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The nth-plant scenario for blended feedstock conversion and preprocessing nationwide: biorefineries and depots

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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 ultimately transform the nation's renewable biomass resources into cost-competitive, high-performance feedstock for production of biofuels and bioproducts. Since the US has put restrictions on production levels of conventional biofuels from edible resources, the nation needs to plan for the widespread accessibility and development of the cellulosic biofuel scenario. 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 conversion plants, or 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 with switchgrass and corn stover (harvested by either a two- or three-pass method) are considered in a Mixed Integer Linear Programming model to deliver on-spec biomass that considers both, a desired quantity and quality at the biorefinery. The model solves for a network of varying size depots that supply to biorefineries of 725,000 dry tons/year. A total delivered feedstock cost that is less than \$79.07/dry tons (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/dry tons reduction in targeted delivery cost could reduce total accessible biomass by 67%. Kansas, Nebraska, South Dakota and Texas were identified as potential states with a strong biofuel economy given that they had six or more biorefineries located in all scenarios. In some 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. We also present results for biorefinery capacities that are double, triple and quadruple in size.

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

1. 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 and set a target of 21 billion gallons per year (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 the food-based biomass resources, cellulosic biomass are non-edible resources including energy crops, municipal solid waste, and agricultural or forest residues (Kim & Dale, 2015). Due to widespread availability and low-cost raw material, cellulosic biomass is a promising alternative for starch-based biomass. However, the cost of production of biofuels from cellulosic biomass 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, the Environmental Protection Agency (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 system. Currently, the cellulosic biofuel supply chain depends on the conventional/centralized supply system where feedstock is harvested, baled and stored locally close to the farms. Bales are then collected from farms and transferred directly to biorefineries. But, given the inherent characteristic of agricultural residues, such as non-flowable and bulky, 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, which are often the case for cellulosic biomass (Lamers et al., 2015a; Jacobson et al., 2014; Hess et al., 2009a). They are complex to handle due to their dispersed geographic location, and quality variability. Therefore, the feedstock logistics for cellulosic biofuel constitutes 35-50% of the total production cost, which constraints the near-term development of a consistent market (Foust et al., 2007).

We posit that an advanced feedstock supply system that ensures the delivery of on-spec biomass at the gate of biorefinery would reduce production costs and ultimately accelerate the national biofuel industry (Hess et al., 2009b; Lamers et al., 2015b). The idea is to move biomass-preprocessing operations from the biorefinery closer to the farmgate and into preprocessing depots. And, because 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 supply region of the supply chain system. These depots would receive biomass with heterogeneous characteristics and provenance from nearby supply regions for drying, grinding, and densification to a uniform format feedstock (Hess et al., 2009b). Pellets 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 cost will depend on quality targets for different conversion pathways. Feedstock blend that meets target carbohydrate and ash content costs 12.12% higher than feedstock blend that meets only carbohydrate requirement (Roni et al., 2018).

When dealing with an advanced feedstock supply system, 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. Converting raw biomass into biofuel involves several stages including harvesting, baling, preprocessing, storage and transportation. A cost-competitive and efficient design of the biofuels supply chain requires the integration of the interdependencies and complexities of all the different stages. Numerous studies have been found in literature to model and optimize the cellulosic biofuel supply chain stages. Some of these studies considered a single feedstock (Kim & Dale, 2016; Lin et al., 2016) while others considered multiple feedstocks (Zhu et al., 2011; Marvin et al., 2012). Almost all of the studies have considered a regional supply area instead of nationwide scenario. Gonzales et al. (2017) developed a GIS-based heuristic to identify the depots and biorefineries throughout the US to locate the stranded and accessible herbaceous biomass. But, the study did not consider the on-spec delivery within target cost. Ekşioğlu et al. (2009) used a mathematical model to identify 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.

The feedstock cost can be divided into three groups, (1) grower payment, (2) logistics cost, and (3) quality costs. Most of the studies found in literature have tried to optimize the logistics cost while maximizing the 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. were carbohydrate, ash and moisture content to identify the optimum feedstock blend to feed biorefinery in Kansas. Roni et al. 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. The Department of Energy's (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/dry tons and \$79.07/dry tons respectively at the biorefinery gate (Davis et al., 2013).

The authors identified a knowledge gap in the literature that no other studies have considered a nationwide delivery of on-spec biomass to biorefineries while meeting a target minimum fuel-selling price (MFSP) 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 as well as the quality costs at the same time 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? And, (iv)What are the possible scenarios for various states in a depot-based system? To answer these questions, we developed a modified version of the least-cost formulation model (Roni et al., 2020) to deliver on-spec biomass while simultaneously optimizing the biorefinery and depot locations and nameplate capacities nationwide to meet the national MFSP target set by DOE. Contributions from this study can be summarized as followed:

(i) Validation that a larger supply radius and a higher quantity of biomass can be accessed using the advanced feedstock supply system with distributed depots to meet competitive biofuel prices.

(ii) Exemplary scenarios with a national mature conversion technology that takes advantage of economies of scale, the nth-plant scenario.

(iii) Finally, this study contributes to the literature with a nationwide database of field-depot and depot-biorefinery location and allocation considering multiple scenarios to meet DOE near- and long-term cost targets. The dataset will be available to other researchers for further analysis and decision-making purpose.

2. Methods

2.1 Model approach

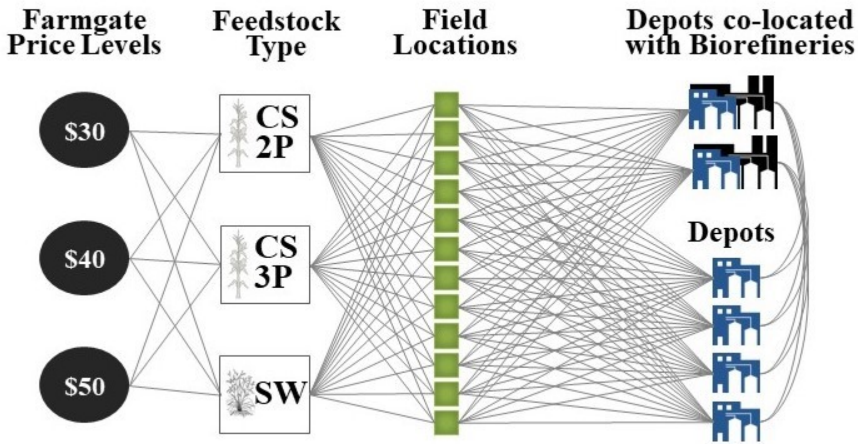


Figure 1. Schematic representation of the decision network analyzed where CS2P is two-pass corn stover, CS3P is three-pass corn stover, and SW is switchgrass.

The mixed-integer linear program (MILP) model presented was developed using the OPTMODEL procedure in SAS Institute Inc. 9.4M4 and the branch and bound algorithm was used to solve the model. Figure 1 represents the decision network used to formulate the advanced supply system and includes different farmgate price levels, feedstock types, field locations, depot locations, and biorefinery locations. The MILP analyzes the 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. The routes from depots to biorefineries are also analyzed to ship a blend of different feedstock types. 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 at higher yield regions will have capacity as large as a biorefinery and those will be in the same location with a biorefinery. Not all depots have biorefineries at that same location. Smaller depots help collect biomass from lower yielding regions and ship the preprocessed feedstock to biorefineries in higher yielding regions. Inputs to the model 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 Idaho National Laboratory (INL) (Roni et al., 2018).

2.2 Model Inputs

2.2.1 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 and $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 million dry tons of corn stover at $40/ dry tons or 89.9 million dry tons of corn stover at $50/ dry tons. 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 greater than or equal to 20% and carbohydrate content greater than or equal to 59% (dry basis-including total anhydro-C6 and C5) (Davis et al., 2013; Davis et al., 2018). 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 (CS 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. Moreover, to accommodate for biomass loss/dry matter loss during storage and transportation, the supply curve from BT16 is decreased by 9% (Roni et al., 2020).

Table 1. Nationwide supply curves for corn stover (CS) and switchgrass (SW) for years 2022, 2030, and 2040

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

2.2.2 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 (land 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. This approach was an alternative to using county centroids and was best illustrated in Ashley, AR and Washakie, WY Counties (Figure 2). 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.

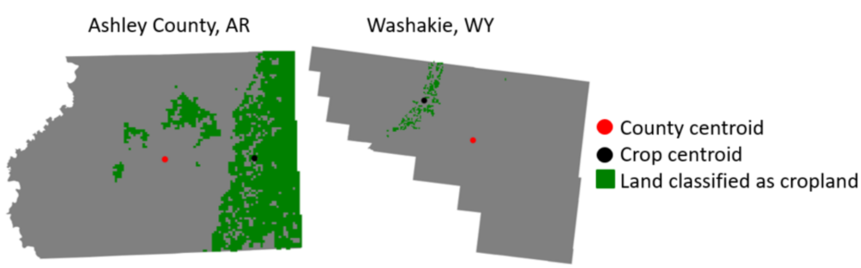


Figure 2. Cropland centroids vs county centroids. [For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article]

2.2.3 Logistic costs

Table 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$/ton)

Cost Description	Feedstock Format	Location	Feedstock		
			CS3P	CS2P	SW
Farmgate Price	Bale	Field	$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[b]	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[c]	Bale	Field to Depot	$0.114		
Transportation Fixed Cost	Pellets	Depot to Biorefinery	$0.829		$0.792
Transportation Variable Cost[c]	Pellets	Depot to Biorefinery	$0.082		$0.081

[a] 2014$. [b] Price to increase moisture content of biomass to 20% (wet basis). [c] $/ton/mile

2.2.4 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 needed to reduce the problem size to solve for optimality. Hence, we used a two-step process in our analysis. First, to find a subset of candidate locations, we solved to maximize corn stover (three-pass only) and switchgrass delivered at $79.07/ dry tons to depots (depots only) using the biomass supply curve for year 2040 in the BT16 and relaxed the quality constraints at the biorefinery. This initial solution found a total of 98.6 million dry tons delivered to 247 depots with an error gap of 5%. We used these 247 depots as candidate locations for depots and/or biorefineries in the MILP model presented in this paper, step two. Further analysis using our initial solution (step one) is described in the discussion section.

3. 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 (X) 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 dry tons ($2016) based on the short- and long-term goals presented by a DOE techno-economic analysis (Davis et al., 2013). Table presents the data sets, parameters, and decision variables in our MILP formulation.

Table 3. Data sets, parameters, and decision variables

Data sets	
F	Set of feedstock types
P	Set of feedstock prices
I	Set of field locations
J	Set of potential depot locations
K	Set of potential biorefinery locations
J_i	Set of potential depot locations within 80 miles of field i
K_j	Set of potential biorefinery locations within 400 miles of depot j
	Set of ash content per ton for feedstock f
	Set of moisture content per ton for feedstock f
	Set of carbohydrate content per ton for feedstock f
	Set of available supply for field i of feedstock type f at price p
	Set of minimum supply for field i of feedstock type f
	Set of total variable cost from field i to depot j to biorefinery k: farmgate price (*gr*), storage (*sb*, *sp*), transportation (*trb*, *trf*), handling and queuing (*qh*), preprocessing costs (*pr*) , ash dockage (*ad*) and moisture dockage (*md*)

	Set of distance between location *i* and location *j*
	Set of distance between location *j* to location *k*
	0 if = 0; 1 otherwise
Parameters	
G	Cost target at delivery
U	Required depot utilization factor (90%)
R	Minimum moisture content at biorefinery
S	Maximum ash content at biorefinery
H	Target carbohydrate content at biorefinery
D	Demand of a biorefinery at 725,000 dry tons/year
E	Constant multiplier for depot capacity
Integer Decision Variables	
	Factor for depot capacity at location *j*
	Amount of feedstock *f* purchased at price *p* from location *i*
	Amount of feedstock *f* shipped from location *i* to location *j*
	Amount of feedstock *f* shipped from location *j* to location *k*
Binary Decision Variables	
	1 if feedstock *f* is purchased at price *p* from location *i*; 0 otherwise
	1 if depot is built in location *j*; 0 otherwise
	1 if biorefinery is built in location *k*; 0 otherwise

The demand assumed at each biorefinery was constant at 725,000 dry tons /year (D). The depot capacities were determined by the model using the product of a constant multiplier 25,000 (E) and an integer decision variable (. We found that the depot construction costs presented by Roni et al. (2019) fitted a linear equation with an adjusted R-square of 0.998. Hence, we used the following fitted regression equation (eq. 2) in our model to estimate the building cost for each depot ():

The total fixed cost (FC) are then calculated using the summation of all the depot building costs (eq. 3).

The total variable cost (VC) to deliver biomass included farmgate price, storage, handling, transportation and preprocessing costs (eq. 4). Since the BT16 supply curve was in \$2014 values, the farmgate price (gr_p) was multiplied with 0.997 to convert it into \$2016. When needed, a cost to reduce ash or increase moisture was incurred at the biorefinery to meet quality specifications.
Table lists the model constraints.

Table 4. Model Constraints

No.	Constraint Name	Mathematical Formulation
1	Feedstock purchase	
2	Maximum supply	
3	Three pass & Two pass	
4	Depot Capacity	
5	Flow balance for field-depot	
6	Depot Utilization	
7	Flow balance for depot-	

	biorefinery

	Flow balance for depot-biorefinery
8	Biorefinery Demand
9	Carbohydrate quality constraint
10	Cost target
11	Integer constraints
12	Binary constraints

Constraint (1) ensures that each feedstock is purchased only at a single price from each field location. Constraint (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. Constraint (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. Constraint (4) decides on the capacity of the depot depending on the total supply to that depot. Constraint (5) is the flow balance between field and depot. Constraint (6) sets a minimum utilization to the depot capacity. Constraint (7) is the flow balance between depot and biorefinery. Constraint (8) ensures that the total supply to a biorefinery meets the required demand. Constraint (9) requires that the total carbohydrate content of all the different feedstocks supplied to a biorefinery meets the minimum carbohydrate requirement. The cost target is maintained using constraint (10) combining the total fixed as well as variable costs. The constraints in (11) ensures non-negativity of the integer decision variables. The set of constraints in (12) are the constraints for binary decision variables.

4. Results

4.1 Scenarios

Four different scenario runs were performed considering the year and cost target, namely (S1) 2022 at \$79.07/dry tons, (S2) 2030 at \$79.07/dry tons, (S3) 2040 at \$79.07/dry tons and (S4) 2030 at \$71.26/ dry tons. 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 0.17-17%. The results for the different years and targeted prices analyzed in this study are presented in Table . When targets for delivery to the reactor throat are at \$79.07/ dry tons, 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/ dry tons). 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.

4.2 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 (blue triangles) and greater than (yellow triangles) the target delivery cost (Figure 5). However, for an ideal scenario, all the biorefineries would meet the cost target. To observe the deviation from the cost target, the average cost for each individual biorefinery was calculated. The summary statistics for the average biorefinery costs were analyzed to determine how far off a biorefinery was from the cost target. While calculating the standard error, the cost target was used as the mean for each scenario. The highest error was found in scenario S4 where we could expect the average cost of 95% of the biorefineries within +/- $1.44 (=2*0.722) of the cost target $71.26/dry tons. 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.

Table 5. Analyzed scenarios

Scenario	Feedstock	Million dry tons / year				Number of Facilities	Summary Statistics for Biorefinery costs ($/dry ton)
		$30	$40	$50	Total		
S1: 2022 $79.07/dt	SW[a]	0	0.01	5.31	5.32	124 Depots 59 Biorefineries 42.8 M dry tons 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 M dry tons 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	305 Depots 231 Biorefineries 168 M dry tons 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 M dry tons 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

The distribution of the biorefinery cost can be further visualized in figure 3 which identifies the minimum, maximum, median and standard deviation for the four scenarios. Out of all the biorefineries 46%, 39%, 48% and 54% were within the cost target for scenarios S1, S2, S3 and S4 respectively.

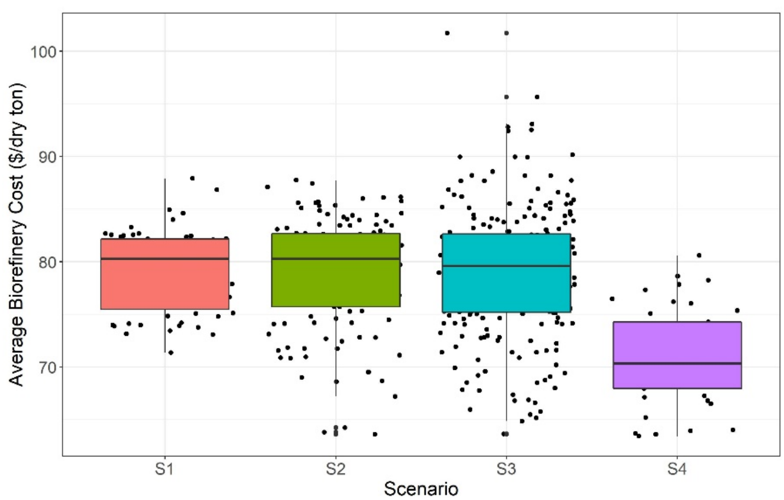
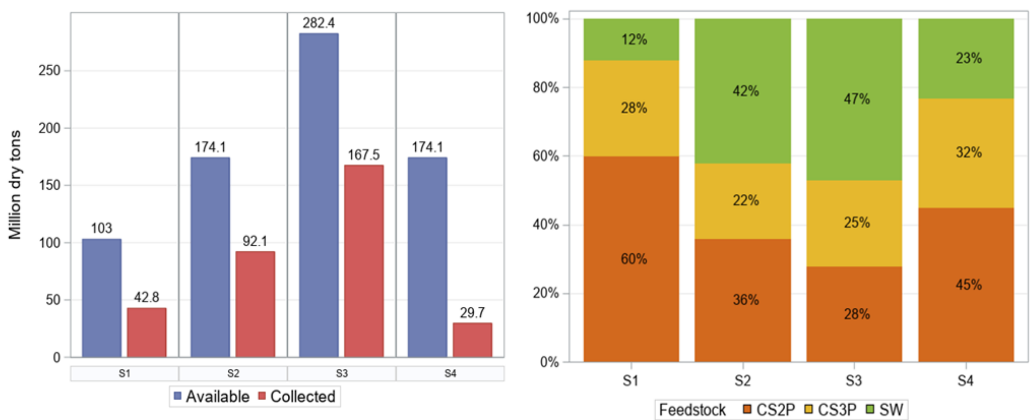


Figure 3. Distribution of the average biorefinery costs for the four scenarios.

4.3 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 4(a) we identified the total percentage of stranded and accessible biomass based on the BT16 supply curve at the $50 farmgate price and 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. 4(a)]. For the short-term cost target, 45-60% of the available biomass were collected by the depots. But using the long-term target, only 20% 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 million dt or 1.3 billion GGE (at 44.8 GGE/dt -Davis et al., 2013).



(a) (b)

Figure 4. (a) Comparison of total available and collected feedstock by the model. (b) Percentage of feedstock collection for the four scenarios (e.g. S1, S2, S3 and S4). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

4.4 Feedstock Ratio

Figure 4(b) 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 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.

4.5 Depot and Biorefinery Locations

Figure 5 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.

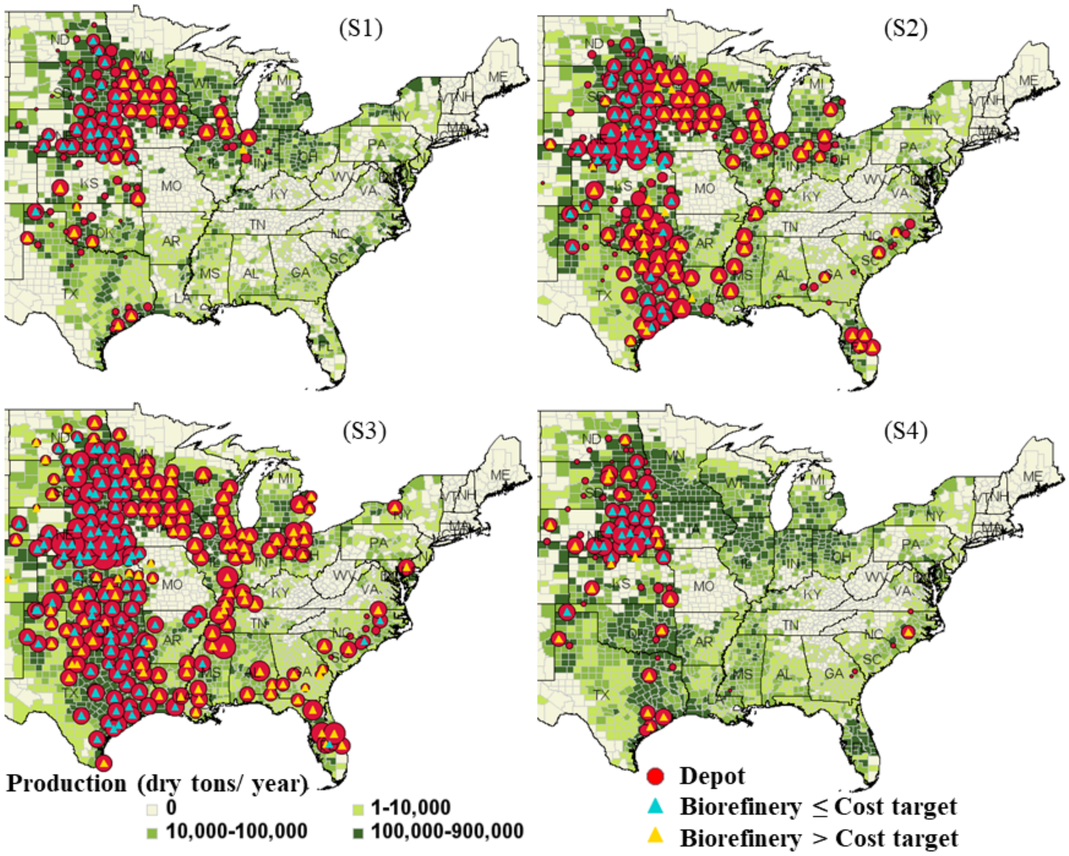


Figure 5. Depot and biorefinery locations in the US for four scenarios: (S1) 2022 @ $79.07/dt, (S2) 2030 @ $79.07/dt, (S3) 2040 @ $79.07/dt and (S4) 2030 @ $71.26/dt. [Need to be printed in color]

4.6 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 (table 6). The locations with a depot size of 725,000 dt could be an ideal location for a conventional supply chain for depots co-located with the biorefineries with a demand of 725,000 dt/year. For example, in scenario S1, 13 biorefineries could be built with a conventional supply chain collecting a total of 9.5 million dt of biomass. Whereas, with an advanced supply chain system we would be able to collect 42.8 million dt taking advantage of the multiple depot sizes and intermediate locations. The two most common depot sizes selected by the model are 725,000 and 25,000 dt/year (250 and 55 depots found across all the scenarios studied respectively). 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 sizes 625,000-700,000 dt/year were found across all the scenarios and only 89 depots of sizes 50,000-125,000 dt/year.

Table 6. Number of Depots for each depot capacity in the scenarios of this study

Scenario	S1: 2022 $79.07/dt		S2: 2030 $79.07/dt		S3: 2040 $79.07/dt		S4: 2030 $71.26/dt	
Depot Capacity (dry tons/ year)	Number of Depots	Percent (%)	Number of Depots	Percent (%)	Number of Depots	Percent (%)	Number of Depots	Percent (%)
25,000	20	16%	14	7%	7	2%	14	18%
50,000	4	3%	11	6%	10	3%	4	5%
75,000	7	6%	8	4%	4	1%	5	6%
100,000	3	2%	8	4%	6	2%	3	4%
125,000	3	2%	5	3%	6	2%	2	3%
150,000	5	4%	8	4%	4	1%	3	4%
175,000	2	2%	3	2%	11	4%	1	1%
200,000	2	2%	3	2%	2	1%	0	0%
225,000	2	2%	7	4%	4	1%	1	1%
250,000	3	2%	2	1%	4	1%	3	4%
275,000	3	2%	4	2%	2	1%	0	0%
300,000	0	0%	0	0%	3	1%	2	3%
325,000	1	1%	5	3%	6	2%	0	0%
350,000	1	1%	1	1%	5	2%	1	1%
375,000	0	0%	1	1%	8	3%	0	0%
400,000	0	0%	6	3%	3	1%	1	1%
425,000	2	2%	4	2%	1	0%	1	1%
450,000	0	0%	1	1%	3	1%	1	1%
475,000	1	1%	0	0%	6	2%	2	3%
500,000	2	2%	1	1%	3	1%	2	3%
525,000	0	0%	3	2%	5	2%	0	0%
550,000	4	3%	3	2%	9	3%	1	1%
575,000	3	2%	5	3%	5	2%	1	1%
600,000	4	3%	2	1%	4	1%	2	3%
625,000	12	10%	8	4%	2	1%	4	5%
650,000	11	9%	7	4%	4	1%	7	9%
675,000	4	3%	8	4%	10	3%	6	8%
700,000	12	10%	8	4%	4	1%	7	9%
725,000	13	10%	68	34%	164	54%	6	8%
Total	**124 Depots**		**240 Depots**		**305 Depots**		**80 Depots**	

4.7 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. Figure 6 groups the total depot and biorefinery facilities found by states and Table specifies the total feedstock supply to those depots. Kansas, Nebraska, South Dakota and Texas were identified as potential states with a strong biofuel economy given that they had six or more biorefineries located in all scenarios. Nebraska 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 (greater than 10): Nebraska (S1, S2, S3, S4), Kansas (S2, S3), Texas (S2, S3), South Dakota (S2, S3) and Oklahoma (S2, S3). Moreover, there were states with multiple depots but zero biorefineries such as

Colorado (S1, S4), Alabama (S2), Georgia (S4), Minnesota (S4), Mississippi (S4) and South Carolina (S4). Those states would need to ship the preprocessed biomass to the biorefinery of a nearby state. In this case, the biorefinery's supply chain will depend on the biomass production of that state as well as the nearby states. The number of such cases increased with lower cost target introducing logistical complexities of longer haul.

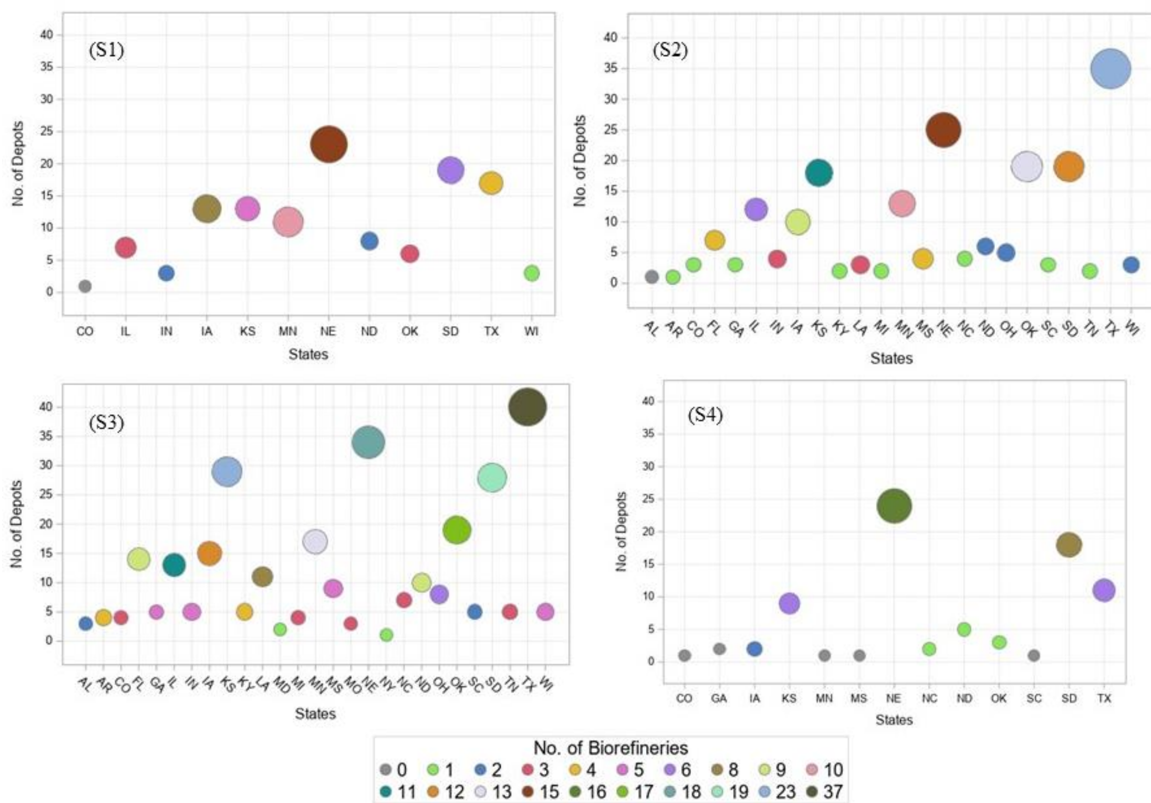


Figure 6. Number of depots and biorefineries in each state for the four scenarios, (S1) 2022 at $79.07/dt, (S2) 2030 at $79.07/dt, (S3) 2040 at $79.07/dt and (S4) 2030 at $71.26/dt. The bubble size indicates the total amount of feedstock shipped to depots for each state. Each of the biorefineries have fixed demand of 725,000 dt/year. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article)

Table 7. Feedstock delivered to depots in different states for four scenarios

State	Shipped to Depot (thousand dry tons/ year)			
	S1	S2	S3	S4
Alabama	-	100	1,375	-
Arkansas	-	625	2,900	-
Colorado	125	624	1,367	112
Florida	-	2,975	7,343	-
Georgia	-	574	1,625	75
Illinois	2,600	4,347	8,300	-
Indiana	1,025	1,900	3,550	-
Iowa	5,662	5,626	8,775	1,124
Kansas	4,000	7,150	16,000	3,603
Kentucky	-	720	2,975	-
Louisiana	-	1,937	5,792	-
Maryland	-	-	747	-
Michigan	-	725	1,625	-

Minnesota	6,641	6,374	9,225	68
Mississippi	-	2,875	4,465	22
Missouri	-	-	975	
Nebraska	10,451	12,963	18,019	12,427
New York	-	-	625	
North Carolina	-	792	2,217	575
North Dakota	1,525	1,602	4,500	672
Ohio	-	1,750	4,316	-
Oklahoma	1,635	9,450	13,075	687
South Carolina	-	657	1,915	75
South Dakota	4,886	9,182	14,200	5,867
Tennessee	-	707	2,425	-
Texas	3,441	16,962	26,050	4,414
Wisconsin	792	1,450	3,575	-

5. Discussion

The main goal of the presented study 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 million dt of feedstock needs to be delivered at the gate of the biorefinery and a total of 493 biorefineries with 725,000 dt capacity have to be built to meet EPA goals. However, the results of the developed model indicated that only 42.8 million dt 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 have to 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 the actual potential for an nth-plant scenario for biofuels, regardless of political boundaries, given that some states in the US may have to 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), where a GIS-based heuristic was developed to identify the number and size of the biorefineries and depots. The study presented that 183.7 million dt of herbaceous biomass could be collected out of the predicted 205 million dt in year 2022 and predicted to meet more than the targeted demand of EPA for year 2022. However, our analysis suggested that the target was highly over estimated. Gonzales et al. (2017) did not consider on-spec delivery with quality nor specific constraints on the cost target.

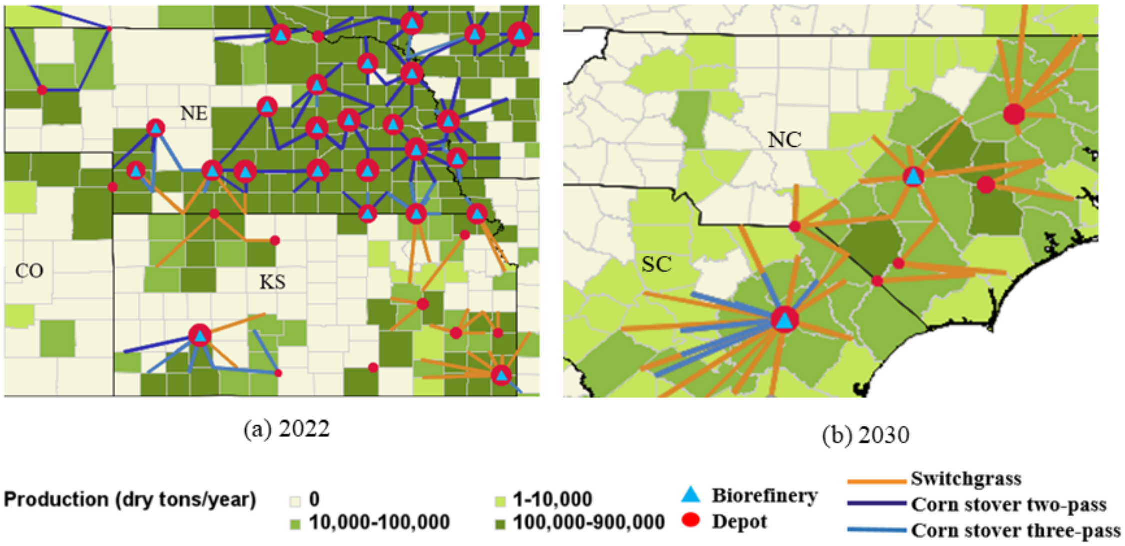


Figure 7. Magnifying on the location of depots and biorefineries in different states. Connecting lines indicate what fields are assigned to a depot (red circle) in the solution. The color of these lines represents the type of feedstock delivered. [Need to be printed in color]

Roni et al. (2018) considered delivery to a single biorefinery and the biorefinery location was fixed at Seridan County of Kansas, USA. The decision variables in the model were the location and size of the depots as well as the least-cost blend of the feedstocks. Four depots were identified in Nebraska, Kansas and Colorado to supply a total of 725,600 dt to one biorefinery. In our study, we identified 37 depots and 20 biorefineries in Nebraska, Kansas and Colorado to supply a total of 14.5 million dt of feedstock [fig. 7(a)]. It can be implied that, deciding on the biorefinery and depot locations simultaneously increased the supply 20 times than what was predicted by Roni et al. (2018). In both cases, supply curves from the BT16 for 2022 was used. Moreover, 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, no depots and biorefineries were established in NC for that scenario. In our analysis, the costal biorefinery in NC was built only for the 2030 and 2040 scenarios [fig. 7(b)].

Given that we had access to the POLYSYS model, also used in the BT16 (Langholtz et al., 2016), we used our initial solution (98.6 million dt in step one) to perform demand runs in POLYSYS to be able to verify how supply curves change once facility locations are established. These demand runs are publicly available in the Bioenergy Knowledge Discovery Framework (Davis, 2020). With the demand runs, about 2.4 million more biomass becomes available, but this total decreases by 11 million dt when the quality constraints are introduced.

While we are reporting results with an assumption that 725,000 dry tons per year is the maximum size for a depot, our model was setup to locate depots of sizes that are multiples of 25,000 dry tons per year. In high yielding regions where the model located a depot bigger than 725,000 dry tons per year, we reported these as two or three depots created in that county. For example, in S2 Fillmore County, NE had 1.65 million dry tons of biomass delivered to depots, which we presented as two depots with a capacity of 725,000 dry tons per year each, and one depot of 200,000 dry tons per year. Three was the maximum number of depots created in one county in all our scenarios. 40 counties in IA, IL, KS, MN, NE, OK, SD, and TX had the resources to locate more than one depot in scenarios S1, S2, and S4. The increase in biomass availability in year 2040 leads to 87 counties locating more than one depot in S3. The reader is able to identify specific quantities and locations in our published dataset. We acknowledge the limitation of considering only one biorefinery size of 725,000 dry tons per year. A distributed depot-based system can certainly take advantage of economies of scale up to sizes as large as 30,000 dry tons per day (Kim & Dale 2015). To analyze the impact of large-scale biorefineries in our study, we increased the capacity of the biorefineries for different scenarios. Unfortunately, increasing this capacity by two-, three-, and four-folds, also increases the computational complexity of our model resulting in an error gap near 100% after running the model for 3 hours. To get a better insight of a national analysis with different biorefinery sizes, we used the 87 high yielding counties identified in S3 as candidate locations for biorefineries that are two-, three-, and four- folds bigger than our original biorefinery size. Figure 8 illustrates the fluctuation of collected biomass with different biorefinery sizes for year 2030 (scenarios 2 and 4). Total biomass increased when the biorefinery size was doubled to 1.45 M dry tons/year but started decreasing as the biorefinery size was further increased. This trend is explained given the supply curves of different regions. While high supply regions will benefit from larger size biorefineries, the low supply regions might not have enough biomass to meet the demand of such large scale facilities. To take advantage of both low and high supply regions with large scale biorefineries, we will introduce a decision variable to represent varying sizes for biorefineries in our future work. Rail and barge transportation will also be considered for pellet shipments.

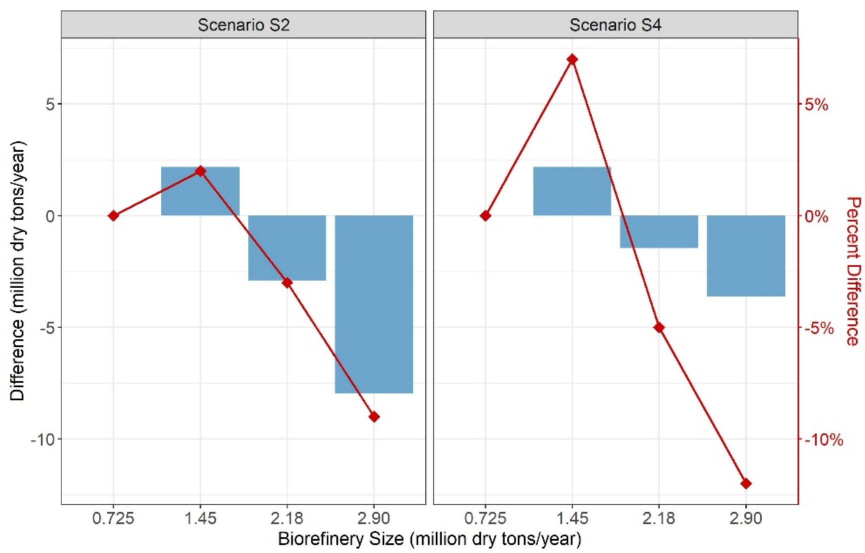


Figure 8. Difference in collected biomass compared to the 725,000 dry tons per year biorefinery for scenario S2 and S4. [Needs to be printed in color]

To overcome our error gaps and model limitations, our future research will also be focused 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. Any alteration in these parameters would lead to major changes in the depot and biorefinery locations as well as the feedstock allocation. As we continue to expand our research direction, we will be sure to examine and identify situations where stochastic optimization is the appropriate method to better represent the uncertainties of biological systems. 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.

6. 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 the decision-makers including supply managers, farmers and business investors which could ensure a sustainable biofuel economy. Both strong policy formulation and innovative conversion technology are required to meet EPA's cellulosic biofuel production mandate. The presented 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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8. Data Availability

The input dataset for the supply curve of this study can be found using the BT16 County Download Tool at the BioEnergy Knowledge Discovery Framework open-source database (Langholtz et al., 2016). The published dataset from the results of this study are attached with the manuscript.

9. Credit Authorship Contribution Statement

Tasmin Hossain: Methodology, Software, Data curation, Writing - original draft, Visualization. Daniela Jones: Conceptualization, Methodology, Validation, Resources, Writing - original draft, Supervision, Project administration. Damon Hartley: Conceptualization, Methodology, Investigation, Resources, Writing - review & editing, Supervision, Data curation. L. Michael Griffel: Visualization, Conceptualization, Methodology, Data curation. Yingqian Lin: Conceptualization, Methodology, Validation. Pralhad Burli: Conceptoualization, Methodology, Validation, Writing - review & editing. David N. Thompson: Supervision, Resources, Writing - review & editing. Matthew Langholtz: Supervision, Resources, Methodology, Writing - review & editing, Investigation, Data curation. Maggie Davis: Resources, Methodology, Supervision, Data curation. Craig Brandt: Resources, Supervision.

10. 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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