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THE NTH-PLANT SCENARIO FOR BLENDED FEEDSTOCK CONVERSION AND PREPROCESSING NATIONWIDE: BIOREFINERIES AND DEPOTS

Highlights

- Nationwide facility database to meet target cost, quality and quantity for biofuels.
- In 2022, 42.8M dt of corn stover and switchgrass could be accessible nationwide
- An $8/dt reduction in delivery cost could reduce total accessible biomass by 67%.
- KS, NE, SD and TX were identified as potential states with a strong biofuel economy
- CO, AL, GA, MN, MS and SC could greatly benefit from a nationwide depot network.

ABSTRACT. *The sustainability of the biofuel industry depends on the development of a mature conversion technology on a national level that can take advantage of the economies of scale: the nth-plant. Defining the future location and supply logistics of conversion plants is imperative to transform the nation's renewable biomass resources into cost-competitive, high-performance feedstock for production of biofuels and bioproducts. With US restrictions on production levels of conventional biofuels from edible resources, the nation needs to plan for the widespread accessibility and development of cellulosic biofuel. Conventional feedstock supply systems will be unable to handle cellulosic biomass nationwide, making it essential to expand the industry with an advanced feedstock supply system incorporating a distributed network of preprocessing depots and biorefineries. Current studies are mostly limited to designing supply systems for specific regions of the country. We developed a national database with potential locations for depots and biorefineries to meet the nation's target demand of cellulosic biofuel. Blended feedstock are considered in a Mixed Integer Linear Programming model to deliver on-spec biomass with a desired quantity and quality at the biorefinery. A total delivered feedstock cost that is less than $79.07/dt (2016$) is evaluated for years 2022, 2030, and 2040. In 2022, 124 depots and 59 biorefineries could be supplied with 42.8 million dt of corn stover and switchgrass. In 2030 and 2040, the total accessible biomass could increase to 215% and 393% respectively when compared to 2022. However, an $8/dt reduction in targeted delivery cost reduces the total accessible biomass by 67%. Kansas, Nebraska, South Dakota and Texas are potential states with a strong biofuel economy as they had six or more biorefineries located in all scenarios. Colorado, Alabama, Georgia,* *Minnesota, Mississippi and South Carolina would greatly benefit from a depot network as these could only deliver to a biorefinery in a nearby state. To elaborate the impact of a nationwide consideration, the findings were compared with existing literature for different US regions.*

Keywords. *Corn stover, Switchgrass, Biofuel, Feedstock quality, Biomass supply chain, Mixed-integer linear programming*

INTRODUCTION

Feasibility studies of agricultural residue conversion to biofuels, bioproducts, and/or biopower are on the rise given biomass' potential to become the major source of US renewable energy (Langholtz et al., 2016). The goal is to mitigate the negative impact of climate change and provide energy security. Currently, the most widely produced biofuel is conventional ethanol (derived from corn starch) which is an effective substitute for fossil fuel in the transportation industry. The US is one of the largest fuel ethanol producers in the world with 200 plants that total a national name plate production capacity of over 16.9 billion gallons (US EIA, 2019), 42% of the global biofuel production share (IEA, 2019). To restrict competition of food resources and pressure on arable lands, US has limited the production of conventional biofuels to 15 billion gallons per year (BGY) and set a target of 21 BGY of non-edible feedstock to boost the total renewable fuel production by 2022, from which at least 16 BGY should be from cellulosic biofuels (US EPA, 2020). Unlike food-based biomass resources, cellulosic biomass are non-edible resources including energy crops, municipal solid waste, and agricultural or forest residues (Kim and Dale, 2015). Due to widespread availability and low-cost raw material, cellulosic biomass is a promising alternative for starch-based biomass. But, the biofuel production cost is unclear due to the complex preprocessing operations, transportation and storage conditions (Limayem & Ricke, 2012).

Since the cellulosic biofuel production in the US was unable to meet the predictions for year to date, EPA reduced the volume required to comply with RFS2 (US EPA, 2020). EPA had previously demanded 10.5 billion gallons of cellulosic biofuel production for year 2020, but had to reduce their targets to 590 million gallons (Bracmort, 2018). This production shortage could be overcome with an efficient supply chain. Currently, we rely on a conventional/centralized supply system where feedstock is harvested, baled and stored close to their provenance and transferred directly to biorefineries. Given the inherent non-flowable and bulky characteristics of agricultural residues, this system is not efficient in handling cellulosic resources. Several studies have shown that, this system fails to handle supply regions with lower yield and larger supply area (Lamers et al., 2015a; Jacobson et al., 2014; Hess et al., 2009a). Logistic complexities stems partly from their dispersed geographic location, and quality variability. Therefore, the feedstock logistics for cellulosic biofuel constitutes 35-50% of the production cost, which constraints the near-term development of a consistent market (Foust et al., 2007).

An advanced feedstock supply system that ensures the delivery of on-spec biomass at the gate of biorefinery would reduce production costs and accelerate the national biofuel industry (Hess et al., 2009b). The idea is to move biomass-preprocessing operations from the biorefinery closer to the farmgate and into preprocessing depots. These smaller facilities, when compared to biorefineries, could be built in the lower yielding regions not accessible by conventional biorefineries (Argo et al., 2013), depots will help increase the biomass supply region. Depots would receive biomass with heterogeneous characteristics and provenance from nearby regions for drying, grinding, and densification to a uniform format feedstock (Hess et al., 2009b). Shipments to biorefineries would be based on a biomass blend/ratio with specified qualities including ash, moisture and carbohydrate content. Because the focus has been to design a cellulosic biofuel supply chain that maximizes quantities delivered at a biorefinery, very few studies have used the concept of biomass blending for on-spec deliveries (Campbell et al., 2013; Shi et al., 2013; Roni et al., 2018; Ekşioğlu et al., 2020; Narani et al., 2019). Blending costs depend on quality targets for different conversion pathways. Feedstock blend that meets target ash and carbohydrate content costs 12.12% higher than only meeting the latter (Roni et al., 2018).

Finding the location and size of the depots and biorefineries alongside with identifying the optimum feedstock blend and logistics cost, can ensure a long-term financial stability of the cellulosic biofuel production. A cost-competitive and efficient system design requires the integration of the interdependencies and complexities of all the different supply chain stages. Some studies in the literature considered a single feedstock (Kim et al., 2016; Lin et al., 2016) while others considered multiple feedstock types (Zhu et al., 2011; Marvin et al., 2012). Almost all of the studies have considered a regional supply area. Gonzales et al. (2017) developed a GIS-based heuristic to identify depots and biorefineries nationwide to locate stranded and accessible herbaceous biomass. The study did not consider on-spec delivery within a target cost. Ekşioğlu et al. (2009) identified the location, size and number of biorefineries as well as average travel distance and transportation costs to produce cellulosic ethanol from corn stover in Mississippi. Bai et al. (2011) proposed Lagrangian Relaxation (LR) based heuristics to predict biorefinery locations in Illinois for optimum biorefinery investment, feedstock and transportation cost. Marvin et al. (2012) developed a mixed-integer linear programming (MILP) model which can handle five different types of agricultural residues to determine the optimal location and size of biorefineries for a nine-state region in Midwestern US. Ng et al. (2017) developed an MILP model with multi-year horizon to minimize total annual cost determining the optimal number, capacity and location of depots and biorefineries, the production inventory and shipment profiles. Corn stover and switchgrass was considered to use the model in Southern Wisconsin.

Feedstock cost include, (1) grower payment, (2) logistics cost, and (3) quality costs. Most of the studies found in literature optimized logistics cost while maximizing supply. Delivering the optimal feedstock blend to the biorefinery considering both quality and quantity of feedstock, is still in its infancy in terms of research. Roni et al. (2019) developed an MILP model to optimize feedstock sourcing decisions and depot locations while considering a least-cost blend formulation for multiple feedstock (agricultural residues, energy and municipal solid waste). The quality biomass parameters considered by Roni et al. (2019) were carbohydrate, ash and moisture content to identify the optimum feedstock blend to feed biorefinery in Kansas. The authors only considered the supply chain for a single biorefinery while identifying the depot locations. Since cellulosic biomass is costly to handle and transport, higher production cost puts another limitation to the advancement of this industry alongside with the quality constraints. DOE goal is to achieve a near-term $3/GGE by 2022 or a long-term goal of $2.5/GGE by 2030, where feedstock handling and delivery costs are $71.26/dt and $79.07/dt respectively at the biorefinery gate (Davis et al., 2013).

The authors identified a knowledge gap in the literature that no other studies consider a nationwide delivery of on-spec biomass to depots and biorefineries while meeting a target minimum fuel-selling price of $3/GGE by 2022 and $2.5/GGE by 2030. This study aims to fill in that research gap by optimizing both the logistics cost and quality costs while handling the complexities of nationwide delivery under a target biofuel price. The novelty in this study is that we provide an economically and technically viable industry path to the development of a national biofuel industry by answering some of the key questions: i) How much biomass can be delivered nationwide under the quality and cost target? ii) What are the logistics cost required for delivery? iii) What are the optimum locations and capacities of depots and biorefineries nationwide? iv) What are the possible scenarios for various states in a depot-based system? To answer these, we developed a modified version of the least-cost formulation model (Roni et al., 2020). Contributions from this study: (1) Validation that a larger supply radius and a higher quantity of biomass can be accessed using a distributed system of depots to meet competitive biofuel prices. (2) Exemplary scenarios with a national mature conversion technology that takes advantage of economies of scale, the nth-plant scenario. (3) Contribution to the literature with a public nationwide database of field-depot and depot-biorefinery location and allocation considering multiple scenarios to meet DOE near- and long-term cost targets.

METHODS

MODEL APPROACH

The mixed-integer linear program (MILP) model was developed using the OPTMODEL procedure in SAS Institute Inc. 9.4M4 and the brand and cut algorithm was used to solve the model. The MILP analyzes different biomass feedstock quantities available at various farmgate prices as well as routes from fields to candidate depot sites where it goes through pretreatment and blending with other types of biomass. Routes from depots to biorefineries are also analyzed to ship a blend of different feedstock types. Figure 1(a) represents the decision network used to formulate the distributed depot system and includes different farmgate price levels, feedstock types, field locations, depot locations, and biorefinery locations. The MILP solves for the maximum amount of biomass feedstock shipped nationwide while meeting a set of biomass characteristics or quality specifications, cost and capacity constraints. In the solution, all biorefineries are co-located with a depot to minimize the transportation cost. Depots that are co-located with biorefineries are in high yielding regions and have a capacity as large as the biorefinery. Smaller depots help collect biomass from lower yielding regions and ship the preprocessed feedstock to biorefineries in higher yielding regions. Model inputs included: the resource quantities presented in the BT16 by Oak Ridge National Laboratory (Langholtz et. al, 2016), the targeted delivery feedstock cost to the reactor throat presented by the National Renewable Energy Laboratory for biochemical conversion (Davis et al., 2013), and logistics costs presented by Roni et al., (2018).

MODEL INPUTS

Available biomass

The base-case scenario county-level feedstock values reported in the BT16 for years 2022, 2030 and 2040 at farmgate prices between \$30-50 (table 1) were inputs to the model (Langholtz et al., 2016). Note that the BT16 supply curves are developed by multiple iterations of different price runs and should be interpreted as either a total of available feedstock *x* at \$30, \$40 or \$50, and not a cumulative total at all farmgate prices. For example, in 2022, there is 29.5 Mdt (million dry tons) of corn stover at \$40/dt or 89.9 Mdt of corn stover at \$50/dt. We assumed that a biorefinery will accept a feedstock blend of switchgrass and corn stover. The blend will contribute towards achieving quality specifications at the biorefinery. Delivering on-spec biomass, includes feedstock with ash content less than or equal to 5% (dry basis), moisture content equal to 20% and carbohydrate content greater than or equal to 59% (Davis et al., 2013). A key approach in obtaining the quality requirements of a feedstock is to modify the harvest operation (Langholtz et al., 2019). Two-pass corn stover has around 4% less ash content and higher carbohydrate content than three-pass (Shinners et al., 2012). However, the per acre yield of two-pass is lower compared to three-pass. The decrease in yield is compensated using a corn stover factor which assumes that two-pass harvest yield is 49% less than three-pass (Langholtz et. al, 2016). Both corn stover harvesting operations are choices for the model.

Table 1. Nationwide supply curves for corn stover (CS) and switchgrass (SW)

Year	Feedstock	Available biomass (million dry tons) based on farmgate prices ($/dry tons)		
		$30	$40	$50
2022	CS	0	29.5	89.9
	SW	0	0.12	13.2
2030	CS	16.7	36.1	116
	SW	0	4.05	59.1
2040	CS	32.7	44.5	144
	SW	0	27	142

Field locations

US counties were considered fields in our model. Given that cropland is not equally distributed through counties, the spatial location of cropland in the 2018 CDL (classified as corn, cotton, rice, sorghum, soybeans, barley, durum wheat, spring wheat, winter wheat, oats, and fallow/idle) was used to geo-reference available biomass at each county as an alternative to using county centroids and was best illustrated in Ashley, AR and Washakie, WY Counties (fig. 1(b)). On average, the difference in centroids was 0.074° (8.2 km) with the highest change been 0.8° (89 km) in San Miguel County, NM.

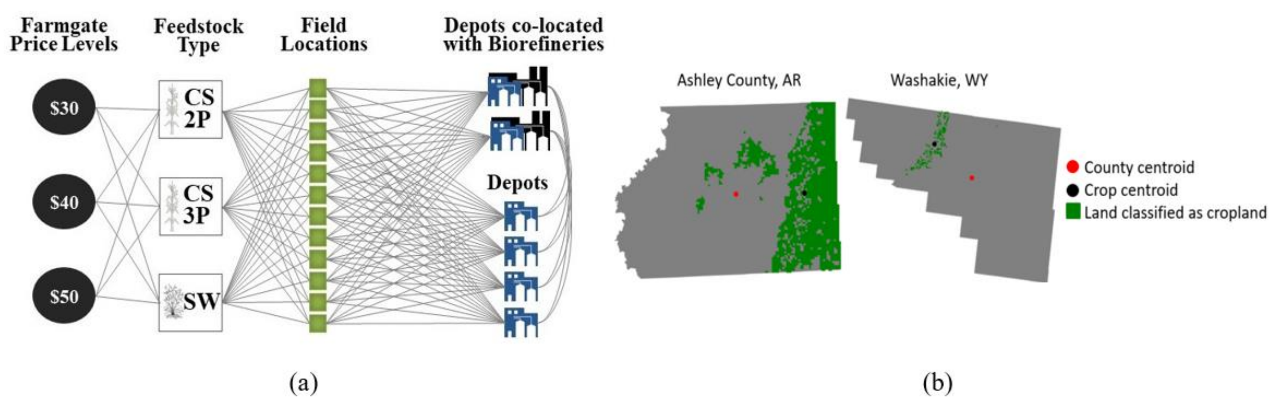


Figure 1. (a) Schematic representation of the decision network analyzed where CS2P is two-pass corn stover, CS3P is three-pass corn stover, and SW is switchgrass. (b) Cropland centroids vs county centroids.

Logistic costs

Table 2 presents the logistics costs used in this study based on Roni et al. (2018). The fixed transportation cost for bales is almost four times higher than the cost for pellets. Storage for bales is almost 11 times greater than that of pellets. The ash dockage and moisture dockage cost were considered when the feedstock failed to meet the ash and moisture specifications.

Table 2. Costs for Advanced Supply Chain (2016$)

Cost Description	Feedstock Format	Location	Feedstock		
			CS3P	CS2P	SW
Farmgate Price	Bale	Field	$30-50[a]		$30-50[a]
Storage	Bale	Field	$3.97	$4.10	$3.02
Storage, Handling and Queuing	Bale to pellets	Depot	$2.09		$2.22
Storage, Handling and Queuing	Pellets	Biorefinery	$0.34		$0.65
Processing Cost	Bale to pellets	Depot	$19.47		$18.77
Ash Dockage	Pellets	Biorefinery	$2.71	$0.98	$0.53
Moisture Dockage	Pellets	Biorefinery	$0.03	$0.03	$0.03
Transportation Fixed Cost or Field-side Handling and Queuing	Bale	Field to Depot		$3.42	
Transportation Variable Cost[b]	Bale	Field to Depot		$0.114	
Transportation Fixed Cost	Pellets	Depot to Biorefinery	$0.829		$0.792
Transportation Variable Cost[b]	Pellets	Depot to Biorefinery	$0.082		$0.081

[a] 2014$, [b] *$/mile. CS3P= Corn stover 3-pass, CS2P= Corn stover 2-pass, and SW= Switchgrass.

Candidate depot and biorefinery locations

Given the computational complexities of an uncapacitated facility location problem with a nationwide scope (2,082 possible locations for depots and biorefineries); we reduced the problem size to solve for optimality and used a two-step process. To find a subset of candidate locations, we solved to maximize corn stover (three-pass only) and switchgrass delivered at $79.07 /dt to depots using the biomass supply curve for year 2040 in the BT16 and relaxed the quality constraints. This initial solution found a total of 98.6 Mdt delivered to 247 depots, which were used as candidate locations for depots and/or biorefineries in the MILP model presented in this paper.

MODEL FORMULATION

The MILP model presented in this paper identifies the optimal location and size of an undetermined number of biorefineries and depots to maximize total feedstock delivered to biorefineries at less than or equal to a specific target price (eq. 1). We analyzed two target prices: $79.07 and $71.26 per dt ($2016) based on the short- and long-term goals presented by a DOE techno-economic analysis (Davis et al., 2013). Table 3 presents the data sets, parameters, and decision variables in our MILP formulation.

$$\max \sum_{j \in J} \sum_{k \in K} \sum_{f \in F} x_{jkf} \tag{1}$$

Table 3. Data sets, parameters, and decision variables

Data sets			
F	Set of feedstock types	α_f	Set of ash content per ton for feedstock f
P	Set of feedstock prices	μ_f	Set of moisture content per ton for feedstock f
I	Set of field locations	β_f	Set of carbohydrate content per ton for feedstock f
J	Set of potential depot locations	a_{ifp}	Set of available supply for field i of feedstock type f at price p

K	Set of potential biorefinery locations	m_{if}	Set of minimum supply for field *i* of feedstock type *f*
d_{ij}	Set of distances between location i and location j	d_{jk}	Set of distances between location j to location k
VC_{ijkfp}	Set of total variable cost from field *i* to depot *j*: farmgate price (gr), storage (sb, sp), transportation (trb, trf), handling and queuing (qh), preprocessing costs (pr) , ash dockage (ad) and moisture dockage (md)		
Parameters			
T	Cost target at delivery	H	Target carbohydrate content at biorefinery
U	Required depot utilization factor (90%)	D	Demand of a biorefinery
M	Minimum moisture content at biorefinery	S	Constant multiplier for depot capacity
A	Maximum ash content at biorefinery		
Decision Variables			
C_j	Factor for depot capacity at location *j* (integer)	Z_{ifp}	1 if feedstock *f* is purchased at price *p* from location *i*; 0 otherwise (binary)
X_{ifp}	Amount of feedstock *f* purchased at price *p* from location *i* (integer)	L_j	1 if depot is built in location *j*; 0 otherwise (binary)
X_{ijf}	Amount of feedstock *f* shipped from location *i* to location *j* (integer)	L_k	1 if biorefinery is built in location *k*; 0 otherwise (binary)
X_{jkf}	Amount of feedstock *f* shipped from location *j* to location *k* (integer)		

Demand at each biorefinery was constant at 725,000 dt/year (D). Depot capacities were determined by the model using the product of a constant multiplier 25,000 (S) and an integer decision variable (C_j). Depot construction costs presented by Roni et al. (2019) fitted a linear equation with an adjusted R-square of 0.998. Equation 2 represents depot fixed costs (FC). Variable costs (VC) to deliver biomass included farmgate price, storage, handling, transportation and preprocessing costs (eq. 3). When needed, a cost to reduce ash or increase moisture was incurred at the biorefinery to meet quality specifications. Constraints in table 4: (1) ensures that each feedstock is purchased only at a single price from each field location. (2) Puts a maximum limit to the amount of feedstock purchased from a field location so that it does not exceed the total amount available at that field. (3) Ensures that the total amount of corn stover harvested from a location using three-pass and two-pass is not more than the available corn stover in that field. (4) Decides on the capacity of the depot depending on the total supply to that depot. (5) Is the flow balance between field and depot. (6) Sets a minimum utilization to the depot capacity. (7) Is the flow balance between depot and biorefinery. (8) Ensures that the total supply to a biorefinery meets the required demand. (9) Requires that the total carbohydrate content of all the different feedstocks supplied to a biorefinery meet the minimum carbohydrate requirement. The cost target is bounded using constraint (10) combining the total fixed as well as variable costs. The constraints in (11) ensures non-negativity of the integer decision variables. Constraints in (12) are for binary decision variables.

$$FC = \sum_{j \in J} (132{,}717 * L_j + 2.297 * (S * C_j)) \quad (2)$$

$$VC_{ijkfp} = \sum_{i\in I}\sum_{f\in F}\sum_{p\in P}\left(0.997 * gr_p * X_{ifp}\right) + \sum_{i\in I}\sum_{f\in F}\sum_{j\in J}\left(sb_f + qh_f + pr_f + trb_{ijf} + sp_f\right) * X_{ijf} + \sum_{j\in J}\sum_{k\in K}\sum_{f\in F}\left(trp_{jkf} + \left(\alpha_f - A\right) * ad_f + \left(M - \mu_f\right) * md_f\right) * X_{jkf} \quad (3)$$

Table 4. Model Constraints

No.	Constraint Name	Mathematical Formulation
1	Feedstock purchase	$\sum_{p\in P} Z_{ifp} \le \begin{cases} 0 \text{ if } m_{if} = 0 \\ 1 \text{ otherwise} \end{cases}$; $\forall\ i \text{ in } I, f \text{ in } F$
2	Maximum supply	$X_{ifp} \le a_{ifp} * Z_{ifp}$; $\forall\ i \text{ in } I, f \text{ in } F, p \text{ in } P$
3	Three pass & Two pass	$X_{i,f=CS3P,p} + \left(X_{i,f=CS2P,p}/CS\ Factor\right) \le a_{i,f=CS3P,p}$; $\forall\ i \text{ in } I, f \text{ in } F, p \text{ in } P$
4	Depot Capacity	$\sum_{i\in I}\sum_{f\in F} X_{ijf} \le S * C_j$; $\forall\ j \text{ in } J$
5	Flow balance for field-depot	$\sum_{p\in P} X_{ifp} = \sum_{j\in J} X_{ijf}$ if $dij < 80$; $\forall\ i \text{ in } I, f \text{ in } F$
6	Depot Utilization	$\sum_{i\in I}\sum_{f\in F} X_{ijf} \ge U * S * C_j$ if $d_{ij} < 80$; $\forall\ j \text{ in } J$
7	Flow balance for depot-biorefinery	$\sum_{i\in I} X_{ijf} = \sum_{k\in K} X_{jkf}$ if $djk < 400$; $\forall\ j \text{ in } J, f \text{ in } F$
8	Biorefinery Demand	$\sum_{j\in J}\sum_{f\in F} X_{jkf} = D * L_k$; $\forall\ k \text{ in } K$
9	Carbohydrate quality constraint	$\sum_{j\in J}\sum_{f\in F} X_{jkf} * \beta_f \ge H * \sum_{j\in J}\sum_{f\in F} X_{jkf}$; $\forall\ k \text{ in } K$
10	Cost target	$FC_j + VC_{ijkfp} \le T * X_{jkf}$
11	Integer constraints	$X_{ifp} > 0, \forall\ i \in I,\ f \in F, p \in P$; $X_{ijf} > 0, \forall\ i \in I,\ j \in J,\ f \in F$ $X_{jkf} > 0, \forall\ j \in J,\ k \in K,\ f \in F$; $C_j > 0, \forall\ j \in J$
12	Binary constraints	$Z_{ifp} \in \{0,1\}, \quad \forall\ i \in I,\ f \in F,\ p \in P$ $L_j \in \{0,1\}, \quad \forall\ j \in J$ $L_k \in \{0,1\}, \quad \forall\ k \in K$

RESULTS

SCENARIOS

Four different scenario runs were performed considering the year and cost target, namely (S1) 2022 at \$79.07/dt, (S2) 2030 at \$79.07/dt, (S3) 2040 at \$79.07/dt and (S4) 2030 at \$71.26/dt. Even after decreasing the set of depot and biorefinery candidates, the problem had around 43,000 variables, 5,500 constraints and 16,000 constraint coefficients. We ran each scenario for 3 hours and obtained an error gap between 12-13%. The results for the different years and targeted prices analyzed in this study are presented in table 5. When targets for delivery to the reactor throat are at \$79.07/dt, the total viable biomass collected has above a two-fold increase (215%) from 2022 to 2030 and almost a four-fold increase (393%) from 2022 to 2040. The increase in total collected biomass could be explained by the increase in biomass availability and inherent higher geographical concentration within regions, making it cost efficient to collect more biomass within the same cost target. While we see a significant increase in potential biomass delivered to biorefineries with respect to time, DOE has lower long-term cost targets for 2030 ($71.26/dt). Based on our analysis, a lower delivering cost target would decrease the total available biomass in 2030 by 68% and 69% when comparing years 2030 and 2022 respectively.

Table 5. Analyzed scenarios

Scenario	Feedstock	Million dry tons / year				Number of Facilities	Summary Statistics for Biorefinery costs ($)
		$30	$40	$50	Total		
S1: 2022 $79.07/dt	SW[a]	0	0.01	5.31	5.32	124 Depots 59 Biorefineries 42.8 Mdt Collected	Min: $71.36 Max: $87.91 Standard dev.: 3.92 Standard error: 0.51
	CS2P[b]	0	7.83	17.6	25.5		
	CS3P[c]	0	9.14	2.85	12.0		
S2: 2030 $79.07/dt	SW[a]	0	3	35.4	38.4	204 Depots 127 Biorefineries 92.1 Mdt Collected	Min: $63.61 Max: $87.76 Standard dev.: 5.31 Standard error: 0.47
	CS2P[b]	2.16	9.21	21.8	33.2		
	CS3P[c]	10.3	4.18	6	20.5		
S3: 2040 $79.07/dt	SW[a]	0	17.8	60.6	78.4	304 Depots 231 Biorefineries 168 Mdt Collected	Min: $63.64 Max: $101.72 Standard dev.: 6.13 Standard error: 0.403
	CS2P[b]	2.54	13.4	30.9	46.9		
	CS3P[c]	24.1	4.22	13.9	42.2		
S4: 2030 $71.26/dt	SW[a]	0	2.11	4.68	6.79	80 Depots 41 Biorefineries 29.7 Mdt Collected	Min: $63.44 Max: $80.59 Standard dev.: 4.62 Standard error: 0.722
	CS2P[b]	3.5	9.05	0.79	13.3		
	CS3P[c]	7.41	2.13	0.05	9.59		

[a] SW = Switchgrass, [b] CS2P = Corn stover two-pass, [c] CS3P = Corn stover three-pass.

SUMMARY STATISTICS

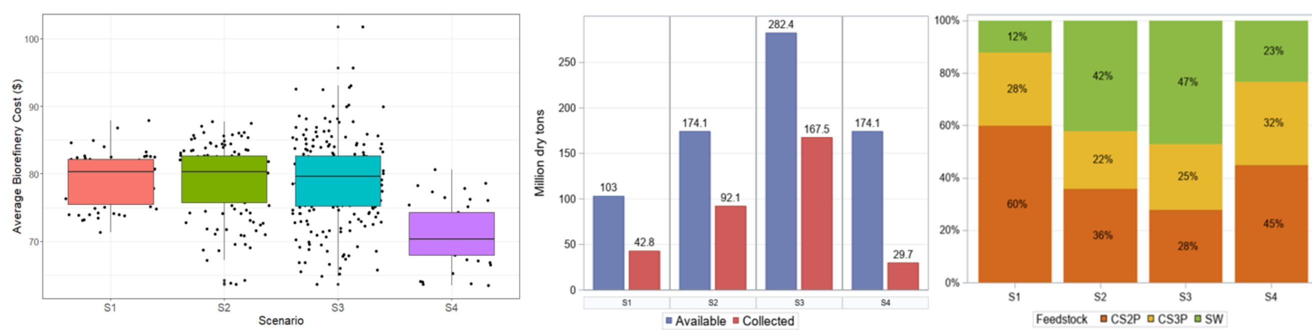
To further reduce our problem complexity, the cost constraint at the reactor throat was applied as an average for a nationwide system. As a result, the solution located biorefineries with less than or equal to and greater than the target delivery cost. However, for an ideal scenario, all biorefineries would meet the cost target. To observe the deviation from the cost target, the average cost for each individual biorefinery was calculated. The highest deviation from the mean was observed in S4, with an average cost of 95% of the biorefineries within +/- $1.44 (=2*0.722) of the cost target $71.26 /dt. This is due to the limited supply of the scenario which makes it complex to build biorefineries at that lower cost target. For all the other scenarios, the deviation was within +/- $1. Figure 2(a) identifies minimum, maximum, standard deviation, and standard error of the mean for all scenarios. 46, 39, 48 and 54% of all the biorefineries were within the cost target for scenarios S1-S4 respectively.

BIOMASS ACCESSIBILITY

The BT16 data predicted that the availability of herbaceous biomass supply within the US would be enough to develop a sustainable biofuel economy. However, availability does not guarantee accessibility of those biomass resources. Resources would be accessible only if they could be collected and shipped to the gate of the biorefinery within a feasible cost. In figure 2(b) we identified the total percentage of stranded and accessible biomass based on the BT16 supply curve at the $50 farmgate price the total feedstock collected by the developed model in this study. A large portion of the feedstock remained stranded or inaccessible when compared to the BT16 supply curve [fig. 2(b)]. Using costs for the short- and long-term targets respectively, 45-60% and 20% of the available biomass was accessible biomass with an advanced supply system. Hence, the goal of $71.26/dt or $2.5/GGE by 2030 might only be achieved for 30 Mdt or 1.3 billion GGE (at 44.8 GGE/dt -Davis et al., 2013).

FEEDSTOCK RATIO

Figure 2(c) illustrates the estimated proportions of total feedstock type collected to maintain the on-spec delivery. When the delivered target price is fixed, almost 50% of the total collected biomass is



(a) (b) (c)

Figure 2 (a) Distribution of the average biorefinery costs for the four scenarios. (b) Comparison of total available and collected feedstock by the model and (c) percentage of feedstock collection for scenarios S1, S2, S3 and S4.

estimated to be switchgrass in the later years (S2 and S3). From the scenarios presented, corn stover two-pass represented the majority of the selected feedstock in the earliest year and at the lowest price (S1 and S4). In S1 the model was restricted by the input supply curve of year 2022. Whereas in S4, the model had to satisfy a lower cost target of \$71.26/dt. This resulted in the collection of biomass mostly from the Corn Belt region. For the other two scenarios (S2 and S3), the input supply curve from BT16 at 2030 and 2040 was high enough to expand the selected regions by the model outside of the Corn Belt and collect a higher percentage of switchgrass.

DEPOT AND BIOREFINERY LOCATIONS

Figure 3 is an illustration of our nationwide analysis for depot and biorefinery locations. The supply curve, represented in shades of green, was estimated using the average supply of corn stover and switchgrass at \$30, \$40 and \$50. Counties with an overlapping triangle and circle represent depots co-located with biorefineries. Moreover, the biorefineries that were within the cost target are mostly situated in the Corn Belt region and in part of Texas due to the higher biomass supply in those regions.

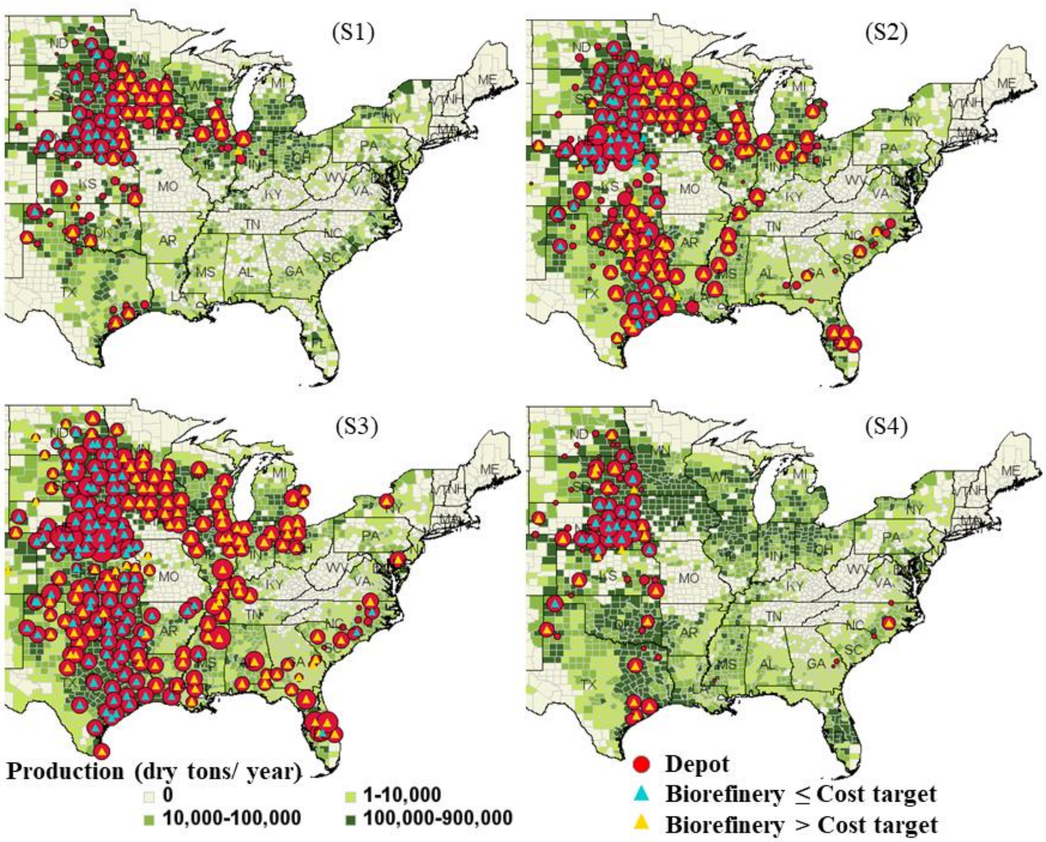


Figure 3. Depot and biorefinery locations in the US for four scenarios: (S1) 2022 @ \$79.07/dt, (S2) 2030 @ \$79.07/dt, (S3) 2040 @ \$79.07/dt and (S4) 2030 @ \$71.26/dt.

DEPOT AND BIOREFINERY CAPACITY

The different capacities of depots built for all scenarios were also analyzed to estimate the scenario for a conventional supply chain. Locations with a depot size of 725,000 dt could be identified as ideal for a conventional supply chain. For example, in S1, 13 biorefineries could be built with a conventional supply chain collecting 9.5 Mdt. Including depot locations allows for an increase of 42.8 Mdt collected biomass. The two most common depot sizes selected by the model are 725,000 and 25,000 dt/year. The biggest depot size reflects a co- location of a biorefinery and a depot minimizing delivery costs from depots to biorefineries. Interestingly, 114 depots of 625,000-700,000 dt/year were located across all the scenarios studied and only 89 depots of sizes 50,000-125,000.

STATEWIDE CAPACITY

Identifying the potential states with high number of depots and biorefineries could benefit the economies of scale of the supply chain system for those local regions (fig. 4).

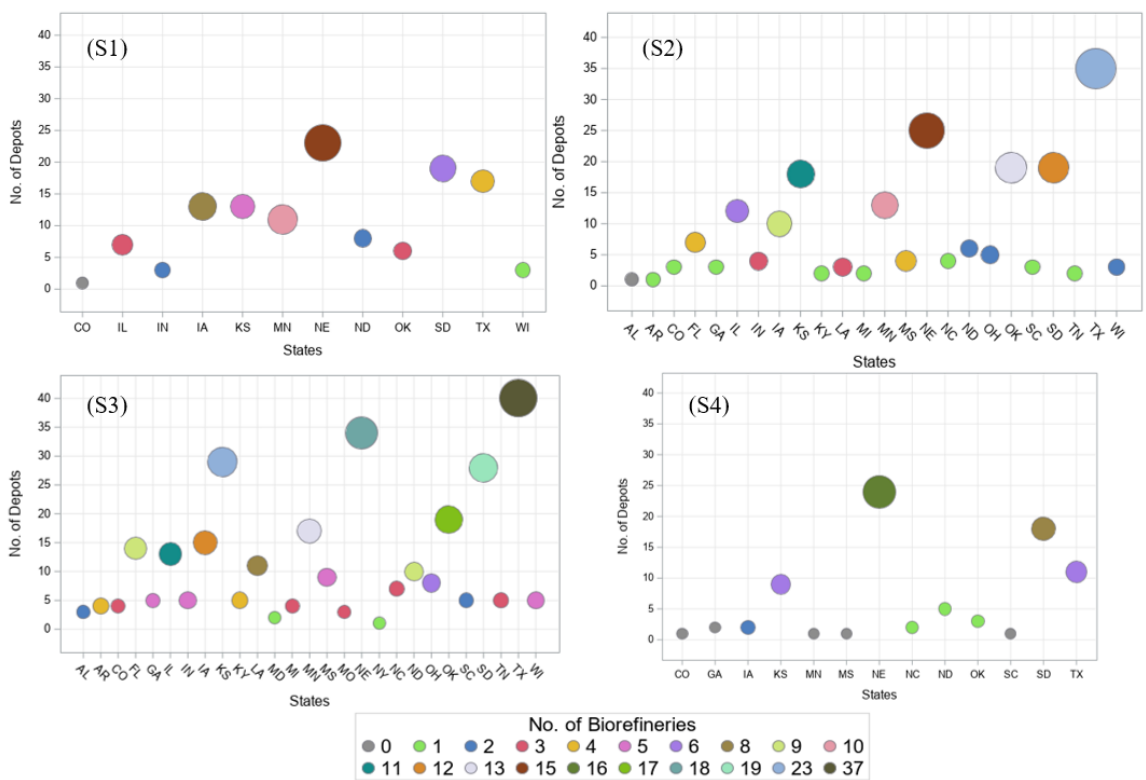


Figure 4. Number of depots and biorefineries in each state for the four scenarios, (S1) 2022 at $79.07/dt, (S2) 2030 at $79.07/dt, (S3) 2040 at $79.07/dt and (S4) 2030 at $71.26/dt. The bubble size indicates the total amount of feedstock shipped to depots for each state. Each of the biorefineries have fixed demand of 725,000 dt/year.

KS, NE, SD and TX were identified as potential states with a strong biofuel economy with six or more biorefineries located in all scenarios. NE was the only state with more than 10 biorefineries for both, S1 and S4 suggesting that it can be a potential biofuel production base for both, the short-term and long-term scenario. A few states had a very high number of biorefineries (>10): NE (S1, S2, S3, S4), KS (S2, S3), TX (S2, S3), SD (S2, S3) and Ok (S2, S3). Some states had multiple depots but zero biorefineries such as CO (S1, S4), AL (S2), GA (S4), MN (S4), MS (S4) and SC (S4). Those states would need to ship the preprocessed biomass to a nearby out-of-state biorefinery. The number of such cases increased with lower cost target introducing logistical complexities of longer haul.

DISCUSSION

The goal was to analyze the nationwide scenario for cellulosic biofuel production and determine the feasibility of the EPA's target of 16 billion gallons by year 2022. Considering a biofuel yield of 44.8 GGE/dt (Davis et al. 2013), around 357 Mdt of feedstock needs to be delivered at the gate of the biorefinery and a total of 493 biorefineries with 725,000 dt capacity each has to be built to meet EPA goals. However, the results of the developed model indicated that only 42.8 Mdt of corn stover and switchgrass could be delivered to a total of 59 biorefineries by year 2022 which is 12% of the total cellulosic feedstock demand. The remaining 88% would come from other cellulosic resources including miscanthus and wheat straw. But, given that corn stover and switchgrass comprise around 70% of the total herbaceous supply (Langholtz et al., 2016), herbaceous biomass alone is not a feasible option. Even when the supply curve of 2030 and 2040 from the BT16 was considered, the model predicted the delivery of 26% and 47% of the EPA's cellulosic feedstock demand respectively.

A nationwide analysis helps identify an nth-plant scenario for biofuels, regardless of political boundaries, given that some states in the US may ship preprocessed biomass to the biorefinery of a nearby state. Optimizing part of the nation would have made the model computationally more efficient but it would introduce error in terms of boundary scenarios. The only previous work found in literature for a nationwide scenario was by Gonzales et al. (2017). However, Gonzales et al. (2017) did not consider on-spec delivery with quality nor specific constraints on the cost target. The study presented that 183.7 Mdt of herbaceous biomass could be collected out of the predicted 205 Mdt in year 2022 and predicted to meet more than the targeted demand of EPA for year 2022. Our analysis suggested that the EPA's target was highly over estimated if feedstock quality and biofuel price target were considered.

Roni et al. (2018) considered delivery to a single fixed biorefinery location in Seridan County of KS and solved to find depot locations and sizes for the least-cost feedstock blend. Four depots were identified in NE, KS and CO to supply a total of 725,600 dt to one biorefinery. In the same region, we identified 37 depots and 20 biorefineries in NE, KS and CO to supply a total of 14.5 Mdt [fig. 5(a)]. This difference may stem from solving for biorefineries and depots simultaneously and is reflected in a 20-fold increase of collected biomass when compared to Roni et al. (2018). In both cases, supply curves from the BT16 for 2022 were used.

Caffrey et al. (2015) used a simplified heuristic to analyze the biomass supply chain management in North Carolina using Switchgrass and Sorghum with different harvest methods (e.g. forage and bales). The storage location and biorefineries were determined using a conventional supply system. The authors suggested that a biorefinery in the Coastal Plain region of NC would be beneficiary due to the higher availability and productivity of agricultural feedstock in the region. The model results from the presented study also suggested one biorefinery in NC close to the coastal region. Although, for year 2022, the available feedstock was not enough to meet the target cost of 79.07 $/dt. Hence, the costal biorefinery in NC was built only for the 2030 and 2040 scenarios [fig. 5(b)].

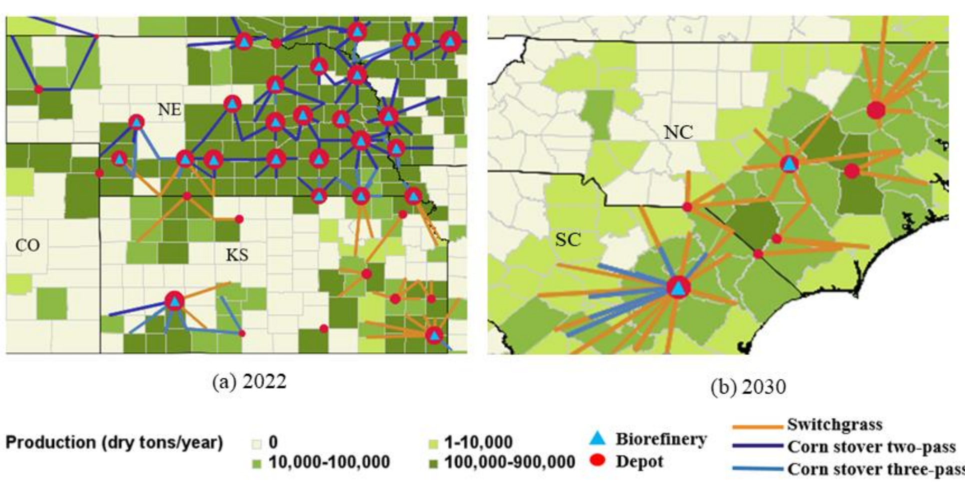


Figure 5. Magnifying on the location of depots and biorefineries in different states. Connecting lines indicate what fields are assigned to a depot (red circle) in the solution.

To overcome error gaps and model limitations, our future research will focus on running the model on a super computer including all the field locations as potential depot and biorefinery candidates. The model results were highly dependent on the cost parameters and the BT16 supply curve. A detailed sensitivity analysis on the model parameters will also be included in our future work. Additionally, a winding factor of 1.2 was included in the model for estimating the road distance. However, the existing road network could be incorporated in the model to get real distances for an improved better estimate on the transportation and overall logistics cost. The authors plan is to modify the model presented to analyze supply chains for additional and/or complementary biomass types such as miscanthus, short rotation woody crops, and animal manure for conversion to fertilizers. Illustrating the versatility of the developed model can be a valuable future aspect of this study.

CONCLUSION

To provide economic sustainability for cellulosic crop production, the location of cellulosic based biomass depots and biorefineries have to be strategic throughout the US, creating sufficient cellulosic biomass demand in the market and reducing the pressure on food production. Findings from this study could be used to provide cost and profit analysis of cellulosic biofuel production to decision-makers including supply managers, farmers and business investors and ensure a sustainable biofuel economy. Both strong policy formulation and innovative conversion technology are required to meet EPA's cellulosic biofuel production mandate. The results of this study pose a question whether the currently set mandates are achievable and if they should be updated to a more realistic scenario.

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ASABE Author Information

THE NTH-PLANT SCENARIO FOR BLENDED FEEDSTOCK CONVERSION AND PREPROCESSING NATIONWIDE: BIOREFINERIES AND DEPOTS

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