Ha	switchgrass area harvested from cropland h in the harvest season at field i
XNS_{is}	Mg	switchgrass not stored at field i after harvest under scenario s
XS_{is}	Mg	switchgrass stored at field i after harvest under scenario s
XO_{mijs}	Mg	switchgrass delivered from field i to biorefinery j in season m
$Surplus_{is}$	Mg	Switchgrass surplus after meeting demand under scenario s at field i
$Shortage_{ms}$	L	demand shortage of biofuel in season m under scenario s
XO_{mjbs}	L	fuel delivered from biorefinery j to blending facility b under scenario s in season m

and was based on Larson et al. (2010). The establishment cost was amortized over the 10-year lifespan of switchgrass and did not vary by land type. Following Yu et al. (2014), opportunity cost (β_{ih}) was defined as either the net returns from current land use or land rent, whichever was higher. Opportunity costs on a land unit basis (hectares) varied spatially in the model based on land use (pasture or crop) and the prior cropping activity (e.g., corn, soybean, wheat, etc.). Establishment cost, opportunity cost, and maintenance cost were related to the area of land converted to switchgrass and unrelated to feedstock yield.

Eq. (7) sums up the expected cost of all operations in the supply chain that were subject to yield uncertainty, including switchgrass harvest (C^{swi}_{hrv}), switchgrass storage (C^{swi}_{stg}), switchgrass transportation (C^{swi}_{trans}), biofuel conversion (C^{bio}_{conv}), biofuel transportation (C^{bio}_{tran}), and biofuel shortage (C^{bio}_{short}) costs.[2] These expected costs are calculated in Eqns. (8)–(13).

$$E(Cost_{2nd-stage}) = E(C^{swi}_{hrv}) + E\left(C^{swi}_{stg}\right) + E(C^{swi}_{trans}) + E(C^{bio}_{conv}) + E(C^{bio}_{trans}) + E(C^{bio}_{short}) \tag{7}$$

$$E(C^{swi}_{hrv}) = \sum_{i\in I}\sum_{h\in H}\sum_{s\in S} Y_{ixs} \times X_{ih} \times \omega \times prob\ (s) \tag{8}$$

$$E\left(C^{swi}_{stg}\right) = \sum_{i\in I}\sum_{s\in S} XS_{is}\ \times \gamma \times prob\ (s) \tag{9}$$

$$E(C^{swi}_{tran}) = \sum_{m\in M}\sum_{i\in I}\sum_{s\in S} XQ_{mis} \times \theta \times prob\ (s) \tag{10}$$

$$E(C^{bio}_{conv}) = \sum_{m\in M}\sum_{j\in J}\sum_{b\in B}\sum_{s\in S} XO_{mjbs} \times \rho \times prob\ (s) \tag{11}$$

$$E(C^{bio}_{tran}) = \sum_{m\in M}\sum_{j\in J}\sum_{b\in B}\sum_{s\in S} XO_{mjbs} \times \delta \times prob\ (s) \tag{12}$$

$$E(C^{bio}_{short}) = \sum_{m\in M}\sum_{s\in S} Shortage_{ms}\ \times \Omega \times prob\ (s) \tag{13}$$

Eqns. (14)–(22) define the constraints imposed on the cost minimization problem to connect the decisions in the first stage and second stage. Eq. (14) limits switchgrass production in each spatial unit to available agricultural land. Eq. (15) restricts total biomass available at each site to total biomass production at the given site. Eqns. (16)–(19) are mass balance/flow constraints. Harvested switchgrass is either directly transported to the biorefinery during harvest or stored for future delivery (Eq. (16)). Eq. (17) sets the cumulative switchgrass delivered to the facility plus the surplus feedstock at the end of the off-harvest period equal to the total biomass stored during the harvest season. Eq. (18) ensures that everything delivered to the biorefinery during each season is converted into ethanol. Eq. (19) guarantees any feedstock shortage plus bioethanol sent to a blending facility meets demand at the facility for each season. Eq. (20) allows at most one biorefinery at each site. Eq. (21) denotes the domain of the binary decision variables. Non-negativity constraints imposed on the continuous decision variables are listed in Eq. (22).

$$X_{ih} \leq\ A_{ih}\ \forall\ i,\ h \tag{14}$$

$$\sum_{h\in H} Y_{ixs} \times X_{ih}\ = XNS_{is} + XS_{is}\ \ \forall\ i, s \tag{15}$$

$$XNS_{is}\ = \sum_{m\in M_{on}}\sum_{j\in J} \frac{XQ_{mijs}}{(1-DT)}\ \ \forall\ i, s \tag{16}$$

$$XS_{is} = \sum_{m\in M_{off}}\sum_{j\in J} \frac{XQ_{mijs}}{(1-DS)\times(1-DT)} + \frac{Surplus_{is}}{(1-DS)}\ \forall\ i, s \tag{17}$$

$$\sigma\sum_{i\in I}\sum_{j\in J} XQ_{mijs} = \sum_{j\in J}\sum_{b\in B} XO_{mjbs}\ \forall\ m, s \tag{18}$$

$$\sum_{j\in J}\sum_{b\in B} XO_{mjbs} + Shortage_{ms} = D_m\ \forall\ m, s \tag{19}$$

$$\sum_{g\in G} z_{jg} \leq\ 1\ \forall\ j \tag{20}$$

[2] A penalty of \$1.32/L was applied to the biofuel shortage assuming that the penalty was 50 percent higher than the conventional gasoline price.

$$z_{jg} \in \{0,\ 1\}\ \forall\ j, g \tag{21}$$

$$X, XNS, XS, XQ, XO, Surplus, Shortage \geq 0 \tag{22}$$

2.2. CVaR minimization model (model 2: risk-averse decision makers)

Feedstock supply is a main source of uncertainty in the biofuel supply chain driven by the fluctuations in the yield, which is dependent on weather and other stochastic events. Consequently, the system may not be able to meet the demand, or there might be excess production resulting in inventory accumulation. The associated risk could be quantified using standard stochastic procedures in the optimization of economic metrics.

VaR and CVaR are commonly used to penalize for risk in stochastic supply chain optimization. Within a given confidence interval ϑ, VaR_ϑ of a random variable is defined as the lowest value t such that with probability ϑ the loss will not be greater than t (Rockafellar and Uryasev, 2000). Similarly, $CVaR_\vartheta$ is the conditional expectation of the loss above the value t. In this study, the random variable was replaced by integrated cost (Cost), and VaR_ϑ was the minimum value t such that the cost was less than or equal to t with probability ϑ. $CVaR_\vartheta$ was the conditional expectation of the integrated cost above the value t. For a discrete distribution of the costs under different yield scenarios, CVaR is more generally defined as the weighted average of the VaR and the costs strictly exceeding VaR (Krokhmal et al., 2002). This can be expressed as:

$$CVaR_\vartheta(Cost, \vartheta) = \frac{\sum_{s \in S} \varnothing(s) \times prob(s)}{1 - \vartheta} + VaR_\vartheta(Cost)$$

where

$$VaR_\vartheta(Cost) = Infimum\{t : Probability(Cost \leq t) \geq \vartheta\}$$

$$\varnothing(s) \geq Cost(s) - VaR_\vartheta(Cost),\ \varnothing\,(s) \geq 0,\ \ VaR_\vartheta(Cost) \geq 0$$

The non-negativity constraint of $\varnothing(s)$ makes sure it is set to zero if $Cost(s)$ was below $VaR_\vartheta(Cost)$ while computing $CVaR_\vartheta(Cost, \vartheta)$. Certain undesirable mathematical properties make VaR a non-coherent measure of risk (Artzner et al., 1999; Rockafellar and Uryasev, 2000). In addition, VaR is often criticized for offering no information on the risks above the defined percentile (Kidd, 2012). Thus, CVaR was minimized with the defined ϑ in this study using the stochastic model developed in Section 2.1 (Eq. (23)) (referred as model 2 hereafter):

$$Minimize : CVaR_\vartheta(Cost, \vartheta) = \frac{\sum_{s \in S} \varnothing(s) \times prob(s)}{1 - \vartheta} + VaR_\vartheta(Cost) \tag{23}$$

Subject to

$$\varnothing(s) \geq Cost(s) - VaR_\vartheta(Cost),\ \varnothing\,(s) \geq 0,\ \ VaR_\vartheta(Cost) \geq 0 \tag{24}$$

$$Eqns.(14) - (22) \tag{25}$$

The CVaR(Cost) minimization was implemented with ϑ equal to 95 percent where VaR(Cost) represented the value corresponding to the 95th percentile of the cost distribution. VaR(Cost) was simultaneously determined while the weighted average of the cost at the 95th percentile and the expectation of the costs exceeding the 95th was minimized in the model. The CVaR minimization model is referred as model 2 hereafter in the study. General Algebraic Modeling System (GAMS) was used to solve the two-stage stochastic MILP for the two different objectives (Rosenthal, 2008).

2.3. Estimating impact of BCAP subsidies

We introduced a subsidy that lowered amortized establishment costs by 50 percent. We also amortized 5 years of annual payments corresponding to land rents as offered in the BCAP.[3] Stochastic optimization outputs with and without BCAP were compared to see the effect of incentives on optimal land allocation and biorefinery configuration. The annualized 10 year switchgrass establishment payment was applied to the establishment cost (α) in Eq. (4) in section 2.1 through lowering α by 50 percent. Similarly, the amortized five-year annual rental payment was applied to the opportunity cost term (β_{ih}) in Eq. (5) as the annual rental payment was based on the land type (i.e. crop or pasture) converted to switchgrass.

3. Data

One novel feature of this study was the use of experimental data collected from field trials in west Tennessee for generating probabilistic yield scenarios rather than assuming a random uniform distribution of feedstock yield as was typically adopted in previous studies. Matured yield of switchgrass from field trials with fertilizer application rate of 67 kg N per hectare between 2006 and 2011 in west Tennessee (Boyer et al., 2012, 2013) was used to generate stochastic yields. Equally spaced yield intervals were created, and each interval was assumed a scenario with probability obtained from the frequency distribution of yield from the field trials data. Taking each interval's mean and standard deviation together with the truncation limits, yields were simulated assuming normally distributed yields to match the number of spatial units under each scenario.

A total of 15 different yield scenarios were used to optimization for each of the two-stage stochastic models (Fig. 1). A higher number of yield scenarios (sample size) allows more flexibility in choosing the risk-aversion parameter (ϑ -percentile) and improves reliability of the CVaR estimate as CVaR is more sensitive to estimation errors than the corresponding VaR (Yamai and Yoshiba, 2005). Spatial yield variation under each yield scenario was mapped based on simulated spatial variation in switchgrass yields across the US. (Jager et al., 2010). The study area was downscaled to 12.95 square km (5 square mile) land spatial units to capture spatial variation in stochastic switchgrass yields.

Potential sites for biorefinery and switchgrass establishment are shown in Fig. 2. A total of 18 industrial parks were identified as candidates for establishing biorefineries. Each spatial unit can locate a biorefinery with either 189 million liters per year (MLY) or 378 MLY capacity. Similarly, a total of 1936 spatial units (existing agricultural lands) were eligible for switchgrass cultivation replacing current crops. An annual demand of 1.1 billion liters (L) of ethanol for west Tennessee was assumed based on the estimate in Yu et al. (2016). A biomass-to-ethanol conversion efficiency of 304 L/Mg for switchgrass was used in the analysis. The sources of cost related data for switchgrass-based ethanol production in west Tennessee are summarized in Table 2.

4. Results and discussion

4.1. Risk-neutral biofuel sector (model 1) without and with BCAP subsidies

Without BCAP subsidies, the optimal supply chain cost, E(Cost), was \$1125 million,[4] while the corresponding VaR(Cost) and CVaR(Cost) risk penalties calculated using Eq. (23) were \$1360 million and \$1441 million, respectively. The annualized cost components of all investment

[3] Switchgrass is not eligible for the matching payment in the BCAP (USDA, 2015).

[4] All the monetary values are stated in 2015 US dollars.

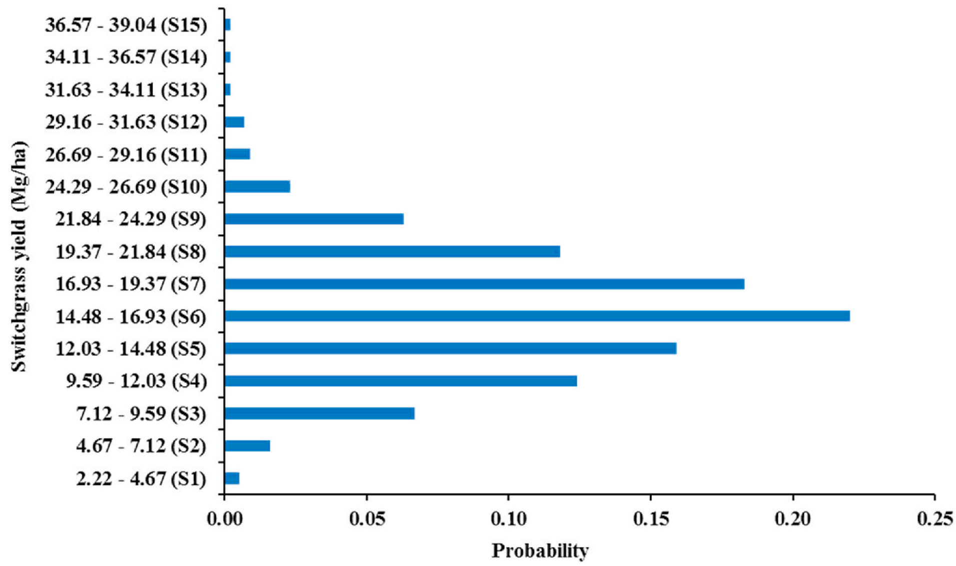

Fig. 1. Switchgrass yield scenario distribution.
Note: S1 through S15 denote stochastic yield scenarios.

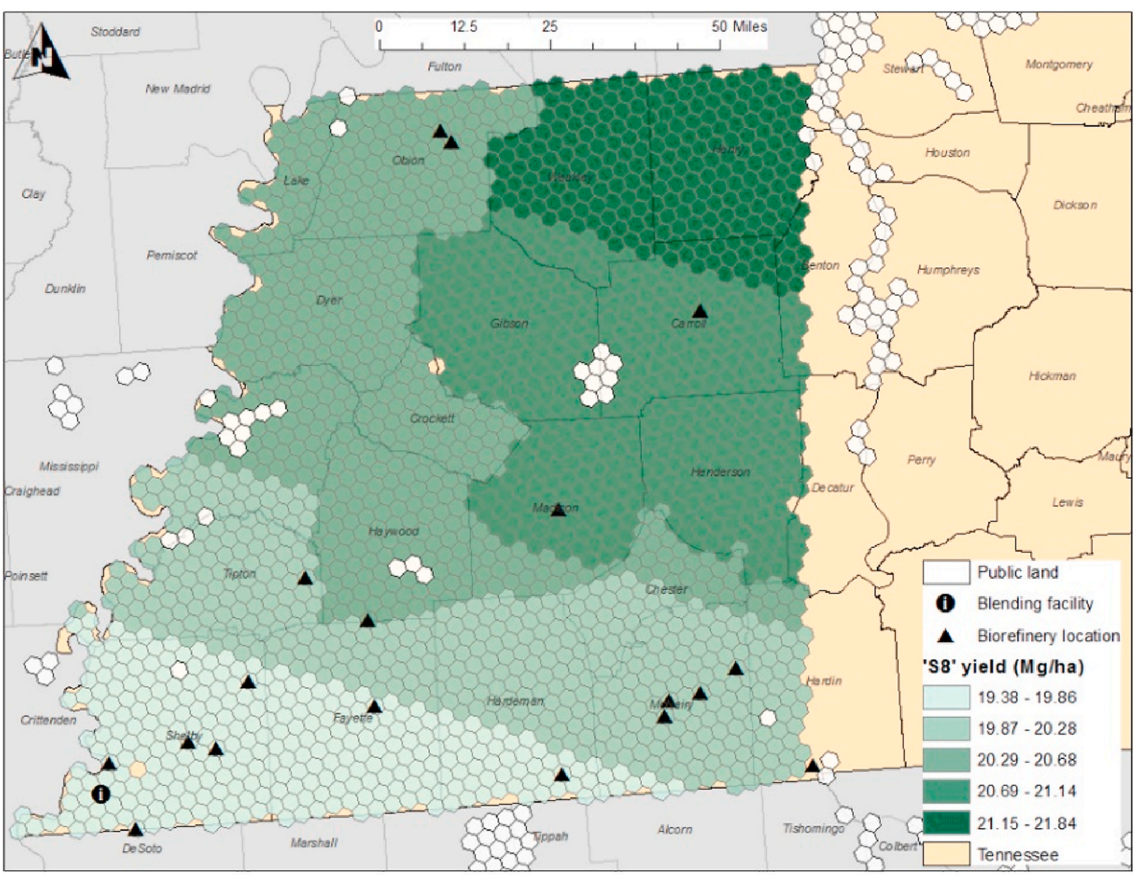

Fig. 2. Potential biorefinery locations and switchgrass yields in each spatial unit.
Note: The range of yield refers to the S8 yield scenario (19.37–21.84 Mg/ha) defined in Fig. 1.

(strategic) and operational level decisions in model 1 for the optimal E (Cost) are summarized in Table 3. About 60 percent of total supply chain cost was associated with biorefinery operations. For the three biorefineries in the supply chain (each with 378 MLY capacity), expected operational cost for biofuel conversion was about $350 million and annualized investment cost was $326 million. Feedstock harvest costs and the biofuel shortage penalty were the next most costly items within the supply chain. The expected cost of switchgrass transportation to the biorefineries was more than double the expected cost of biofuel transportation to the fuel-blending depot. Annualized feedstock establishment and maintenance costs were proportional to total land converted to switchgrass production. Opportunity cost was dictated by the type of

Table 2
Data source.

Category	Source
Land conversion to switchgrass	
Land rents	USDA NASS (U.S. Department of Agriculture, 2013–2015a)
Crop yields	USDA, SSURGO (U.S. Department of Agriculture Nature Resources Conservation Service, 2012)
Crop price and area	USDA NASS (U.S. Department of Agriculture, 2013–2015b)
Crop production cost	POLYSIS (Ugarte and Ray, 2000), USDA ERS (U.S. Department of Agriculture, 2015)
Switchgrass yield	Jager et al. (2010), Boyer et al. (2012), Boyer et al. (2013)
Switchgrass production and harvest cost	Larson et al. (2010), University of Tennessee (2015)
Production	
Establishment	American Agricultural Economics Association (2000)
Annual maintenance	American Society of Agricultural and Biological Engineers (2006)
Harvest	
Fuel and labor	University of Tennessee (2015)
Storage	
Covers and pallets	University of Tennessee (2015)
Transport	
Trailer, fuel and labor	University of Tennessee (2015)

Table 3
Annualized cost (million $) components in model 1 without BCAP subsidies.

Operation component	Cost	Operation component	Cost
Biorefinery investment cost	326	E(Grinding cost)	49
Feedstock establishment cost	49	E(Biomass transportation cost)	62
Opportunity cost	20	E(Biofuel transportation cost)	25
Maintenance cost	36	E(Biorefinery operation cost)	350
E(Harvest cost)	101	E(Shortage penalty cost)	85
E(Storage cost)	22		

Note: Model 1 represents the risk-neutral biofuel sector's decision of E(Cost) minimization. All numbers are in 2015 US million dollars. E is the expectation operator.

land on which switchgrass was planted (pastureland or cropland).

With BCAP subsidies, the overall optimal cost, E(Cost), of the supply chain was reduced by 4.1 percent to $1081 million. The corresponding CVaR(Cost) risk measure was marginally reduced from the no BCAP scenario and totaled $1399 million. Optimal land allocations for switchgrass establishment and the locations of biorefineries in model 1 for the two BCAP scenarios are shown in Fig. 3. Considerable spatial variation in switchgrass yields was observed across the 1936 land spatial units and the variation influenced the selected location for biorefineries. The model located biorefineries near higher yielding croplands to reduce transportation costs of bulky switchgrass but traded off lower switchgrass transportation costs with increased biofuel transportation costs to the blending facility. The interactions among lower land opportunity costs, higher yields, and shorter travel distances with cropland near potential conversion facility sites contributed to the placement of the supply chain given BCAP incentives.

About 14 thousand hectares of cropland and 265 thousand hectares of pastureland were converted to switchgrass. Biorefinery locations and land use choice in the strategic level decisions changed with the BCAP incentives (Fig. 3). The more compact feedstock draw areas in the BCAP scenario are influenced by the BCAP subsidies in several different ways in the model. The BCAP land rental subsidies on higher cost cropland lowered the opportunity cost of cropland relative to pastureland. Lower cropland opportunity costs, higher yields per hectare over which to spread first-stage (establishment, opportunity, and maintenance) costs, and shorter field to biorefinery travel distances (with lower transportation costs) contributed to more cropland near potential biorefinery sites coming into the solution. Thus, cropland planted with switchgrass increased to 73 thousand hectares with BCAP land rental payments, whereas pastureland/hayland converted to switchgrass decreased to 205 thousand hectares. This suggests that BCAP incentives may have had the unintended effect of displacing food and fiber production from cropland in the design of the supply chain. However, converting cropland to perennial grasses such as switchgrass also has the potential to reduce water-induced soil erosion that is a pervasive problem on cropland in West Tennessee (Zhong et al., 2016). Our results suggest that targeting BCAP subsidies towards more erodible cropland may align the program with the long-term US agricultural policy goal to reduce soil erosion (McGranahan et al., 2013).

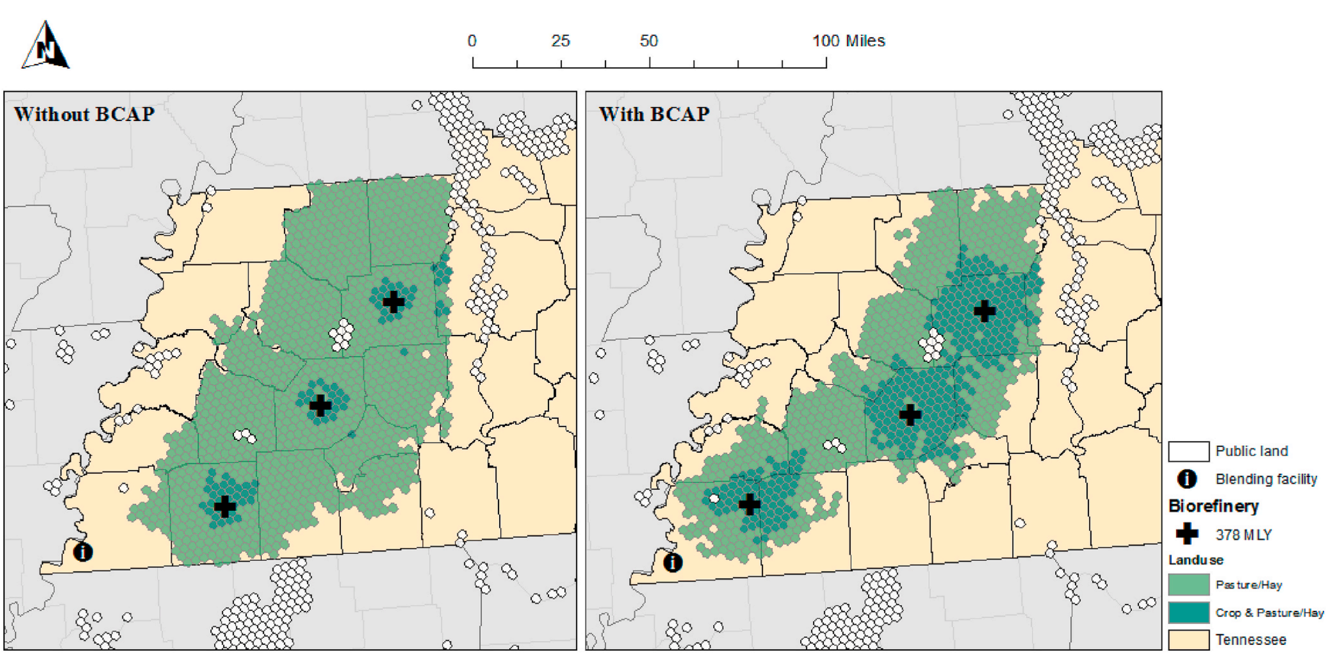

Fig. 3. Optimal investment decisions in model 1 with and without BCAP subsidies.
Note: Model 1 represents the risk-neutral biofuel sector's decision of E(Cost) minimization. E is the expectation operator.

Sizeable changes in the costs of certain supply chain activities were observed under the BCAP (Table 4). Expected switchgrass transportation cost dropped by $6 million, whereas expected biofuel transportation cost slightly increased from the no BCAP scenario. Expected biofuel transportation cost decreased because one of the biorefineries was located nearer the blending facility serving West Tennessee. Gross[5] opportunity cost of land use increased by about $12 million with BCAP subsidies because more cropland near biorefineries was selected for switchgrass production. However, the net opportunity cost of cropland was reduced by nearly $11 million given the BCAP land rent payment making the unit cost of switchgrass ($ Mg^{-1}) on some cropland to be less than pastureland. By comparison, the net feedstock establishment cost was reduced by 50 percent with the BCAP establishment payment but the payment did not influence land use in the same way as the BCAP land rental payments.

4.2. Risk-averse biofuel sector (model 2) without and with BCAP subsidies

Stochastic optimization considering switchgrass yield risk using CVaR(cost) minimization (model 2) resulted in the anticipated tradeoff of higher expected supply chain costs with lower risk penalties when compared to the risk-neutral case (model 1). In the absence of the BCAP, the optimal CVaR(cost) risk penalty of $1358 million was lower than the $1441 million risk penalty incurred for the risk-neutral case, but the corresponding E(Cost) calculated using Eq. (1) was higher at $1249 million. Imposing a penalty for switchgrass yield risk on the design of the supply chain resulted in substantially different land use when compared to the risk neutral case (see Figs. 3 and 4). Nearly one-third more land was converted to switchgrass production with the CVaR (cost) risk penalty model and established 367 thousand total hectares compared to 279 total hectares for the risk neutral model. In addition, more cropland was converted to switchgrass when penalizing yield risk. Switchgrass established on cropland comprised 12 percent (43 thousand hectares) of supply chain area for the CVaR(cost) risk penalty minimization model but made up only 5 percent (14 thousand hectares) of supply chain area with the expected cost minimization model. The CVaR (cost) model diversified production risk by distributing the larger area converted to switchgrass over a wider geographical footprint and included more cropland with higher yield potential in the supply chain (Fig. 4).

Penalizing for yield risk in the model substantially increased the costs of feedstock procurement in Table 5 because of more land area converted to switchgrass. Costs related to the opportunity cost of land and establishment, maintenance, harvest, and storage of feedstock jumped 35 percent between the E(cost) minimization model and the CVaR(cost) minimization solution (see Tables 3 and 5). Biorefinery operation costs dropped from $350 million in the risk-neutral model to $332 million in the risk penalty model. However, the biofuel shortage penalty rose from $85 million in the risk neutral model to $153 million (764 MLY) in the risk penalty model. The CVaR(cost) model minimized risk through a combination of increasing the amount of switchgrass production and storage to reduce feedstock shortfalls, reducing operating cost by producing less biofuel at the three biorefineries, and purchasing biofuel elsewhere to make up for the shortfall in meeting the demand for biofuel.

With the BCAP, the expected CVaR(Cost) risk penalty is $1299 million, lower than the $1358 million value without BCAP. The corresponding E(Cost) was also lower than the no BCAP scenario at $1181 million. Optimal land allocation for switchgrass and biorefinery locations for both BCAP scenarios are in Fig. 4. With the BCAP incentives, penalizing for yield risk resulted in supply area in switchgrass of 360 thousand hectares that was similar to the 367 thousand hectares converted without the BCAP. Imposing a risk penalty on the design of supply chain substantially altered the composition of land types converted to switchgrass. Switchgrass established on cropland made up 40 percent (152 thousand hectares) of total supply chain area compared to only 12 percent (43 thousand hectares) without the BCAP. The supply chain shifted to the northeast, away from the blending facility. Given the reduction in net opportunity costs with the BCAP rental payments, the risk penalty model sought out higher yielding croplands over a wider geographical space to diversify yield risk in the feedstock supply chain.

Table 6 shows changes in the various cost components of the risk-averse biofuel sector for the two BCAP scenarios. The expected biofuel shortage cost dropped by nearly $38 million through a more stable supply of switchgrass with the BCAP subsidies. Expected biorefinery operation cost increased by 10 million, primarily driven by a subsequent increase in expected biofuel transportation cost when BCAP was in place. Gross opportunity cost of land use increased by nearly $27 million with BCAP subsidies due to the selection of high yield croplands. The annual rent payment and feedstock establishment payment of BCAP contributed to the net opportunity cost and net feedstock establishment cost, respectively.

Table 4
Deviation in annualized costs (million $) component in model 1 with and without BCAP subsidies.

Annualized cost component	Without BCAP	With BCAP
Gross feedstock establishment cost	49	48
Net feedstock establishment cost	49	24
Gross opportunity cost	20	32
Net opportunity cost	20	9
E(Biomass transportation cost)	62	56
E(Biofuel transportation cost)	25	24

Note: Gross opportunity and gross feedstock establishment costs refer to the costs of establishment and opportunity costs had not been subsidized with annual establishment and land rent payments, respectively, from BCAP. Model 1 represents the risk-neutral biofuel sector's decision of E(Cost) minimization. E is the expectation operator.

4.3. Comparing the impacts of BCAP on the risk-neutral and risk-averse biofuel sectors

Fig. 5 shows BCAP subsidies lowered E(Cost) by 3.86 percent for the risk-neutral biofuel sector (model 1) and 5.41 percent for the risk-averse biofuel sector (model 2). Similarly, the respective CVaR(Cost) risk penalties associated with models 1 and 2 were reduced by 2.89 and 4.36 percent with the BCAP. Model 2 minimized the high costs associated with lower yield scenarios, which led to use of more land for switchgrass cultivation. Additional land use in model 2 ensured more establishment and annual land rent payments for the biofuel sector under BCAP. Thus, the percentages of cost savings and risk reduction for the risk-averse biofuel sector were higher than the risk-neutral sector (Fig. 5).

The expected costs of supplying biomass to the biorefinery were $80 Mg^{-1} and $102 Mg^{-1} for the risk-neutral and risk-averse biofuel sectors, respectively, which were further reduced to $68 Mg^{-1} and $89 Mg^{-1}, respectively, if BCAP subsidies were available when designing the supply chain. From the perspective of biofuel, the expected costs of biofuel delivery to the blending facility were $1.02/L and $1.13/L for the risk-neutral and risk-averse biofuel sectors, respectively. With BCAP subsidies, the expected biofuel delivery costs reduced to $0.98 L^{-1} and $1.07 L^{-1} for the risk-neutral and risk-averse biofuel sectors, respectively.

5. Conclusions and policy implications

Considering the investment risk associated with converting

[5] Gross refers to the land opportunity cost before the annualized land rent payment from BCAP was applied.

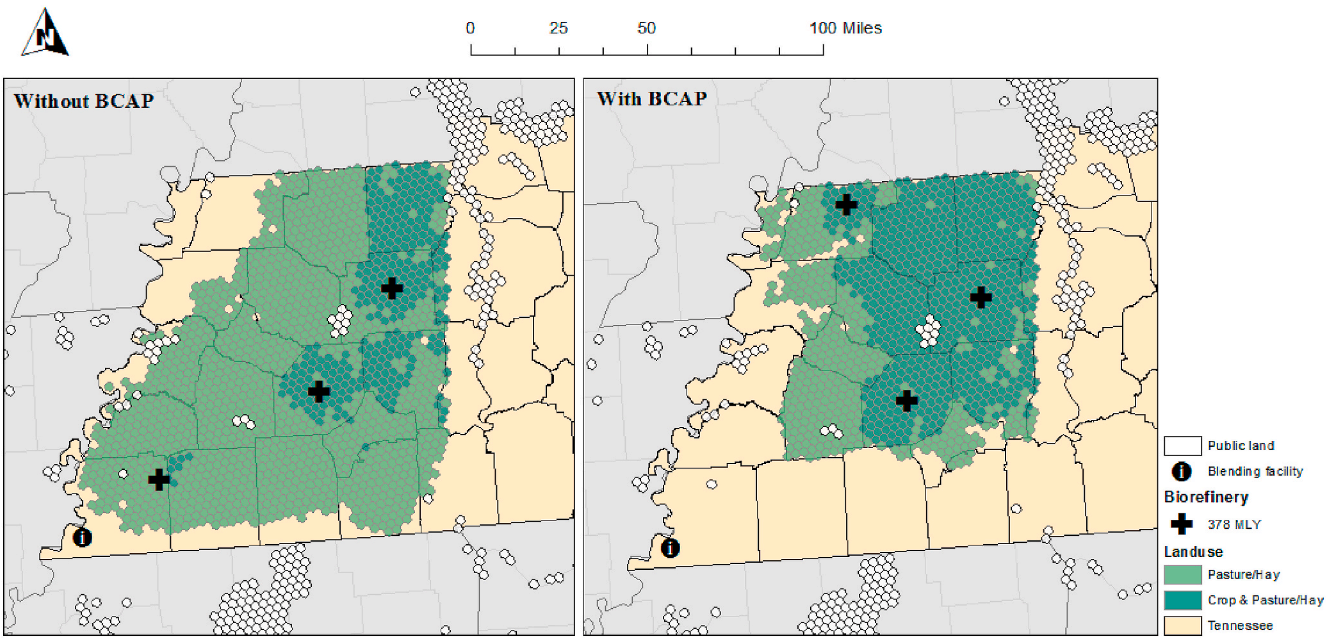

Fig. 4. Optimal investment decisions in model 2 with and without BCAP subsidies.
Note: Model 2 represents the risk-averse biofuel sector's decision of CVaR(Cost) minimization.

Table 5
Annualized cost (million $) components in model 2 without BCAP subsidies.

Operation component	Cost	Operation component	Cost
Biorefinery investment cost	326	E(Grinding cost)	47
Feedstock establishment cost	64	E(Biomass transportation cost)	61
Opportunity cost	31	E(Biofuel transportation cost)	23
Maintenance cost	47	E(Biorefinery operation cost)	332
E(Harvest cost)	133	E(Shortage penalty cost)	153
E(Storage cost)	32		

Note: Model 2 represents the risk-neutral biofuel sector's decision of E(Cost) minimization. All numbers are in 2015 US million dollars. E is the expectation operator.

Table 6
Deviation in annualized cost (million $) components in model 2 with and without BCAP subsidies.

Annualized variables	Without BCAP	With BCAP
Gross feedstock establishment cost	64	63
Net feedstock establishment cost	64	31
Gross opportunity cost	31	58
Net opportunity cost	31	16
E(Biorefinery operation cost)	332	342
E(Biofuel transportation cost)	23	30
E(Shortage penalty cost)	153	115

Note: Gross opportunity and feedstock establishment costs refers to the costs if establishment and opportunity costs had not been subsidized with annual establishment and land rent payments, respectively, from BCAP. Model 2 represents the risk-averse biofuel sector's decision of CVaR(Cost) minimization. E is the expectation operator.

established cropland or pastureland to dedicated energy crops for cellulosic biofuel production, this study assessed the impacts of a federal incentive program, BCAP, on the investment decisions (including land use choice) of a biofuel sector under feedstock supply uncertainty. The optimal design of the biofuel supply chain of both risk-neutral and risk-averse decision makers were analyzed using an augmented two-stage stochastic MILP that incorporated land use along with biorefinery configurations in the strategic decision.

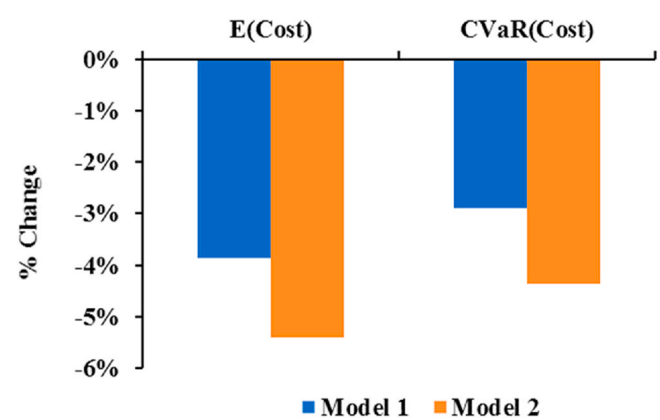

Fig. 5. Percent change in economic and risk metrics in models 1 and 2 given BCAP subsidies.
Note: Model 1 represents the risk-neutral biofuel sector's decision of E(Cost) minimization, while model 2 represents the risk-averse biofuel sector's decision of CVaR(Cost) minimization. E is the expectation operator.

Ex-ante analysis of a switchgrass-based biofuel sector in west Tennessee using the augmented stochastic model suggests that the optimal supply chain of the risk-averse biofuel sector utilized more land for switchgrass cultivation compared to the land use decisions of the risk-neutral biofuel sector as the former aimed to reduce the high costs associated with feedstock scarcity from the low yield scenarios. Providing BCAP subsidies improved both economics and risk of the biofuel sector; however, the risk-averse decision makers were more responsive to BCAP subsidies in the strategic decisions for land use choice compared to the risk-neutral sector. The demand to reduce potential biofuel shortage for the risk-averse biofuel sector pushed decision makers to adopt the higher yield cropland with higher opportunity costs that were effectively compensated by BCAP land rent payments. As a result, both the expected cost and CVaR of the supply chain were reduced at a higher percent for the risk-averse biofuel sector compared to the risk-neutral sector with BCAP subsidies. The improved economic condition of the biofuel sector in our study was consistent with previous studies that found increased profits for perennial bioenergy crops with BCAP payments (Dolginow et al., 2014; Skevas et al., 2016).

Our findings also suggest that conversion of cropland to bioenergy crop production could be amplified given BCAP subsidies. The finding of the unintended consequence of BCAP subsidies on cropland use is in line with Wolde et al. (2017) that also indicated matching payment under BCAP leads to an adverse impact on land competition and biomass price. However, replacing cropland with switchgrass can potentially mitigate water-induced soil erosion, a prevalent problem on cropland in West Tennessee (Zhong et al., 2016), and reduce GHG emissions associated with net carbon sequestration (Yu et al., 2016). The diverse potential outcomes from BCAP subsides highlights the complexity of developing a balanced incentive program for both U.S. agricultural and bioenergy sectors. Our study suggests that targeting BCAP subsidies towards the area with more erodible cropland could be one tactic to mitigate those conflicting outcomes. Moreover, our findings illustrate that the decision makers' preference and regional characteristics, such as land resource, can potentially affect the effectiveness of a government program. Thus, incorporating those factors in the design of an incentive program presumably better addresses multiple policy targets.

Our study has the limitation of being a regional case study analysis and does not evaluate the full impact of land use change resulting from BCAP. However, the *ex-ante* case study reported in this study offers important insights into the potential influence of BCAP incentives on supply chain design given uncertain feedstock yields and decision makers' risk preferences. Our findings provide useful information that could be incorporated into a more comprehensive policy analysis using a national model. Therefore, future work could expand the scope to a national scale using less aggregated spatial data than in the present study to evaluate the full impact of land use so that the costs and benefits to society from BCAP incentives can be properly assessed to support policy development.

CRediT authorship contribution statement

Bijay P. Sharma: Data curation, Formal analysis, Methodology, Writing - original draft, Software, Visualization. **T. Edward Yu:** Conceptualization, Data curation, Investigation, Project administration, Supervision, Validation, Writing - review & editing. **Burton C. English:** Conceptualization, Funding acquisition, Resources, Validation. **Christopher N. Boyer:** Validation, Resources, Writing - review & editing. **James A. Larson:** Validation, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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