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Analyzing the Trade-Offs between Meeting Biorefinery Production Capacity and Feedstock Supply Cost: A Chance Constrained Approach

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Abstract: Commercial-scale switchgrass production for cellulosic biofuel remains absent in U.S. A well-recognized difficulty is the steady provision of high-quality feedstock to biorefineries. Switchgrass yield is random due to weather and growing conditions, with low yields during establishment years. Meeting biorefinery production capacity requirements 100% of the time or at any other frequency requires contracting sufficient amount of agricultural land areas to produce feedstock. Using chance-constrained programming, the trade-offs between the degree of certainty that refinery demand for feedstock and the cost of contracting production acreage is assessed. Varying the certainty from 60% to 95%, we find the costs of production, logistics and transportation ranged from 27% to 96% of the cost of 100% certainty. Investors and managers need to consider the cost of certainty of biomass acquisition when contracting for production acreage.

Keywords: biofuel; switchgrass (*Panicum virgatum* L.); uncertainty; risk; chance constrained programming

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1. Introduction

The United States (U.S.) Renewable Fuel Standard (RFS) mandates the production of 16 billion gallons of cellulosic ethanol by 2022. The U.S. cellulosic biofuel industry is well behind this target. Little cellulosic biofuel is currently produced at the commercial scale in the U.S. Of the existing commercial cellulosic ethanol plants, three are idled, one is on hold, one is under construction, and one is operational [1].

Challenges and opportunities facing the development of the cellulosic biofuel development have been extensively researched. Previous studies primarily focus on cellulosic feedstock production, conversion technologies, end uses, and segments along the value chain in the U.S. Among all the cellulosic feedstock options, perennial switchgrass (*Panicum virgatum* L.) is a promising cellulosic feedstock because it can be produced on marginal agricultural land. This feature reduces land substitution for food production, reduces soil erosion potential on environmentally sensitive land, offsets greenhouse gas emissions, and supports biodiversity [2,3]. Financial support through federal programs are available for establishing switchgrass and to assist with the logistical costs of transporting feedstock to biorefineries [4]. Previous research suggests growing switchgrass can be profitable with vertical contracting systems between farmers and biorefineries [5]. Further, landowners are willing to plant switchgrass if the opportunity cost of converting from current uses to switchgrass production is low and downside risk can be prevented [6,7].

Technical and economic analyses demonstrate that commercial-scale switchgrass-driven biofuel production is feasible under certain market conditions [8–10]. Deterministic and stochastic studies have analyzed feedstock production and costs, logistic, and optimal facility location to invest and establish the preprocessing centers and biorefineries in Tennessee, Oklahoma, and Dakotas (e.g., [11–15]). Yet, the absence of cellulosic ethanol production in these well-studied states indicates that the investment risk remains high for biofuel industry [16].

Like all dryland perennial crops, switchgrass yield is stochastic and affected by weather and growing conditions. In addition, switchgrass requires two to three years to establish and reach yield potential. Switchgrass yields vary with soil quality and annual weather conditions [17]. Many feedstock supply chain and economic studies assumed deterministic switchgrass yields over a 10 to 15 year lifetime (e.g., [11,18–24]). However, an increasing number of recent studies consider feedstock supply uncertainty as an important determinant of optimal facility and preprocessing locations (e.g., [16,21,25–28]), in addition to considering economic, social, and environmental goals (e.g., [29,30]). For biorefinery management, capacity utilization is likely a critical factor for profitability. Ignoring the three-year establishment period for switchgrass and the inherent variability in yield may translate into biomass shortages at the biorefinery or high costs of contracting production acres. Assuming switchgrass yields follow a roughly symmetric distribution, if acres are contracted to meet plant capacity using mean yields, the facility will experience a biomass shortfall in roughly 50% of the operating years.

This research extends previous economic modeling efforts on optimal biomass contracting by incorporating spatial and temporal yield variability for switchgrass establishment and production. A chance constrained program [31,32] is developed to model the biorefinery by minimizing the sum of costs of acquiring biomass feedstock over a ten-year period. The programming model is constrained to require that feedstock demand is met with a degree of certainty in each of the ten-year planning horizon. The analysis focuses on the state of Oklahoma, which has a substantial amount of pasture and hay land that could be converted to switchgrass production.

2. Chance Constrained Programming and Application in Biofuel Supply Chain Research

Chance constrained programming (CCP) is a useful approach for modeling uncertainty in optimization problems. CCP was introduced by [31,32]. CCP assumes that the decision maker faces uncertain circumstances, and is forced to make a decision based on the predetermined frequency of which constraints must be satisfied. For a producer, the probability (or likelihood) of a resource constraint (or a production targeted level) being satisfied is set to be greater than or equal to some predetermined values. The advantage of CCP is its simplicity with respect to satisfying a constraint at some probability. CCP is widely applicable to problems that involve making decisions (or plans) under risk and uncertainty, including water resource management (e.g., [33–38]), agriculture (e.g., [39–41]), finance (e.g., [42,43]), power flow and generation (e.g., [44,45]), and renewable energy (e.g., [46,47]). One of the main critiques of CCP is that it cannot provide alternative solutions to decision makers if constraints are not met (e.g., [48,49]).

CCP has been used in a handful of biofuel supply chain analysis. [50] formulated a chance constrained model to determine a biofuel supply chain network while ensuring that the probability of utilizing certain amount municipal wastes was satisfied. [51] demonstrates the use of CCP with multiple distribution assumptions for biofuel demand. Compared with deterministic and two-stage stochastic programming model results, CCP provides the most conservative, risk-averse solution [51]. CCP has also been used along with other stochastic programming approaches such as two-stage or multi-stage stochastic programming in municipal solid waste power supply [52] and renewable energy storage [53]. While CCP had shown this is a useful tool in early stage planning of biofuel industry, it appears that this approach has not been applied in switchgrass acquisition and biorefinery capacity fulfillment. If a biorefinery contracts farmers to produce switchgrass as its main feedstock, the foremost question for the biorefinery is how much land will be needed and what are the optimal locations of these acres. Uncertainty in biomass supply will affect realized biorefinery output as unmet demand or oversupply of feedstock.

3. Materials and Methods

The application of chance constrained approach in a switchgrass supply is formulated considering feedstock production area and location, logistic costs, travel distance from the location of switchgrass production to a biorefinery, and the associated costs. The analysis in this manuscript assumes that all potential switchgrass producers have identical opportunity costs and receive the same contracting prices from each biorefinery.

3.1. Optimization Model

A linear chance constrained programming model is formulated to determine optimal switchgrass production areas and shipping routes between that biomass supply and demand. The model's objective is to minimize total costs of feedstock production, logistics, and transportation, assuming that each biorefinery has a t-year contract with farmers to supply switchgrass biomass (Equation (1)).

$$\min_{x \geq 0} EC^P + EC^L + EC^S \tag{1}$$

where EC^P is total expected switchgrass production costs, EC^L is total expected switchgrass logistic costs, and EC^S is total expected switchgrass transportation costs. Each biorefinery j contracts acres x_{ij} from producer i.

In Equation (2) expected production costs EC^P are calculated using the mean yield of switchgrass Y_{it} at location i, in year t, multiplied by the per acre cost production (α_{ij}) and contracted acres x_{ij}:

$$EC^P = \sum_{ijt} \alpha \cdot x_{ij} \cdot Y_{it} \tag{2}$$

Transportation costs per ton from production location i to biorefinery j are β_{ij}, EC^S the total expected cost of switchgrass transportation is calculated as:

$$EC^S = \sum_{ijt} \beta_{ij} \cdot x_{ij} \cdot Y_{it}. \tag{3}$$

Equation (4) calculates the total expected logistic costs, where γ is the logistic costs per dry Mg of switchgrass.

$$EC^L = \sum_{ijt} \gamma \cdot x_{ij} \cdot Y_{it} \tag{4}$$

Model constraints include acreage constraints and chance constraints on the probability of delivering the annual capacity to each biorefinery. The switchgrass production area in location i cannot exceed the available land (L_i_) that can be used for switchgrass production (Equation (5)).

$$\sum_{j} x_{ij} \leq L_i \ \ \forall\, i \tag{5}$$

Given yield variability during the establishment through post-establishment years, the minimum probability of meeting annual switchgrass demand is denoted θ_t (Equation (6)). The annual biomass demand M_j for each biorefinery ensures that the probability (Pr) of meeting M_j in year t is at least θ_t.

$$Pr\left[\sum_{i} x_{ij} \cdot y_{it} \ \geq M_j\right] \geq \ \theta_t \ \ \forall\, t \tag{6}$$

In Equations (5) and (6), y_{it} is a random yield at location i, in year t, with the probability density function $f(y_{it})$. A triangular distribution is imposed on dryland switchgrass yield [54,55] assuming yields are not serially correlated. A triangular distribution for switchgrass yield was used because the yield data for each period t is limited, given that switchgrass would be new to many producers. Information on minimum, maximum, and most likely yields are comparatively easier to obtain. These are all parameters needed of the triangular distribution. The triangular distribution is fully parameterized with the maximum yield Y_{it}^{max}, the minimum yield Y_{it}^{min}, and the yield mode Y_{it}^{mod}. Further, the cumulative density function can be expressed as a linear equation (Equation (7)):

$$M_j - \sum_i x_{ij} \cdot \left[Y_{it}^{max} - \sqrt{\theta_t \cdot \left(Y_{it}^{max} - Y_{it}^{min}\right) \cdot \left(Y_{it}^{max} - Y_{it}^{mod}\right)} \right] \leq 0 \;\; \forall \, j, \, t. \quad (7)$$

Then, expected yield Y_{it} for each location i, year t, is the sum of minimum yield, maximum yield, and most likely yield Y_{it}^{mode} divided by three (Equation (8)):

$$Y_{it} = \frac{Y_{it}^{max} + Y_{it}^{min} + Y_{it}^{mod}}{3} \;\; \forall \, i, \, t. \quad (8)$$

3.2. Study Region and Data

3.2.1. Oklahoma and Decision Making Unit

Oklahoma, located in south central of the U.S., is a transition zone from humid continental (north) to humid subtropical (east and southeast) to semi-arid (west). Oklahoma is primarily an agricultural state. Over 70% of the state land areas, more than 13 million ha, are employed for agricultural production [56] with about 20% of agricultural hectares cropped. About 40% of crop hectares are in hay production to support the state's large cattle industry. Most of Oklahoma's counties are relatively sparsely populated with most of its population located in central and northeastern counties.

Two biorefinery locations are selected based on previous research in Oklahoma (Figure 1). The first location is in Grady County [57], and the second is in Okfuskee County [27]. A cost minimizing switchgrass-based biofuel supply chain was formulated assuming these biorefineries vertically contract with farmers to convert hay production land to establish and produce switchgrass. Investors or managers of these biorefineries choose least cost switchgrass production sites, mainly determined by regional agricultural productivity, as well as logistics and transportation costs to situate the switchgrass contracting areas. The biorefinery planning period of contracting switchgrass production is ten years, although the biorefinery project life period could be twenty years. This is a common assumption that the expected life a switchgrass stand is ten years [58] (Recent research have shown that switchgrass lifetime can be longer than 10 years [59]).

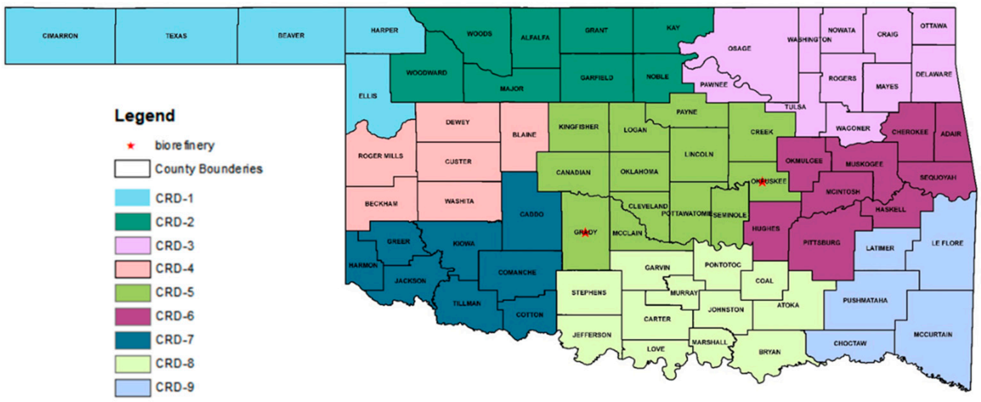

Figure 1. Study Region, Crop Reporting Districts (CRD), and Location of the Biorefineries.

A distance matrix was generated between centroids of counties where biorefineries are located and centroids of other nearby counties with hay land available to produce switchgrass using ArcGIS [60]. If the switchgrass contracting areas are located in the Grady and Okfuskee counties (i.e., biorefinery locations), the distance is measured from the centroid of these two counties to its furthest boundary. The maximum one-way transportation distance is 80 km as suggested by [18].

3.2.2. Switchgrass Yields

Lengthy switchgrass yield time series data are not available for multiple Oklahoma locations. The Environmental Policy Integrated Climate (EPIC) model [61] is employed to simulate switchgrass yield for Oklahoma Crop Reporting Districts (CRDs). Each CRD is considered a homogeneous production area. CRDs are composed of five or more counties in Oklahoma (Figure 1). There are nine CRDs in Oklahoma.

Data required for simulating switchgrass in EPIC include weather, soil type, and operation inputs (fertilizers), and planting, fertilizer, and harvesting dates. Weather and wind data from weather stations located in the center of each CRD were used. Representative agricultural land soil types for each CRD were identified from the USDA Natural Resources Conservation Service (NRCS) Soil Survey Geographic Database (SSRUGO). Twenty-six representative cropland soil types were identified. Each EPIC evaluation was 100 years long, with switchgrass re-establishment every ten years. Switchgrass was planted in May at the beginning of each ten-year interval, harvested annually in December, and then terminated at the end of each ten-year period. On April 1, starting in year two of each ten-year cycle, 100 kg per ha of nitrogen was applied. Over the 100 simulated years, ten observations of switchgrass yields were generated for each year in the ten-year cycle. For example, ten yield observations were generated for the establishment year of switchgrass. Table 1 presents the statistics of yield observations for each year and CRD generated by EPIC simulations. CRD-3 and CRD-6, located in humid northeastern Oklahoma, have higher modal switchgrass yields compared with other CRDs. Each county in a CRD was assumed to have the annual simulated CRD switchgrass yield.

3.2.3. Production, Logistic, and Transportation Costs and Land Availability

A production cost of USD 58.39 per dry Mg [62] and a logistic cost of USD 23.70 per dry Mg for switchgrass [62] were assumed (Table 2). Production costs are composed of payments to biomass, harvesting and collection, and field storage. Logistic costs are the sum of processing, handling, and queuing at the biorefinery. Transportation costs include the movement of material from location i to biorefinery j, plus loading, trucking, and unloading. A linear regression determined by [63] is used to calculate unit transportation costs for different routes. The fixed transportation cost of USD 3.62 per Mg, and variable transportation cost USD 0.0708 per dry Mg-km. The cost function is (Equation (9)):

$$\beta_{ij} = 3.62 + 0.0708 \cdot d_{ij} \tag{9}$$

where β_{ij} is the transport cost per dry Mg if transport biomass from location i to location j, and d_{ij} is the round-trip distance in km between locations i and j.

Land available for each county is constrained to the 2017 harvested hay land areas (USDA-NASS). Hay land is a good candidate for switchgrass production in Oklahoma because of its proximity to roads, and because existing haying equipment can be used to harvest switchgrass. Although Oklahoma has a vast amount of pasture land, 65% of its pasture land is rangeland [64]. Rangeland may not be accessible or suitable for switchgrass production because of its relatively low productivity, inaccessible terrain, or critical ecological service.

Table 1. Statistics of switchgrass yields (dry Mg per ha) in each CRD in years 1–10.

Crop Reporting District (CRD)	Statistic	Year									
		1	2	3	4	5	6	7	8	9	10
CRD-1	min [a]	3.93	3.98	5.38	4.64	5.33	5.02	3.22	4.37	4.63	4.24
	max [b]	11.12	14.43	11.45	12.47	11.66	11.43	15.64	12.75	14.34	10.24
	mode [c]	7.21	7.31	8.26	7.79	8.96	8.14	7.51	8.18	9.05	7.14
CRD-2	min	3.59	3.09	2.73	4.16	4.03	4.14	2.9	2.81	3.61	2.57
	max	14.72	17.3	14.92	19.56	16.07	16.75	19.41	13.95	13.11	14.74
	mode	7.16	7.66	7.31	8.57	7.56	7.2	7.19	6.36	7.21	6.1
CRD-3	min	2.72	2.99	2.32	3.01	3.4	3.29	2.18	2.34	2.57	2.27
	max	14.46	20.56	19.96	19.41	20.82	18.12	19.56	17.42	15.36	15.95
	mode	7	7.75	7.43	7.82	7.62	7.39	7.11	7.1	7.08	5.9
CRD-4	min	3.29	3.08	2.74	3.59	3.41	3.86	2.88	3.39	3.27	2.91
	max	16.27	16.39	16.57	20.43	17.25	17.74	18.33	14.24	15.72	16.54
	mode	6.84	7.29	7.35	7.98	7.56	6.73	7.44	6.83	6.83	6
CRD-5	min	3.17	3.73	3.03	3.62	3.55	3.89	2.91	3.27	3.43	3.08
	max	13.85	16.43	20.53	18.41	19.57	18.63	17.56	14.74	13.75	17.36
	mode	6.78	7.87	7.61	7.64	7.59	7.34	7.11	6.56	6.66	5.98
CRD-6	min	3.75	3.71	2.76	3.51	3.97	4.22	3.13	3.45	3.94	3.04
	max	15.15	17.75	19.53	23.45	21.01	17.28	17.12	15.52	14.47	16.16
	mode	7.26	7.94	7.63	8.63	8.31	7.88	7.29	7.14	7.06	6.3
CRD-7	min	2.62	3.24	2.87	3.18	3.18	3.94	2.66	3.09	3.28	2.89
	max	12.33	18.7	16.58	20.45	16.83	21.34	23.07	17.11	18.13	13.64
	mode	6.47	7.7	7.98	7.91	7.33	8	7.67	6.94	7.74	6.49
CRD-8	min	3.17	2.81	3.45	3.74	3.68	4	2.55	3.74	3.47	3.18
	max	13.15	16.87	19.53	20.26	21.75	20.23	21.75	16.11	16.49	18.12
	mode	7.05	7.87	7.99	8.08	7.92	7.7	7.46	7.6	7.21	6.48
CRD-9	min	2.7	2.79	2.19	2.94	2.48	3.53	2.31	2.91	2.64	2.45
	max	9.78	11.26	14.13	15.76	15.69	14.13	14.39	11.04	11.53	13.99
	mode	5.41	5.57	5.59	5.79	5.91	5.7	5.45	5.44	5.15	4.72

[a]. min refers to minimum yield level. [b]. max refers to maximum yield level. [c]. mode refers to 'most likely yield level'. Median yields were used as mode.

Table 2. Parameters.

Symbol	Parameters	Value	Source
α	Product Cost (USD/Mg)	58.39	Roni et al., 2019
γ	Logistic Cost (USD/Mg)	23.7	Roni et al., 2019
M	biomass demand (dry Mg/year)	724,000	Davis et al., 2015

3.2.4. Biorefinery Production Capacity and Switchgrass Biomass Demand Scenarios

A facility with a biomass demand of 2205 dry Mg per day of biomass operating at 90% efficiency will require 724,000 dry Mg per year [65] (Table 2). Given a 10-year growth period for switchgrass, it may be cost prohibitive for a biorefinery to expect that 100 percent of this demand can be met annually. Table 3 presents a set of demand scenarios for switchgrass based on the probability of meeting each biorefinery annual targeted conversion capacity. The scenario SA constraints the preassigned probability of meeting biorefinery conversion capacity is 100% from years 1 to 10. Scenarios S100, S95, S90, S85, S80, S75, S70, S65, and S60 require that over the first three years, the probability of meeting annual biorefinery demand are 35%, 45%, and 55%, respectively. From year four to year ten, the probabilities of meeting demand vary from 100% to 60%.

Table 3. Definition of scenarios based on probability meeting biorefinery annual demand.

Scenarios [a]	Establishment Years			Post-Establishment Years
	Year 1	Year 2	Year 3	Years 4~10
SA	100%	100%	100%	100%
S100	35%	45%	55%	100%
S95	35%	45%	55%	95%
S90	35%	45%	55%	90%
S85	35%	45%	55%	85%
S80	35%	45%	55%	80%
S75	35%	45%	55%	75%
S70	35%	45%	55%	70%
S65	35%	45%	55%	65%
S60	35%	45%	55%	60%

[a]. Scenarios defined using probability meeting biorefinery annual demand. SA:100% of the time the biorefinery annual demand can be met. S100-S60: probability of meeting biorefinery demand is 35% for the first year, 45% for the second year, 55% for the third year, and varies from 100% to 60% for years 4 to 10.

4. Results

4.1. Switchgrass Production Area and Locations

The optimal solution for contracting switchgrass areas and locations is determined under each biorefinery demand scenario (Figure 2 and Table 4). Although the two biorefineries, Grady and Okfuskee, have the same capacity, their solutions on feedstock draw areas are different. Under the SA scenario, a 100% probability of meeting biorefinery annual demand, the feedstock draw areas for a biorefinery in Grady is 124,135 ha of land, while the Okfuskee biorefinery is 116,493 ha. The feedstock draw area for the biorefinery in Grady is smaller than the Okfuskee biorefinery feedstock draw area if preassigned probabilities for the first three years are less than 100% (S100~S60). The difference is mainly due to land productivity where feedstocks were drawn. Both Grady and Okfuskee birefineries are located in CRD-5 which is the central crop district. The Okfuskee biorefinery is near the eastern boundary of the CRD-5 while the Grady biorefinery is near the southwestern end of the CRD-5 (Figure 1). Beside drawing feedstock from counties located in CRD-5, Okfuskee draws feedstock from counties located in CRD-3 and CRD-6, while Grady draws feedstock from counties located in CRD-7 and CRD-8. The switchgrass yields are higher in CRD-3 and CRD-6 than CRD-7 and CRD-8 because of projected higher precipitation.

Table 4. Switchgrass area (ha) and location under different scenarios.

Biorefinery	County (Crop Reporting District)	Scenarios [a]									
		SA	S100	S95	S90	S85	S80	S75	S70	S65	S60
Grady	Caddo (CRD-7)	9582	14,130	16,494	19,481	19,637	22,217	24,674	25,569	25,569	25,569
	Canadian (CRD-5)	22,215	8170	1317							
	Cleveland (CRD-5)	8940	8940	8940	8940						
	Garvin (CRD-8)	18,418	18,418	18,418	12,902	17,295	11,358	5739	1733		
	Grady (CRD-5)	31,214	31,214	31,214	31,214	31,214	31,214	31,214	31,214	31,214	31,214
	McClain (CRD-5)	18,765	18,765	18,765	18,765	18,765	18,765	18,765	18,765	18,765	18,765
	Stephens (CRD-8)	15,002	15,002	15,002	15,002	15,002	15,002	15,002	15,002	13,700	10,749
Okfuskee	Creek (CRD-5)	16,194	16,194	16,194	16,194	16,194	16,194	16,194	13,301	10,266	7307
	Hughes (CRD-6)	15,772	15,772	15,772	15,772	15,772	15,772	15,772	15,772	15,772	15,772
	Lincoln (CRD-5)	18,126	20,882	13,756	10,196	6762	3442	226			
	McIntosh (CRD-6)	16,298	13,171	16,298	16,298	16,298	16,298	16,298	16,298	16,298	16,298
	Okfuskee (CRD-5)	17,043	17,043	17,043	17,043	17,043	17,043	17,043	17,043	17,043	17,043
	Okmulgee (CRD-6)	21,028	21,028	21,028	21,028	21,028	21,028	21,028	21,028	21,028	21,028
	Seminole (CRD-5)	12,032	12,032	12,032	12,032	12,032	12,032	12,032	12,032	12,032	12,032
	Total	240,627	230,761	222,272	214,867	207,041	200,364	193,987	187,756	181,687	175,777

[a]. SA:100% of the time the biorefinery annual demand can be met. S100-S60: probability of meeting biorefinery demand is 35% for the first year, 45% for the second year, 55% for the third year, and varies from 100% to 60% for years 4 to 10.

As the probability of meeting biorefinery annual capacity decreases during the switchgrass post-establishment period (years 4 to 10), the feedstock draw area is reduced for both biorefineries (Figure 2 and Table 4). If meeting the annual capacity post establishment years 75% of the time (S75) is acceptable, the total draw area for both biorefineries is 193,987 acres, or about 84% of draw area under S100. For the Okfuskee biorefinery, feedstock draw areas in Lincoln county were affected the most, decreasing from 13,171 under S100 to 226 under S75. Lincoln is 74 km from the Okfuskee biorefinery and located in CRD-5. From McIntosh county to the Okfuskee biorefinery, the travel distance is longer compared with from Lincoln county to the Okfuskee biorefinery. McIntosh is located in CRD-6, where switchgrass yields are higher. Seven counties supply switchgrass to the Grady biorefinery under S100, but only five counties are need to meet a 75% level of certainty (S75).

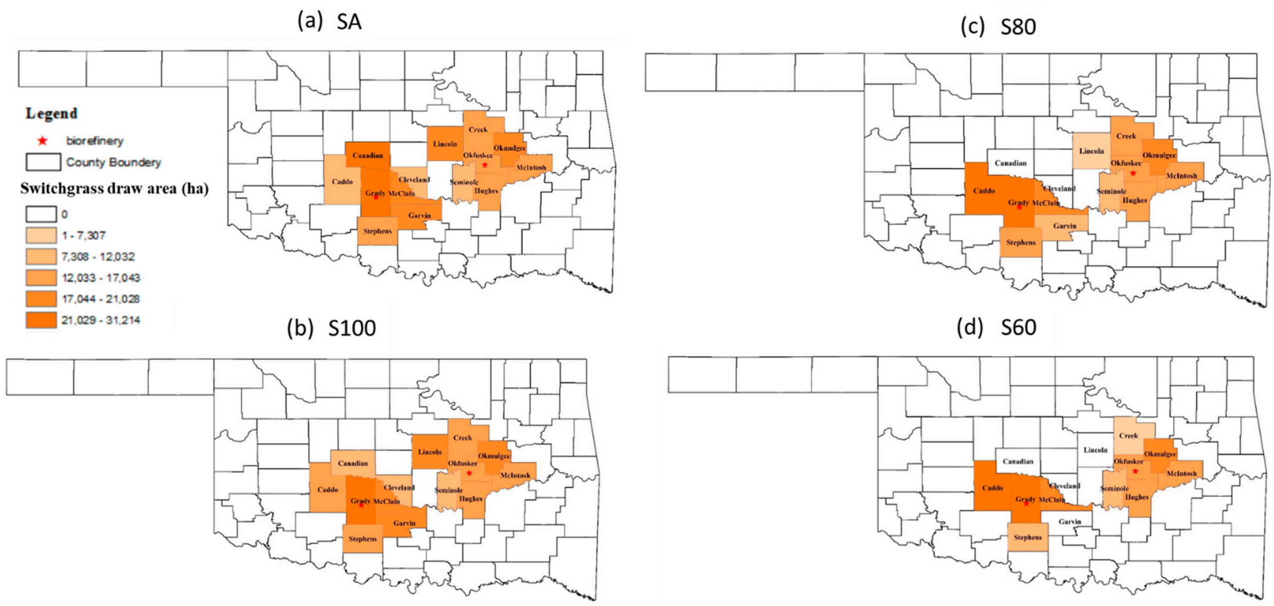

Figure 2. Switchgrass draw area and locations under scenarios. (**a**) SA-100% of the time the biorefinery annual demand can be met; (**b**) S100-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 100% for years 4 to 10; (**c**) S80-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 80% for years 4 to 10; (**d**) S60-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 60% for years 4 to 10.

4.2. Estimated Costs

Total production, transportation, and logistics costs decline as the preassigned probability of meeting biorefinery production capacity over establishment- and post-establishment decrease (Table 5). Switchgrass transportation costs were affected most, compared with the costs of production and logistics. Smaller, more local feedstock draw areas were required and the distance traveled from producing county to biorefinery shortened as the chance of meeting the biorefinery full capacity drops. Comparing S75 to S100, transportation costs decreased by 20%, production and logistic costs fell by 16%, and total costs dropped by 17%. As is expected, due to increasing marginal cost on probability of meeting biorefinery production capacity, total costs increase at an increasing rate as this probability is increased from 60% (S60) to 100% (SA). Figure 3 shows the resulting convex cost curve and the trade-offs between the total expected cost and probability of meeting the production capacity. Higher probability reflects a higher degree of certainty to meet the biorefinery production capacity. However, as expected, higher degrees of certainty required even higher economic costs. A biorefinery manager and owner could be better off without achieving the 100% certainty in meeting production capacity if the costs are much higher than profits or the remaining capacity can be met with other feedstock.

Table 5. Cost Associated with Each Scenario (million U.S. dollars).

Scenarios [a]	Production Cost	Transportation Cost	Logistic Cost	Total
SA	1317	296	535	2147
S100	1264	281	513	2058
S95	1220	269	495	1984
S90	1179	257	478	1914
S85	1138	248	462	1848
S80	1101	237	447	1785
S75	1065	227	432	1724
S70	1030	218	418	1666
S65	996	210	404	1611
S60	964	202	391	1557

[a]. SA:100% of the time the biorefinery annual demand can be met. S100–S60: probability of meeting biorefinery demand is 35% for the first year, 45% for the second year, 55% for the third year, and varies from 100% to 60% for years 4 to 10.

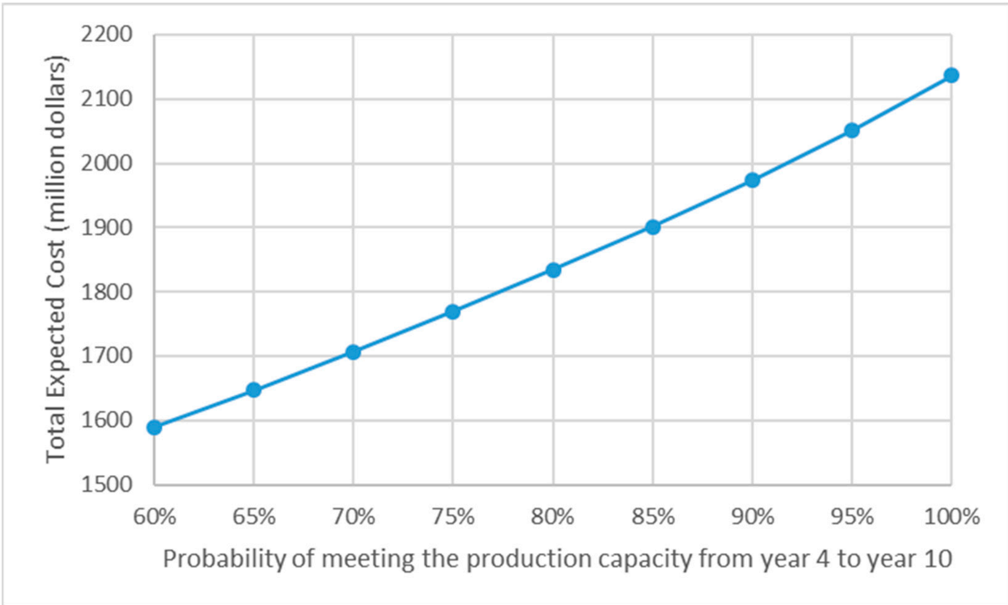

Figure 3. Trade-offs between total expected cost and probability of meeting the production capacity.

4.3. Excess Supply of Switchgrass

The expected annual volume of switchgrass produced and transported from fields to biorefineries is higher than the facility capacity. Requiring the biorefinery meeting the annual capacity 100% of establishment and post-establishment (SA) generates excess supply from years 2–10 for Grady biorefinery and years 2–7 for Okfuskee biorefinery (Figure 4). A lower degree of certainty during establishment period (years 1 to 3) results in higher excess supply in the first three years under all scenarios. However, a lower probability of meeting biomass demand for first three years results in lower excess supply of switchgrass or even eliminated it in years 4 to 10, and lower biomass acquisition costs. A decrease in the probability of meeting annual biorefinery capacity during the establishment and post-establishment reduces excess supply across the project period and associated cost.

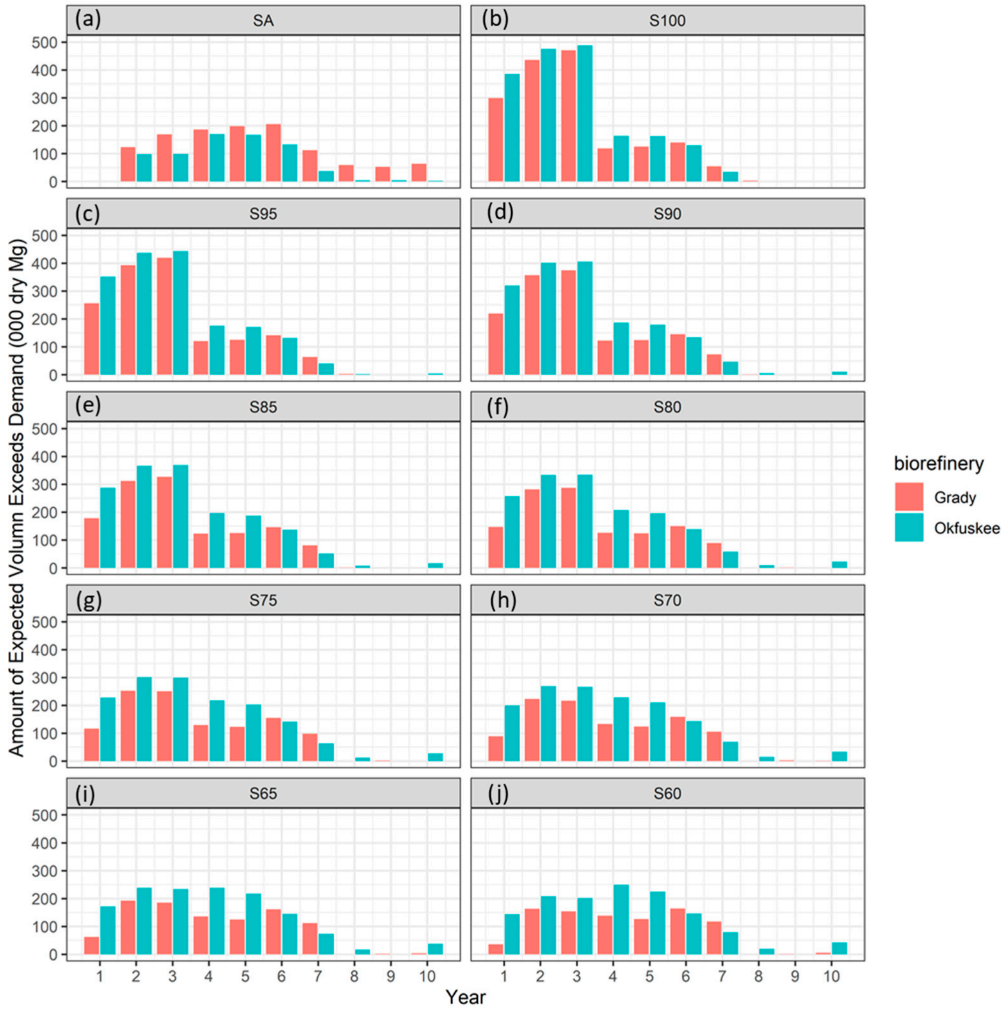

Figure 4. Expected biomass volume exceed annual demand under different scenarios. (**a**) SA-100% of the time the biorefinery annual demand can be met; (**b**) S100-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 100% for years 4 to 10; (**c**) S95-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 95% for years 4 to 10; (**d**) S90-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 90% for years 4 to 10; (**e**) S85-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 85% for years 4 to 10; (**f**) S80-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 80% for years 4 to 10; (**g**) S75-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 75% for years 4 to 10; (**h**) S70-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 70% for years 4 to 10; (**i**) S65-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 65% for years 4 to 10; (**j**) S60-probability of meeting biorefinery demand is 35%, 45%, and 55% for the first three years respectively, and 60% for years 4 to 10.

5. Conclusions

One of the well-recognized reasons that hinge the second-generation biofuel industry development is feedstock production uncertainty. Existing technical and economic analysis demonstrate the feasibility of scaled-up biofuel production from converting switchgrass to drop-in fuel. However, uncertainty in procuring a steady flow of feedstock to meet the biorefinery capacity is an important planning issue. Resulting acquisition costs can be high for higher levels of biomass supply certainty.

In this research, the Oklahoma case study used a chance constrained approach to model the cost of acquiring biomass feedstock with a predetermined probability of meeting the full capacity assuming switchgrass as the only feedstock available. Results show the land area required and the costs of meeting biorefinery production capacity increase at an increasing rate as the probability of meeting the full capacity increases. Land required, costs, and excess supply amount also differ between biorefinery locations with identical capacity due to transportation distances and spatial and temporal land productivity. A lower probability of meeting the full production capacity during switchgrass establishment years (years 1–3) is a reasonable strategy as the total costs can be reduced by more than 4%. If further reduce the probability in the switchgrass post-establishment year, the cost can be dropped by 27% compared with 100% of the time to meet biorefinery production capacity in years 1 to 10.

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