A MARKET INCENTIVES ANALYSIS OF SUSTAINABLE BIOMASS BIOETHANOL SUPPLY CHAINS WITH CARBON POLICIES

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Title

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

Given the increasing demand for energy, climate change, and environmental concern of fossil fuels, it is becoming increasingly significant to find alternative renewable energy sources. Bioethanol as one sort of cellulosic biofuel produced from lignocellulosic biomass feedstocks has shown great potential as a renewable resource. Delivering a competitive, sustainable biofuel product requires comprehensive supply chain planning and design. Developing economically and environmentally optimal supply chain models is necessary in this context. Also, designing biomass bioethanol supply chain (BBSC) models addressing social issues requires using second-generation biomass which is not a source of food for humans. Currently, corn as a first-generation feedstock is the primary source of bioethanol in the United States which has given growth to new social issues such as the food versus fuel debate. Considering incentives for first-generation bioethanol producers to switch to second-generation biomass and associated production technologies will help to address such social issues.

The scope of this study focuses on analyzing economic and environmental market incentives for second-generation bioethanol producers while considering different carbon policies as penalties and restrictions for emissions coming from BBSC activities. First, we develop an integrated life cycle emission and energy optimization model for analyzing an entire second-generation bioethanol supply chain using switchgrass as the source of biomass while finding the most appropriate potential locations for building new cellulosic biorefineries in North Dakota. Second, we propose a supply chain model by comparing a first-generation (corn) and a second-generation (corn stover) bioethanol supply chain to analyze how policymakers can incentivize first-generation bioethanol producers to switch their technology and biomass supply from first-generation to second-generation biomass. Third, we develop the model further by investigating the

impact of four different carbon policies including the carbon tax, carbon cap, carbon cap-and-trade, and carbon offset on the supply chain strategic and operational decisions.

This research will help to design robust BBSCs focused on sustainability in order to optimally utilize second-generation biomass resources in the future. The findings can be utilized by renewable energy policy decision makers, bioethanol producers, and investors to operate in a competitive market while protecting the environment.

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DEDICATION

This work is dedicated to my gorgeous and loving wife

Farnaz Namayandeh

and to my beloved father & mother

Seyed Morteza Haji Esmaeili

Fatemeh Abdollahi Nik

for all the sacrifices they made for me to accomplish my dream.

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LIST OF ABBREVIATIONS

BBSC ....Biomass Bioethanol Supply Chain

MILP ....Mixed Integer Linear Programming

CBSC ....Corn-based Bioethanol Supply Chain

CSBSC ....Corn-stover-based Bioethanol Supply Chain

SBSC...Switchgrass-based Bioethanol Supply Chain

CO_2e..Carbon Dioxide Equivalent

GHG..Greenhouse Gas

GIS ....Geographic Information Systems

ASD...Agricultural Statistical District

MGPY ....Million Gallons Per Year

DDG..Dried Distillers Grain

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1. INTRODUCTION

1.1. Background and motivation

High reliance on nonrenewable fuel sources in the transportation sector, different social and environmental issues, and energy crisis have motivated a noticeable amount of research in the improvement of cellulosic biofuel utilizing renewable biomass feedstock from energy crops, forest residues, and agricultural residues, which are promising options for transportation fuel (Park, Szmerekovsky, Osmani, & Aslaam, 2017; F. Zhang, Wang, Liu, Zhang, & Sutherland, 2017; J. Zhang, Osmani, Awudu, & Gonela, 2013). Biomass is a critical renewable energy source because of its low adverse environmental effect regarding CO_2 emissions (Hendricks, Wagner, Volk, Newman, & Brown, 2016). One kind of renewable energy that can be utilized in many ways to replace fossil fuel-based energy is biofuel (including bioethanol and biodiesel). Biofuel has been vigorously promoted by policies in the United States and around the world as a means to reduce oil dependence and greenhouse gas (GHG) emissions and to address issues on energy security and global climate change (Huang, Chen, & Fan, 2010).

Bioethanol, which is being considered in this research, is one sort of cellulosic biofuel where corn is the major source of current bioethanol production as a first-generation renewable resource in the United States. However, there have been frequent complaints of first-generation bioethanol related to global food security because of bioethanol production directly from food crops (J. Zhang et al., 2013). An alternative is lignocellulosic biomass feedstock (known as second-generation biomass) which is a proper source for producing bioethanol. Bioethanol can be produced from different biomass feedstocks such as corn, wheat, and sugarcane which are known as first-generation biomass and are dominant sources for biofuel in the United States. Nevertheless, many companies in the United States are developing advanced second-generation renewable energy using non-food feedstock such as corn stover, switchgrass, and woody residues because of their advantages over first-generation-based bioethanol, including food security and carbon emission. Utilizing renewable energy that is produced from second-generation biomass provides economic, environmental, and social benefits to supply chains (SCs) (Park, 2018).

With globalization, there has been vast growth in networks of suppliers, distributors, and transportation providers, where sustainability should be considered in SCs for not only maximizing the financial performance but also for minimizing adverse impacts on the business environment (Park, 2018) because it is certain that sustainability issues in business will increase due to various interactions of supply chain activities (Lee & Wu, 2014). In this respect, sustainability has multi-faceted meaning including the implications for social responsibility, the environment, the economy, and business ethics. Recently, the sustainable development movement concentrated on the environmental features of sustainability as a result of global warming issues resulting from carbon dioxide (CO_2) and other GHGs. Hence, managing supply chains sustainably has become a growing concern for numerous businesses across a wide range of companies globally. The Energy Policy Act (EPA) of the US government encourages the use of alternative fuel sources such as bioethanol that is extracted from renewable energy sources which are less CO_2 severe (Park, 2018). Considering all this, sustainability requires focusing on policy formulation across a bioethanol supply chain.

Since first-generation biomass is the primary source of biofuel, especially bioethanol, in the US, considering incentives for first-generation bioethanol producers to switch to second-generation biomass and related settings can be an effective way to move biomass bioethanol supply chains (BBSCs) toward more sustainability. By incorporating the effects of monetary incentives and emissions penalties in the decision-making process, we would better streamline bioethanol supply chains. It is becoming more and more explicit that government intervention through incentives for renewable energy is potentially advantageous. They can encourage the expansion of renewable energy to benefit society, the economy, and the environment (Mohamed Abdul Ghani, Vogiatzis, & Szmerekovsky, 2018).

The increase in GHG emissions such as carbon dioxide (CO_2), and methane (CH_4) has resulted in global warming, climate change, and environmental issues (Park, 2018). These have persuaded policymakers to introduce restrictive environmental regulations. As reported by the Intergovernmental Panel on Climate Change in 2014, global emissions of GHGs have ascended to incomparable levels (Du, Hu, & Song, 2016). Although the US experienced one of the coldest winter in its history in 2019, the global temperatures are still warmer than average in a way that 2018 was the fourth-hottest year on record (MacFarlane, 2019; Resnick, 2019). This global climate change should motivate companies all over the world to consider environmental issues in their business. Several countries presented various carbon emission reduction policies including carbon cap, carbon tax, carbon offset, cap-and-trade, and joint implementation to restrain carbon emissions. These policies not only assist in emission reduction but also bring economic benefits to companies (Mohammed, Selim, Hassan, & Syed, 2017).

This research provides a framework that incorporates sustainability including economic, environmental and social issues. Economic objectives have been addressed by considering costs and revenues in the optimization models along with analyzing incentives to address social issues. Moreover, different carbon policies have been implemented to meet global environmental goals. Overall, this research will help to design a sustainable bioethanol supply chain by utilizing a second-generation biomass within a short time. The findings can be used by the bioethanol industries in the United States, especially North Dakota, to operate efficiently and effectively while protecting the environment.

1.2. Purpose of research

It is significant to analyze and measure what causes environmental issues and how we can reduce emissions in SCs. Therefore, it is worthwhile for researchers and practitioners to consider sustainability in bioethanol SCs to boost sustainable development for the next generation (Park, 2018). Moreover, incentivizing first-generation bioethanol producers to switch their production technologies where second-generation biomass can be utilized, would be an applicable method to address environmental and social issues. To the best of our knowledge, there is no work on incentivizing first-generation bioethanol producers to change their technologies and input biomass. In this regard, our paper introduces a new study for incentivizing entities along the supply chain using mathematical programming. Our objective is to discover the impacts of incentives offered by government (as revenue gain for ethanol producers) and emission penalties faced by first-generation ethanol producers (as revenue loss) as financial levers which will prevent bioethanol producers from using first-generation biomass feedstock while designing second-generation bioethanol supply chain networks.

Further, in our study, we investigate the impact of various carbon regulatory policies on BBSC network design. Carbon policies that we study are carbon cap, carbon tax, carbon cap-and-trade, and carbon offset policy (Mohammed et al., 2017). The overall objectives are to develop BBSCs while maximizing total profit and minimizing total carbon emissions across the supply chain while utilizing second-generation biomass is incentivized. This paper aims to address the stated objectives by investigating the following vital questions:

– Which supply and demand zones should be assigned to bioethanol refineries to maximize profit and reduce carbon emissions?

– What are the optimal production and transportation quantities between the BBSC entities?

– What is the impact of various carbon policies on the design and planning of BBSCs?

– What is the impact of monetary incentives on first-generation bioethanol producers to change their feedstock and associated technologies?

– What is the trade-off between supply chain total profit and carbon emission under different carbon policies?

– How do the optimal supply chain decisions under different carbon policies affect sustainability?

– Which second-generation biomass (between corn stover and switchgrass) is a better alternative to first-generation biomass (corn) economically and environmentally?

– How do the optimal supply chain decisions simultaneously incorporating incentives under different carbon policies affect economic and environmental performance?

1.3. Importance of research

Biofuels produced from various biomass renewables only met 7% of the annual United States requirement of liquid transportation fuels in 2012. The Renewable Fuel Standard (RFS) enforces the use of biomass renewables to produce 36 billion gallons per year (BGPY) of biofuels by 2022 where a minimum of 16 BGPY is to be bioethanol refined from second-generation feedstocks which will displace 20% of annual gasoline demand (Osmani, 2014).

At present, first-generation bioethanol production is widely commercialized in the United States. However, the extensive utilization of first-generation bioethanol has brought new issues such as the food versus fuel debate and higher food prices, as first-generation bioethanol is produced from edible biomass (Gonela, Zhang, & Osmani, 2015). This has led to the promotion of second-generation biomass/bioethanol in recent years that can address many sustainability-related issues. Therefore, government intervention has been critical for supporting and promoting a biomass switch for renewable energy producers which is typically done by incentive programs (Mohamed Abdul Ghani et al., 2018). Since second-generation biomass is preferred socially and environmentally over first-generation while first-generation biomass is broadly being used in the United States, it is necessary to consider incentives for first-generation bioethanol producers to switch their technologies which will be compatible with second-generation biomass.

The implementation of optimization techniques to analyze the sustainability aspects along with different government incentives develop and promote a new paradigm for the biomass industry (Mohamed Abdul Ghani et al., 2018). Moreover, considering environmental issues under different carbon policies can help BBSC modeling to be more comprehensive. The integration with environmental aspects can help policymakers to better understand how different carbon policies would reduce the adverse effects of GHG emissions (Mohammed et al., 2017).

Design and optimization of sustainable BBSCs with incentives are essential to account for government mandates, provide financial viability, decrease environmental damage, and enhance social benefits. It allows policymakers to develop feasible policies and would encourage renewable energy production.

Our research aims to identify an efficient way to utilize financial incentives while using second-generation biomass (to address social issues of first-generation ethanol) to maximize profit and reduce emissions across the BBSC, using data from the state of North Dakota for a case study. The contribution and structure of this research are as follows:

Chapter 2 proposes mixed integer linear programming (MILP) models maximize profit for a second-generation-based bioethanol SC that uses switchgrass as a biomass feedstock. These models consider energy use along with emissions. The proposed model considers the cost of all steps of the entire supply chain from renting the lands and cultivating switchgrass to the final stage selling bioethanol. Also, in the proposed models, the best potential locations in North Dakota have been found to build new plants for producing bioethanol.

The research problem in Chapter 3 compares profit maximization for a first-generation (corn) BBSC with that for a second-generation (corn stover) BBSC, with and without environmental impacts. These models consider the costs of BBSC stages from the edge of the farms to the final demand zones where already existing biorefineries are being used. In this context, analysis of market incentives is done to motivate first-generation biorefineries to switch their technologies to produce bioethanol from second-generation biomass.

Finally, chapter 4 proposes a stochastic linear programming formulation to compare the expected profit of a first-generation SC (corn) with two different second-generation SCs (that use corn stover and switchgrass as biomass feedstocks) while environmental impact is considered through four different carbon policies. The proposed models try to find the better second-generation alternative biomass where a lower incentive needs to be paid to first-generation bioethanol producers to switch their technologies to be compatible with second-generation biomass.

2. OPTIMAL SITING OF BIOREFINERIES FOR A SWITCHGRASS-BASED BIOETHANOL SUPPLY CHAIN USING ENERGY CONSUMPTION AND EMISSIONS: A CASE STUDY IN NORTH DAKOTA

2.1. Abstract

Due to the growing demand for energy and environmental issues related to using fossil fuels, it is becoming tremendously important to find alternative energy sources. In this context, bioethanol produced from switchgrass is considered as one of the best alternative forms of energy to fossil fuels. This study develops a two-stage supply chain modeling approach that first determines feasible locations for constructing switchgrass-based biorefineries in the state of North Dakota by using Geographic Information Systems (GIS) analytics. In the second stage, the profit of the corresponding switchgrass-based bioethanol supply chain is maximized by developing a mixed-integer linear program that aims to commercialize the production of switchgrass-based bioethanol while the impacts of energy use and carbon emission costs on the supply chain decisions and siting of biorefineries are included. The numerical results show that carbon emissions and energy consumption penalties have impacts on optimal biorefinery selections and supply chain decisions. From sustainability points of view, our findings conclude that there is no need to penalize both emissions and energy use simultaneously to achieve desirable environmental benefits, otherwise, the supply chain becomes non-profitable. By only penalizing the energy consumption, a 0.7% and 2% drop in emissions and energy use are achieved, respectively, while there is a 4.4% reduction in profit. Moreover, imposing emissions or energy consumption penalties makes the optimization model to choose closer supply sources while having higher land rental costs. Such policies would promote sustainable second-generation biomass production, thus decreasing reliance on fossil fuels.

2.2. Introduction

The dependency on non-renewable fuel sources in the transportation sector and their negative social and environmental consequences have increased research motivations in the field of biofuel production (F. Zhang et al., 2017; J. Zhang et al., 2013). Biofuels, such as bioethanol, are produced from renewable biomass feedstocks such as energy crops, forest residues, and agricultural residues. They have been regarded as promising alternatives to fossil fuels for the sustainable development of the world economy due to their high potential to mitigate environmental pollution (Ren et al., 2016). Biomass is a highly dispersed and geographically dependent source of biofuels production. It is also known as an important renewable energy source due to its low negative environmental impact in terms of carbon emissions (Hendricks et al., 2016). As a type of biofuel, bioethanol can be successfully combined with gasoline in different percentages for use as fuel (Ghaderi, Moini, & Pishvaee, 2018). With respect to the environmental benefits of bioethanol, the production of the first-generation bioethanol from food crops such as corn has been growing in different countries during the past decade. However, such a growing production raised serious concerns regarding the shortage of corn-based foods (Osmani & Zhang, 2017). For this reason, researchers and practitioners have recently focused on second-generation (especially cellulosic) biomass feedstocks such as switchgrass which does not require cropland for cultivation. In the US, the federal government has enacted several legislations to incentivize the production of second-generation bioethanol and cap the production of first-generation bioethanol from corn starch (Schnepf & Yacobucci, 2013). For instance, the Renewable Fuel Standard (RFS) requires the production of 36 billion gallons per year (BGPY) of biofuels by 2022 while only 15 BGPY of that can be produced from corn starch. Out of the remaining 21 BGPY, a minimum of 16 BGPY should be cellulosic-based bioethanol (Osmani & Zhang, 2017). Therefore, it is important to make the cellulosic second-generation bioethanol profitable for producers. Other than economic benefits, maximizing environmental performance such as considering emissions and energy consumption has become increasingly necessary (Ahi & Searcy, 2015; Halil Ibrahim Cobuloglu & Büyüktahtakin, 2014). Therefore, it is necessary to balance activities across the switchgrass-to-bioethanol supply chain to maximize the supply chain profit while minimizing environmental issues. This approach leads to a sustainable second-generation bioethanol production in order to get the benefits of such a source of renewable energy.

Research on biofuel production of biomass has been growing recently due to biomass' potential to become an alternative energy source that is more sustainable compared to the production of fossil fuels. Babazadeh et al. (Babazadeh et al., 2017) proposed a model for designing a multi-product biodiesel supply chain which can determine the optimum numbers, locations, and capacities of facilities, along with suitable transportation modes, appropriate technologies, material flows, and production plans. A few research activities have recently focused on cellulosic-based (especially switchgrass) bioethanol supply chain design to minimize the total supply chain cost by defining strategic (i.e. location of biomass storage and size of new biorefineries) and tactical (i.e., the amount of biomass shipped and processed) supply chain decisions (Akgul, Zamboni, Bezzo, Shah, & Papageorgiou, 2011; Mansoornejad, Chambost, & Stuart, 2010). Ghaderi et al. (Ghaderi et al., 2018) proposed a multi-objective robust possibilistic programming model for designing a sustainable switchgrass-based bioethanol supply chain network under epistemic uncertainties considering environmental and social life cycle analysis. Their results demonstrate that with an increase of 2.43% in the economic objective function, environmental and social protection would be achieved. Recently, the optimization of biofuel supply chains with the integrated consideration of economic, energy and environmental aspects has emerged as a new trend since it can help decision-makers to design a suitable biofuel supply chain with multiple objectives (Ren et al., 2016). There are only a few studies that have investigated CO_2e (carbon dioxide equivalent) emissions and total energy consumption or energy efficiency at the same time for biofuel supply chains. For instance, Gonela et al. (Gonela, Zhang, Osmani, et al., 2015) proposed a stochastic mixed-integer linear program (MILP) to design a hybrid generation bioethanol supply chain that maximizes supply chain profit under Green House Gas (GHG) emissions, irrigation land-use restrictions, and energy efficiencies. Also, Ren et al. (Ren et al., 2016) developed a life cycle energy and emissions optimization model for designing a biofuel supply chain under uncertainty without considering logistics expenses. They proposed bi-objective multiple feedstock models using first-generation biomass to find the optimal amount of energy consumption and carbon emissions. However, these studies did not conduct sensitivity analysis for energy use and emissions penalties to investigate how these two environmental factors can affect the selection of biorefinery locations.

To bridge the above research gaps, this paper considers the switchgrass-based bioethanol supply chain (SBSC) network design in the state of North Dakota. Switchgrass is known as one of the most promising sources of second-generation renewable energy (Sokhansanj et al., 2009). It can be cultivated on marginal land (i.e. land not suitable for use as cropland or pastureland (J. Zhang et al., 2013)); hence, its cultivation makes new jobs in areas where there is not enough fertile land for crop cultivation (Zhu, Li, Yao, & Chen, 2011). Other than job creation, literature listed several economic, environmental and social benefits for the cultivation of switchgrass which can be found in Gold and Seuring (Gold & Seuring, 2011). These benefits lead to the promotion of second-generation bioethanol from cellulosic biomass in recent years. In order to maximize these environmental and socials benefits, biorefineries are usually constructed in locations which are close to supply zones, highways, railroads, and major cities to facilitate the transportation of farmers, workers, biomass feedstocks, and biofuels (Sultana & Kumar, 2012; F. Zhang et al., 2017). Therefore, determining the optimal locations of biorefineries based only on economic criteria such as minimizing transportation expenses would not result in achieving environmental, social and human resource benefits of biofuel production (Sultana & Kumar, 2012). For this reason, this study follows a two-stage modeling approach to model the second-generation bioethanol supply chain. First, with respect to geographic criteria such as the location of suppliers, major cities, water supplies, highways, and railroads potential (suitable) locations for building bioethanol plants are determined. GIS analysis is used in this stage for geographical analysis. In the second stage, a MILP model is developed for the proposed supply chain to maximize the profit while considering energy use and carbon emissions impacts. The model aims to find the best (optimal) locations to build new cellulosic bioethanol plants from the determined potential locations resulted from GIS analysis. It also determines the optimal assignments of the demand zones to the optimal biorefinery locations to minimize transportation, energy and carbon emission expenses. Different penalties for energy consumption and emissions are applied to investigate their impacts on the selection of biorefinery locations and SBSC planning.

This study considers geographical factors for finding the optimal locations for switchgrass-based bioethanol plants instead of using predetermined locations in North Dakota. It also enables policymakers to find the critical values for emissions and energy consumption penalties while the supply chain is still profitable.

The remainder of this chapter is structured as follows: Section 2.3 introduces the proposed model; Section 2.4 presents the results and corresponding discussion; finally, the study is concluded and managerial policies are presented in Section 2.5.

2.3. Materials and methods

2.3.1. Problem statement

This study aims to design a sustainable SBSC network by developing a two-stage modeling approach. In the first stage, GIS analytics is applied to determine a group of feasible (suitable) locations for bioethanol plants and in the second stage, a MILP model is developed to maximize the profit of the supply chain by determining optimal biorefinery locations while considering different carbon emissions and energy use penalties. More details can be found in the methodology section. In this study, the SBSC network includes three major parts: biomass supply zones (suppliers), bioethanol plants (biorefineries), and in-state and out-of-state demand zones. The bioethanol supply chain network and the associated activities within each part are shown in Figure 1. The biomass feedstock (switchgrass) flows from the suppliers to the bioethanol plants (biorefineries) by truck. Then the bioethanol produced in plants either goes to in-state demand zones by truck or to out-of-state demand zones by rail.

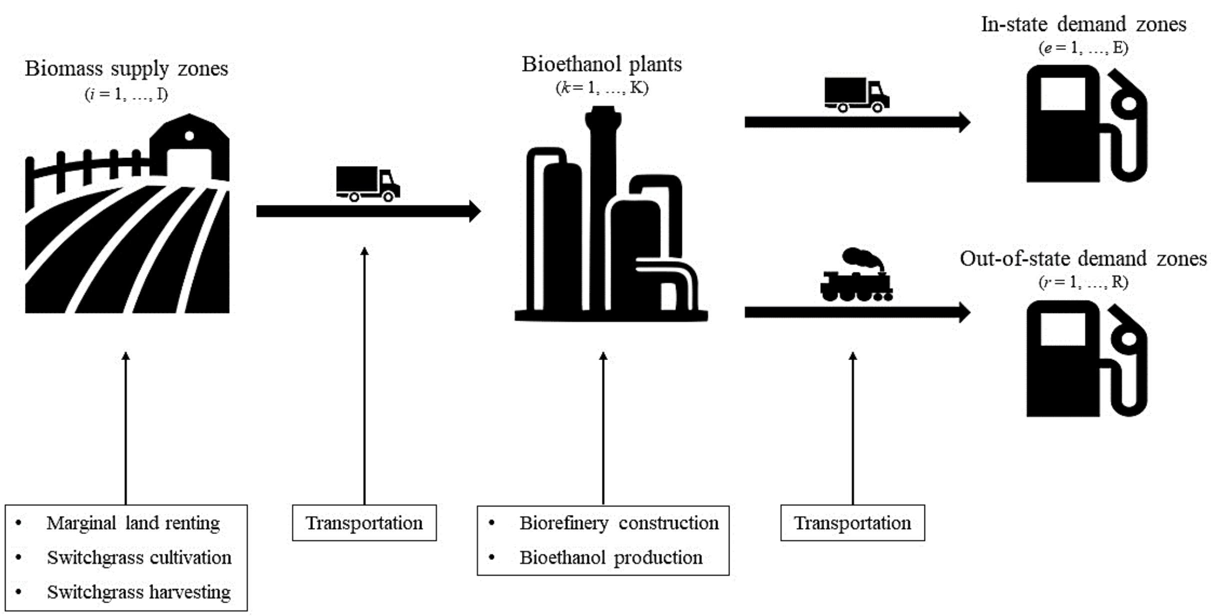


Figure 2.1. SBSC network and the associated activities with each stage

2.3.2. Methodology

This section explains the two-stage modeling approach developed to design an SBSC network. In the first stage, GIS analytics uses the topography and geographical factors in the state of North Dakota to determine the feasible locations for building biorefineries (bioethanol plants). These siting determinants were identified in previous literature discussing the designation of suitable locations for constructing biorefineries (F. Zhang, Johnson, & Johnson, 2012; F. Zhang et al., 2017). They are listed in the following:

- Locations within one mile of a state or federal road transport infrastructure;
- Locations within one mile of a rail transportation network;
- Locations around cities or villages with a population census of at least 2000;
- Areas within a quarter-mile and one mile of a water body (rivers, lakes, etc.);
- Locations with rich supplies of switchgrass biomass.

As discussed in previous studies, these geographical factors are the main drivers in finding potential locations for building biorefineries as they enhance long term social, environmental, and human resource benefits for farmers, workers and bioethanol producers (F. Zhang et al., 2012, 2017). For instance, it is essential to locate biorefineries at locations where both rail and road are available to facilitate the transportation of switchgrass and the distribution of bioethanol. A large population census is also crucial to assure the labor availability for facilities. Locations close to a water body are also preferred for biorefineries to minimize variable operating expenses (F. Zhang et al., 2012). Furthermore, locations adjacent to supply zones with abundant supplies of switchgrass are preferred to reduce transportation costs, emissions, and energy consumption.

The results from the GIS analysis are used in the second stage modeling approach in order to develop a MILP model that maximize the profit of the SBSC network. The objective function of the optimization model includes revenues from bioethanol and switchgrass-based bioethanol co-product (which is called lignin pallet) sales; cultivation and harvesting costs of switchgrass, transportation expenses due to shipping switchgrass to biorefineries and shipping bioethanol to demand zones, production and construction costs of bioethanol plants, and finally penalties associated with energy consumption and carbon emissions of the supply chain activities. Such an optimization model enables the users to determine the optimal (best) biorefinery locations from the list provided by GIS analysis such that minimizing transportation, energy consumption, and carbon emission expenses. With this respect, the optimization model will determine the assignments of suppliers and demand zones to each selected biorefinery. Therefore, the effects of both economic and environmental factors on supply chain decisions will be simultaneously included.

For the proposed model, we make the following empirical-based assumptions: (1) the bioethanol producers are in charge of switchgrass procurement (acquisition) including renting marginal lands, the cultivation and harvesting process, and shipment of switchgrass; (2) the bioethanol producers are also responsible for bioethanol transport but not for switchgrass-based bioethanol co-product; and (3) demand is sufficient so that all of the bioethanol produced will be purchased by demand zones.

The notations, parameters and decision variables of the optimization model are presented in Table 2.1 and the input parameters are shown in Table A1 in Appendix A.

Table 2.1. Sets, decision variables, and parameters for the models

Notation			
Indices/Sets		λ	Mean yield rate of switchgrass (tons/ha)
I	Set of suppliers, indexed by *i*	v	Cultivation cost of switchgrass (\$/ha)
K	Set of biorefineries, indexed by *k*	h	Harvesting cost of switchgrass (\$/ha)
E	Set of in-state demand zones, indexed by *e*	r_i	Marginal land rental cost at supply zone *i* (\$/ha)
R	Set of out-of-state demand zones, indexed by *r*	a_i	Available marginal land at supply zone *i* (ha)
		θ	Bioethanol conversion rate from switchgrass (gallons/ton)
Decision variables		6	Bioethanol co-product conversion rate at biorefineries (tons/gallon)
Y_k	1 if a biorefinery is opened at location k; 0 otherwise	ACE	Emission factor of switchgrass acquisition (kg CO_2e/ton)
Q_{ik}	Quantity of switchgrass transported from supply area *i* to biorefinery *k* via truck (tons)	STE	Emission factor of transporting switchgrass via truck (kg CO_2e/ton-mile)
X_{ke}	Quantity of bioethanol transported from biorefinery *k* to in-state demand zone *e* via truck (gallons)	PRE	Emission factor of bioethanol production from switchgrass (kg CO_2e/gallon)
Z_{kr}	Quantity of bioethanol transported from biorefinery *k* to out-of-state demand zone *e* via rail (gallons)	BTE	Emission factor of transporting bioethanol via truck (kg CO_2e/gallon-mile)
CP	Quantity of bioethanol co-products produced at biorefineries (tons)	BRE	Emission factor of transporting bioethanol via rail (kg CO_2e/gallon-mile)
Parameters		ACG	Energy consumed during switchgrass acquisition (MJ/ton)
π	Bioethanol selling price (\$/gallon)	PRG	Energy consumed during bioethanol production (MJ/gal)
φ	Bioethanol co-product selling price (\$/ton)	STG	Energy consumed during transporting switchgrass via truck (MJ/ton-mile)
ρ	Production cost at biorefineries (\$/gallon)	BTG	Energy consumed during transporting bioethanol via truck (MJ/gallon-mile)
γ^g	Transportation fixed cost of switchgrass via truck (\$/ton)	BRG	Energy consumed during transporting bioethanol via rail (MJ/gallon-mile)
η^g	Transportation variable cost of switchgrass via truck (\$/ton-mile)	ξ	Carbon tax/Environmental cost factor of emissions (\$/kg CO_2e)
γ^t	Transportation fixed cost of bioethanol via truck (\$/gallon)	ψ	Energy cost factor of fossil fuel consumed (\$/MJ)
η^t	Transportation variable cost of bioethanol via truck (\$/gallon-mile)	d_{ik}	Distance from supply zone *i* to biorefinery *k* (miles)
γ^r	Transportation fixed cost of bioethanol via rail (\$/gallon)	d_{ke}	Distance from biorefinery *k* to in-state demand zone *e* (miles)
η^r	Transportation variable cost of bioethanol via rail (\$/gallon)	d_{kr}	Distance from biorefinery *k* to out-of-state demand zone *e* (miles)
f^b	Annualized fixed capital cost for opening a biorefinery (\$)	DEM_e	Annual bioethanol demand level at in-state demand zone *e* (gallons)
CAP	Capacity of biorefineries (gallons)	DEM_r	Annual bioethanol demand level at out-of-state demand zone *r* (gallons)

The objective function used in this study to address decisions is as follows:

$$
\begin{aligned}
Max\ Z = {} & \pi\left(\sum_{k\in K}\sum_{e\in E} X_{ke} + \sum_{k\in K}\sum_{r\in R} Z_{kr}\right) + \varphi . CP \\
& - \frac{1}{\lambda}\left(\sum_{i\in I}\sum_{k\in K} r_i . Q_{ik} - v . \sum_{i\in I}\sum_{k\in K} Q_{ik} - h . \sum_{i\in I}\sum_{k\in K} Q_{ik}\right) \\
& - \sum_{i\in I}\sum_{k\in K}(\gamma^g + \eta^g . d_{ik})Q_{ik} - f^b . \sum_{k\in K} Y_k \\
& - \rho\left(\sum_{k\in K}\sum_{e\in E} X_{ke} + \sum_{k\in K}\sum_{r\in R} Z_{kr}\right) - \sum_{e\in E}\sum_{k\in K}(\gamma^t + \eta^t . d_{ke})X_{ke} \\
& - \sum_{k\in K}\sum_{r\in R}(\gamma^r + \eta^r . d_{kr})Z_{kr} \\
& - \xi\left(ACE . \sum_{i\in I}\sum_{k\in K} Q_{ik} + STE . \sum_{i\in I}\sum_{k\in K} d_{ik} . Q_{ik}\right. \\
& + PRE\left(\sum_{k\in K}\sum_{e\in E} X_{ke} + \sum_{k\in K}\sum_{r\in R} Z_{kr}\right) + BTE . \sum_{k\in K}\sum_{e\in E} d_{ke} . X_{ke} \\
& \left. + BRE . \sum_{k\in K}\sum_{r\in R} d_{kr} . Z_{kr}\right) \\
& - \psi\left(ACG . \sum_{i\in I}\sum_{k\in K} Q_{ik} + STG . \sum_{i\in I}\sum_{k\in K} d_{ik} . Q_{ik}\right. \\
& + PRG\left(\sum_{k\in K}\sum_{e\in E} X_{ke} + \sum_{k\in K}\sum_{r\in R} Z_{kr}\right) + BTG . \sum_{k\in K}\sum_{e\in E} d_{ke} . X_{ke} \\
& \left. + BRE . \sum_{k\in K}\sum_{r\in R} d_{kr} . Z_{kr}\right)
\end{aligned} \tag{2.1}
$$

The objective function in Eq. (2.1) maximizes profit (revenue - cost) for the SBSC. The first two elements in the objective function are supply chain revenues coming from two final products: bioethanol and switchgrass-based bioethanol co-product. Other elements in the objective function respectively present the cost components of the model including marginal land rental cost for switchgrass cultivation, switchgrass cultivation cost, harvesting cost of switchgrass, transportation cost of switchgrass, biorefinery capital cost, biorefinery production cost, transportation cost of bioethanol via truck to in-state demand zones, transportation cost of bioethanol via rail to out-of-state demand zones, emissions cost, and energy cost. Supply chain emissions are penalized with a cost of ξ (carbon tax). The amount of CO_2e emitted due to supply chain activities such as switchgrass acquisition, bioethanol production, and switchgrass and bioethanol transportation have been considered as emissions sources in the SBSC. The energy cost factor (ECF) ψ is set as a penalty for the total amount of energy consumed in the SBSC to reduce energy consumption. Switchgrass acquisition, bioethanol production, and switchgrass and bioethanol transportation are considered as sources of energy consumption in the supply chain.

The constraints of the model are shown in Eqs. (2.2) - (2.12):

$$\sum_{k \in K} Q_{ik} \leq \lambda . a_i \qquad \forall i \in I \tag{2.2}$$

$$\theta \sum_{i \in I} Q_{ik} = \sum_{e \in E} X_{ke} + \sum_{r \in R} Z_{kr} \qquad \forall k \in K \tag{2.3}$$

$$6\left(\sum_{k \in K} \sum_{e \in E} X_{ke} + \sum_{k \in K} \sum_{r \in R} Z_{kr}\right) = CP \tag{2.4}$$

$$\sum_{e \in E} X_{ke} + \sum_{r \in R} Z_{kr} \leq CAP . Y_k \qquad \forall k \in K \tag{2.5}$$

$$\sum_{k \in K} X_{ke} = DEM_e \qquad \forall e \in E \tag{2.6}$$

$$\sum_{k \in K} Z_{kr} = DEM_r \qquad \forall r \in R \tag{2.7}$$

$$Y_k = \{0,1\} \quad \forall k \in K \tag{2.8}$$

$$CP \geq 0 \tag{2.9}$$

$$Q_{ik} \geq 0 \quad \forall i \in I, \forall k \in K \tag{2.10}$$

$$X_{ke} \geq 0 \quad \forall k \in K, \forall e \in E \tag{2.11}$$

$$Z_{kr} \geq 0 \quad \forall k \in K, \forall r \in R \tag{2.12}$$

Constraint (2.2) forces the amount of switchgrass harvested at area *i* to be less than or equal to the maximum switchgrass available to be harvested on marginal lands for each zone. The material flow constraints for biomass-to-bioethanol are given in Eq. (2.3) and biomass to bioethanol co-product is specified by Eq. (2.4). Constraint (2.5) represents the capacity constraints of bioethanol plants and whether they should be constructed. Constraint (2.6) assures that the volume of bioethanol produced in biorefineries fulfills the demand of in-state demand zones. Likewise, constraint (2.7) declares that the volume of bioethanol produced in biorefineries satisfies the demand for out-of-state demand zones. Finally, constraints (2.8) - (2.12) confirm the nature and non-negativity of variables used in the model. The MILP is solved via OpenSolver 2.9.0 using the CBC (COIN-OR Branch-and-Cut) optimization engine (Mason, 2012; OpenSolver, 2018).

2.3.3. Case study

This study examines the SBSC in the state of North Dakota as a case study. Environmental, climate, and soil conditions of the Northern Great Plains of the United States (US), in which North Dakota is located, are ideal for the commercial cultivation of switchgrass (J. Zhang et al., 2013). Biomass supply zones are the beginning of the SBSC network flow where marginal lands are located. Marginal lands almost exist in all 53 counties of North Dakota; thus, switchgrass can be cultivated all over the state. These counties have been divided into nine agricultural statistical districts (ASDs) including NW, NC, NE, WC, Central, EC, SW, SC, and SE serving as switchgrass suppliers in the design of the SBSC network (Gonela, Zhang, & Osmani, 2015). Figure 2.2 shows the switchgrass supply zones and North Dakota infrastructure considered for designating possible bioethanol plants. This figure shows high populated cities, lakes, rivers, roads, railroads, and ASDs colored according to their potential for switchgrass cultivation.

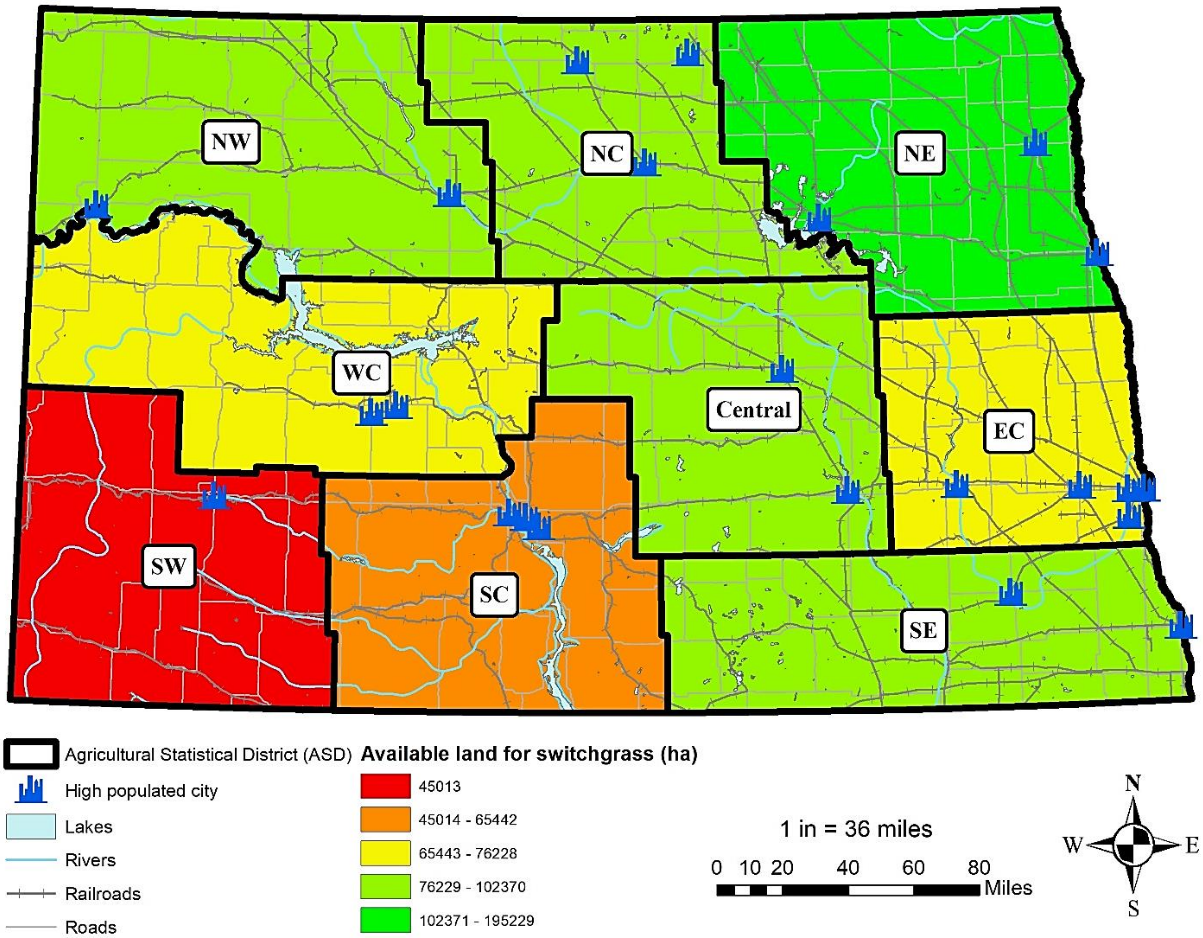


Figure 2.2. Switchgrass supply zones and North Dakota infrastructure for siting bioethanol plants

In this study, the capacity of switchgrass-based biorefineries has been set to 150 million gallons per year (MGPY) which is the maximum capacity for cellulosic biorefineries that have been commercialized (Kou & Zhao, 2011). Moreover, Table 2.2 shows the total marginal land available along with marginal land rental cost in North Dakota for switchgrass cultivation.

According to the United States Department of Agriculture, cropland accounted for 69.1%, pastureland 26.1% and marginal land (other uses) 4.8% of the 15.89 million hectares of total farmland under cultivation in North Dakota (National Agricultural Statistics Service, USDA, Census of Agriculture, 2019). This study focuses only on the marginal land for switchgrass cultivation which totals around 0.76 million hectares. Considering marginal lands for switchgrass cultivation avoids competition for lands used for human and animal consumption. Also, for the marginal land rental cost, since the marginal lands have not been used so far, there is no published marginal land rental cost available; Therefore, we used pastureland rental cost for each supply zone as the cost for renting marginal land.

Table 2.2. Biomass feedstocks availability and marginal land rental cost

Agricultural Statistical District (ASD)	Available land for switchgrass cultivation (ha) [a]	Marginal land rental cost ($/ha) [b]
SE	76,229	$67.95
EC	74,394	$49.42
NE	195,229	$40.77
SC	65,442	$45.71
CENTRAL	84,683	$49.42
NC	88,533	$39.54
SW	45,013	$35.83
WC	75,253	$34.59
NW	102,370	$24.71

[a] (NASS Census of Agriculture, 2019)
[b] (NASS Statistics by State, 2019)

The bioethanol produced in North Dakota is sold for the fulfillment of both in-state and out-of-state demands in the US. According to our conversations with bioethanol experts in ND, there are six in-state demand zones including Fargo, Grand Forks, Jamestown, Bismarck, Dickinson, and Minot which have fuel racks where bioethanol is blended with gasoline. These demand zones are all located in ND where the biorefineries are also located. Also, there are four out-of-state demand zones including Houston (TX), Los Angeles (CA), Portland (OR), and Seattle (WA). Considering out-of-state demand zones makes our case study more realistic which policymakers can rely on the corresponding findings. About 10 percent of North Dakota bioethanol production is sold within the state (shipped by truck) and the other 90 percent is shipped by rail to other states (ND Studies Energy Curriculum, 2019). Accordingly, the demand associated with each demand zone is assigned proportionally based on population. The in-state and out-of-state demand zones are shown in Figure 2.3.

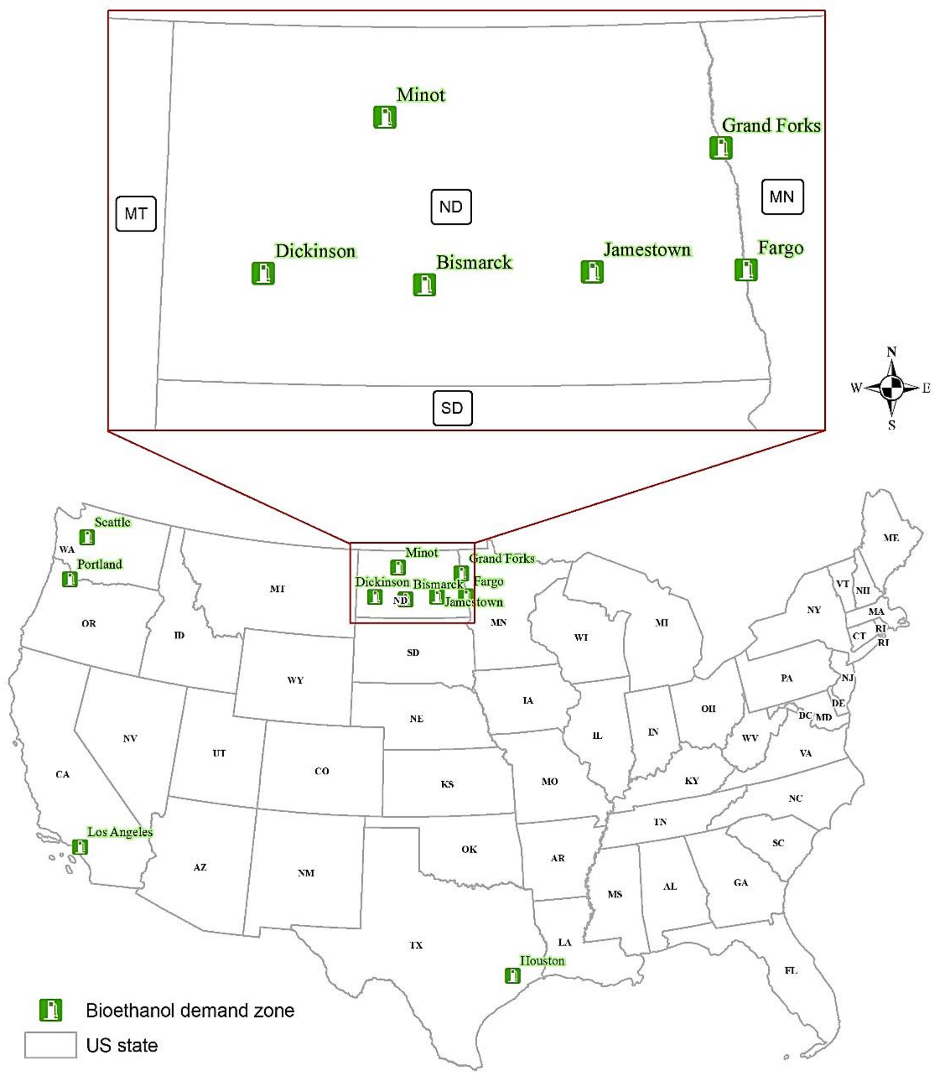


Figure 2.3. In-state and out-of-state demand zones

2.4. Results and discussion

There is a large stream of research in modeling biofuel feedstock supply chains and facility location problems using different approaches especially GIS which has turned out to be a valuable tool for designing biomass-biofuel supply chains (F. Zhang et al., 2017). The ideal locations to build new bioethanol plants in North Dakota were determined based on GIS analysis and served as input for the MILP model which specifies which facilities should be opened to satisfy the demand. According to GIS analysis, there are four possible cellulosic biorefinery locations in North Dakota for switchgrass-based bioethanol production which meet the required criteria for building a new bioethanol plant. According to Figure 2.4, these locations are in Ward, Grand Forks, Richland, and Stutsman counties which were chosen as biorefinery names accordingly. All four biorefineries are in different districts (ASD) which are scattered through North Dakota, so they can better fulfill the demand.

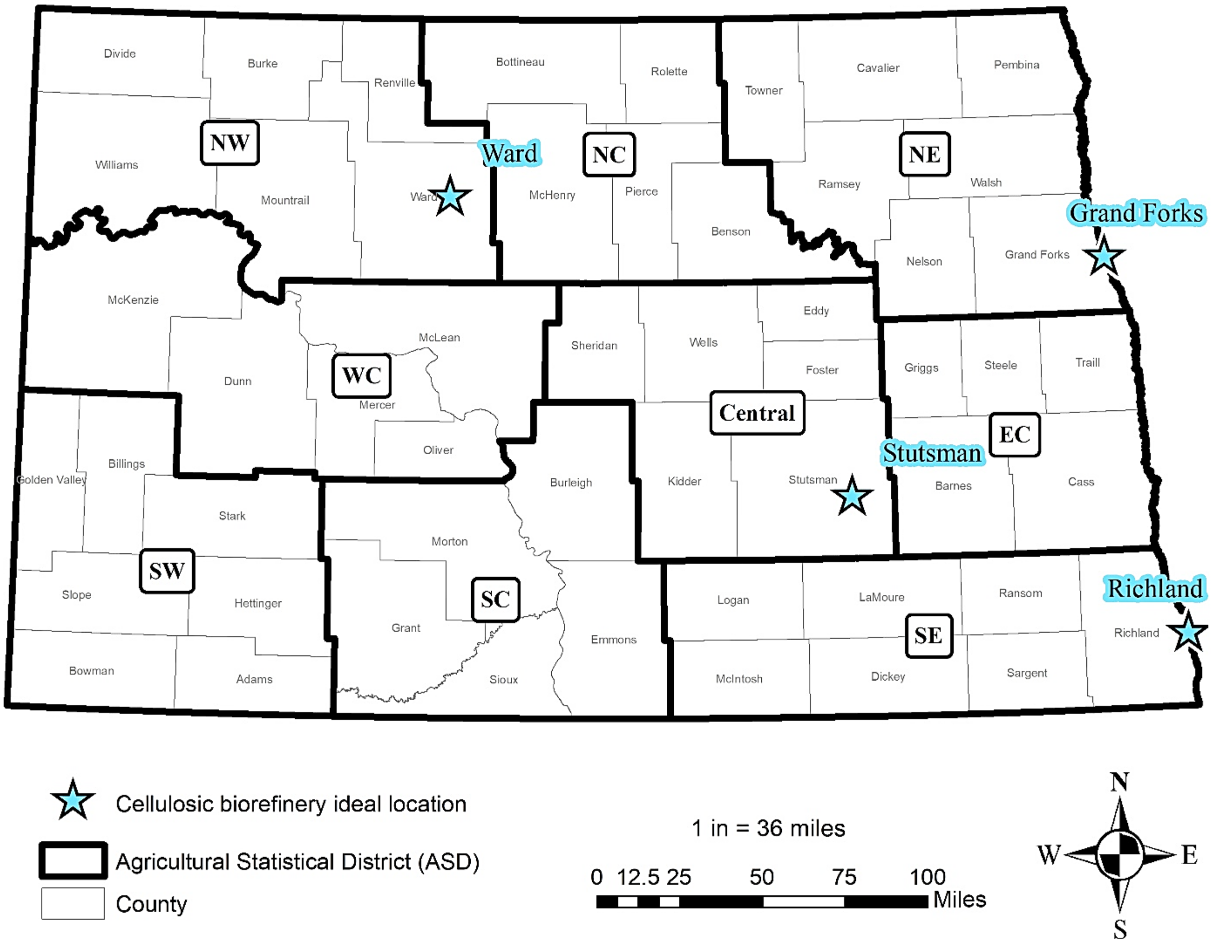


Figure 2.4. North Dakota map showing possible cellulosic biorefinery sites for switchgrass-based bioethanol production

2.4.1. Maximizing profit without emissions and energy consumption penalties

As discussed previously, we use 150 MGPY as the maximum capacity for a biorefinery. Therefore, the maximum amount of bioethanol that can be produced across the four possible sites in North Dakota is 600 MGPY. To examine the effects of demand variation, we consider four different demand levels (150, 300, 450, and 600 MGPY). This enables us to analyze how demand levels can affect bioethanol facility selection decisions. As shown in Figure 2.5, the contribution of different cost components is almost the same through four different demand levels. Considering different demand levels while setting the penalties for emissions and energy use to zero, the biorefinery construction cost has the highest percentage of cost followed closely by bioethanol production cost. Just these two cost elements comprise 67.2% of the total cost of the supply chain indicating that finding the best locations and production technologies for bioethanol plants are two of the most important decisions for policymakers. Transportation and cultivation costs are also significant, while land rental and harvesting costs are the smallest. Overall, the cost can be seen to grow in an almost linear fashion with the available capacity.

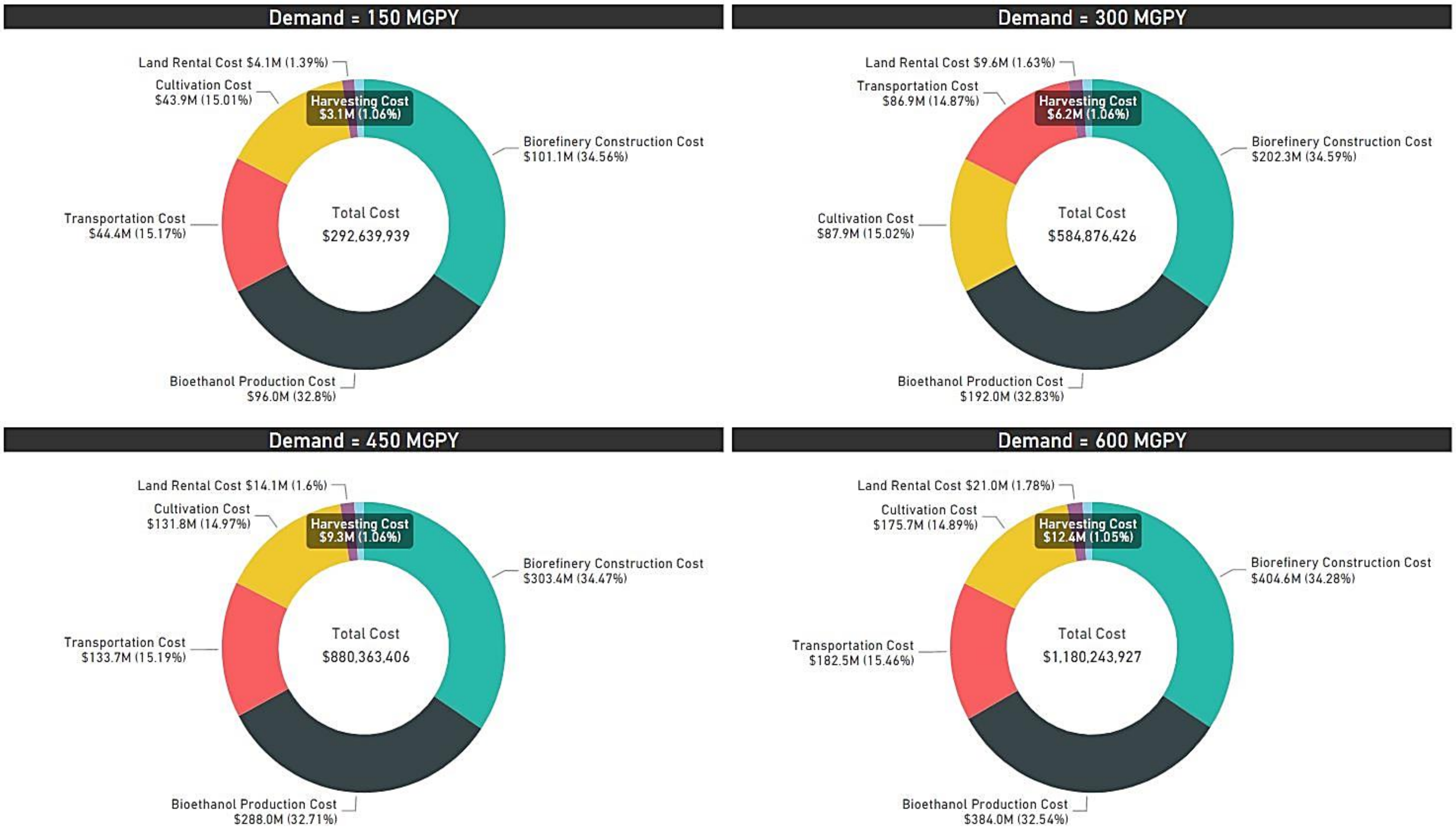


Figure 2.5. Cost breakdown of SBSC with different demand levels disregarding emissions and energy consumption penalties

Table 2.3 shows the optimal assignment of supply and demand zones to bioethanol plants. When the annual demand is 150 MGPY, Ward is the first bioethanol plant chosen by the MILP. That is Ward biorefinery is the first location where policymakers and investors can build a new cellulosic bioethanol plant which has the lowest logistical costs compared to other locations identified by GIS analysis. The Ward biorefinery is in the NW district where it can supply all its required biomass feedstock from switchgrass cultivation lands in the NW and NC districts. When the demand level increases to 300 MGPY, the Stutsman biorefinery located in the Central district is selected as the second bioethanol plant to open. In this scenario, the EC district lands along with Central district lands are rented to fulfill the required biomass feedstock for Stutsman biorefinery. In this situation, the Ward biorefinery tries to meet most of the demand of out-of-state demand zones including Los Angeles, Portland, and Seattle as well as Minot in North Dakota and the Stutsman biorefinery seeks to mostly fulfill the in-state demand (all in-state demand zones except Minot) along with Houston and the remaining bioethanol needed for Los Angeles. When the demand level is increased to 450 MGPY, the Grand Forks biorefinery is opened in the NE district by the MILP as the third biorefinery. When the demand level is set to its maximum (600 MGPY), Richland biorefinery is opened in the SE district as the fourth biorefinery plant to produce biofuel from switchgrass cultivated in the SE and EC districts. In this scenario, all four potential biorefineries are opened and assigned their closest supplier and demand zones. There are three supplier districts, WC, SW, and SC, which are not used in the optimal solution as the other six supplier districts can supply enough switchgrass to produce 600 MGPY bioethanol. This also means the marginal lands in North Dakota have the potential to produce more switchgrass than biorefineries in North Dakota can process. Overall, considering different demand levels indicates that the order priority for opening cellulosic biorefineries in North Dakota is Ward, Stutsman, Grand Forks, and Richland.

Table 2.3. Optimal assignment of supply zones and demand zones to bioethanol plants disregarding emissions and energy use penalties

Demand (MGPY)	Supplier district	Biorefinery	Out-of-state demand zone	In-state demand zone
150	NW, NC	Ward	All out-of-state demand zones	All in-state demand zones
	-	Grand Forks	-	-
	-	Richland	-	-
	-	Stutsman	-	-
300	NW, NC	Ward	Los Angeles, Portland, Seattle	Minot
	-	Grand Forks	-	-
	-	Richland	-	-
	CENTRAL, EC	Stutsman	Houston, Los Angeles	Fargo, Jamestown, Grand Forks, Bismarck, Dickinson
450	NW, NC	Ward	Los Angeles, Portland, Seattle	Minot
	NE	Grand Forks	Houston	Fargo, Grand Forks
	-	Richland	-	-
	CENTRAL, EC	Stutsman	Houston, Los Angeles	Jamestown, Bismarck, Dickinson
600	NW, NC	Ward	Los Angeles, Portland	Minot
	NE	Grand Forks	Houston, Los Angeles, Seattle	Grand Forks
	SE, EC	Richland	Houston	Fargo
	CENTRAL, EC	Stutsman	Los Angeles	Jamestown, Bismarck, Dickinson

2.4.2. The impact of a carbon tax on the supply chain

In this section, the emissions penalty is not set to zero in the objective function, however, the energy use penalty is set to zero. In our model, an emissions cost is incurred based on carbon emissions from biomass acquisition (such as cultivating, harvesting, and collecting), transportation from supplier districts to biorefineries, bioethanol production, and transportation between biorefineries and demand zones. By considering these four emission sources, our model assesses the effects of carbon emissions generated in the switchgrass-to-bioethanol process. The environmental cost per unit of CO_2e (kg of CO_2e) is imposed as a carbon tax.

To consider the effects of a carbon tax, five different scenarios are considered for the carbon tax rate in the presence of the four demand level scenarios to better analyze the impact of emissions on the supply chain and bioethanol plant siting decisions. In our study, biorefineries are in charge of paying the penalties to the government for emissions coming from all activities through the supply chain. The different carbon tax values are "No Penalty" with \$0 carbon tax, "Regular" with \$0.1231 carbon tax which is based on an estimation of environmental costs of CO_2 emissions (Nguyen & Gheewala, 2008; X-Rates, 2018), "Reaction Point" with varied carbon tax according to the demand level which is the minimum carbon tax for which the supply chain starts to react to the carbon tax and reduce its emissions, "Profit = \$0" with varied carbon tax according to the demand level which is the minimum carbon tax for which the total supply chain profit is \$0, "Another Biorefinery Needed" with varied carbon tax according to the demand level which is the minimum carbon tax for which the supply chain adds another biorefinery.

Table 2.4. Emissions and profit with different demand levels under different carbon taxes

		Carbon tax				
		No Penalty	Regular	Reaction Point	Profit = $0	Another Biorefinery Needed
Demand (MGPY)	Values	$0	$0.1231	varied	varied	varied
150	Total profit	$70,735,060	$65,895,171	$65,895,171 (carbon tax = $1.06)	$0 (carbon tax = $1.82)	$(2,487,703,373) (carbon tax = $70)
	Emissions [a]	39,316,733	39,316,733	38,184,906	38,184,906	36,688,217
300	Total profit	$141,873,566	$132,601,966	$125,308,674 (carbon tax = $0.22)	$0 (carbon tax = $1.89)	$(20,799,938,779) (carbon tax = $280)
	Emissions	75,317,633	75,317,633	74,791,924	74,791,924	74,431,385
450	Total profit	$209,761,577	$195,291,611	$185,076,825 (carbon tax = $0.21)	$0 (carbon tax = $1.79)	$(51,864,095,228) (carbon tax = $445)
	Emissions	117,546,438	117,546,438	117,020,730	117,020,730	116,789,324
600	Total profit	$273,256,099	$253,269,524	-	$0 (carbon tax = $1.68)	No more biorefineries
	Emissions	162,360,481	162,360,481	No changes	162,360,481	-

[a] Emissions values are in kg CO_2e unit

Table 2.4 demonstrates the effects of the different carbon tax rates on the total profit and total carbon emissions of the supply chain. When demand is 150 MGPY, the minimum carbon tax which makes the supply chain reduce its emissions is \$1.06 per kg CO_2e. In this case, emissions are decreased by 2.9% and profit is reduced by 6.8%. This means that reducing emissions through a carbon tax requires a 6.8% economic compensation. Furthermore, the maximum profit of the supply chain remains positive until a carbon tax of more than \$1.82 is imposed. In this case, increasing the carbon tax does not reduce the emissions unless a very high carbon tax (at least \$70/kg CO_2e) is applied for which the model opens another biorefinery to reduce emissions. In this situation, there will be a reduction in emissions, but the supply chain is no longer profitable. When demand is 300 or 450 MGPY, the same trends are seen. The minimum carbon taxes which result in the supply chain reducing emissions ("Reaction Point" scenario) are \$0.22 and \$0.21 per kg CO_2e, respectively, for 300 and 450 MGPY. In these cases, emissions reductions are 0.7% and 0.4% while reductions in profit are 11.7% and 11.8%, respectively. This indicates that as demand increases, a greater loss in profit is necessary to reduce emissions. Similarly, the supply chain stops making a profit if the carbon tax is higher than \$1.89 and \$1.79 respectively when demand is 300 and 450 MGPY without a decrease in emissions. Clearly, emissions are lower when a very high carbon tax is imposed, however, with such high carbon taxes the supply chain does not make any profit. The carbon taxes that affect the selection of bioethanol plants under the "Another Biorefinery Needed" scenario are \$280 and \$445 for the demand of 300 and 450 MGPY, respectively. When demand is 600 MGPY, there is no decrease in emissions since the supply chain is at its maximum capacity and there are no options to reduce emissions. All in all, the carbon taxes from "Reaction Point" scenarios show the most promise as the supply chain makes a profit while emissions decrease.

Table 2.5. Impact of different carbon taxes on bioethanol plant land allocation decisions

		Carbon Tax				
		No Penalty	Regular	Reaction Point	Profit = $0	Another Biorefinery Needed
Demand (MGPY)	Bioethanol plant	$0	$0.1231	varied	varied	varied
150	Ward	✓	✓	-	-	✓
	Grand Forks	-	-	-	-	-
	Richland	-	-	-	-	-
	Stutsman	-	-	✓	✓	✓
300	Ward	✓	✓	✓	✓	✓
	Grand Forks	-	-	-	-	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓
450	Ward	✓	✓	✓	✓	✓
	Grand Forks	✓	✓	✓	✓	✓
	Richland	-	-	-	-	✓
	Stutsman	✓	✓	✓	✓	✓
600	Ward	✓	✓	✓	✓	✓
	Grand Forks	✓	✓	✓	✓	✓
	Richland	✓	✓	✓	✓	✓
	Stutsman	✓	✓	✓	✓	✓

As shown in Table 2.5, the number of bioethanol plants under different demand scenarios is constant until a very high carbon tax (“Another Biorefinery Needed” scenario) is applied. Even when the supply chain stops making a profit, the emission cost is not high enough to beat the construction cost of another biorefinery. Under different demand scenarios, when the carbon tax reaches a very high level (“Another Biorefinery Needed” scenario), one more biorefinery will be opened. A thought-provoking point of Table 2.5 is that with the demand of 150 MGPY when the carbon tax reaches the “Reaction Point” ($1.09/kg CO_2e here), the model chooses Stutsman biorefinery instead of Ward which indicates the importance of demand level besides carbon tax rate for selecting bioethanol plants. On the other hand, from the results of Table 2.4, we concluded that the supply chain starts to reduce its emissions when the “Reaction Point” carbon tax scenario is implemented. The reason for this drop can be found in Table 2.6. Table 2.6 shows how emissions from different sources in the supply chain change for different carbon tax values with a demand under 300 MGPY. According to Table 2.6, emissions coming from the biomass acquisition process and bioethanol production are constant regardless of the carbon tax. However, emissions coming from the transportation of biomass from suppliers to biorefineries and the transportation of bioethanol from biorefineries to demand zones change as the carbon tax grows. The emissions from transportation are much higher than biomass acquisition and bioethanol production emissions which confirms the importance of distances and the amount of product being shipped. Since the amount of switchgrass and bioethanol is fixed under each demand level to fulfill the production requirement, the model can only find a better solution by changing the assigned paths in the network.

Table 2.6. Emissions from different sources by carbon tax with a 300 MGPY demand level

	Carbon Tax				
	No Penalty	Regular	Reaction Point	Profit = $0	Another Biorefinery Needed
Emissions sources	$0	$0.1231	$0.22	$1.89	$280
Biomass acquisition	545	545	545	545	545
Bioethanol production	2,400	2,400	2,400	2,400	2,400
Transport from supplier to biorefinery	22,404,399	22,404,399	21,878,691	21,878,691	21,927,586
Transport from biorefinery to demand zone	52,910,289	52,910,289	52,910,289	52,910,289	52,500,854
Total*	75,317,633	75,317,633	74,791,924	74,791,924	74,431,385

* All emissions are in kg CO_2e units

As illustrated in Table 2.6, the emissions drop when a “Reaction Point” carbon tax ($0.22/kg CO_2e) is imposed because of a reduction in emissions coming from the transportation of biomass from suppliers to biorefineries which means the model chooses other suppliers with shorter distances to biorefineries regardless of the marginal land rental cost. When a carbon tax less than the “Reaction Point” carbon tax is imposed, the land rental cost is highly influential in the selection of supply sources. However, as the carbon tax increases, the additional cost from transportation emissions becomes more important and closer supply sources with higher land rental costs but shorter transportation distances are chosen. Therefore, the model finds the cheapest supplier based on transportation and land rental costs.

Analyzing Tables 2.4 – 2.6 together generates important insights which can help policymakers to better address environmental issues and develop more sustainable supply chains. Considering these tables, we can see how increasing carbon taxes can decrease emissions. First, the reduction in emissions comes from transportation emissions as supply source proximity becomes more important than land rental cost. Second, we identify the “Reaction Point” carbon tax for which the supply chain is still profitable, but emissions are reduced. Third, we see that a carbon tax which results in the opening of a new biorefinery is too large to be practical in that it will result in an unprofitable supply chain.

2.4.3. The impacts of an energy consumption penalty on the supply chain

In this section, the energy consumption penalty is not set to zero in the objective function, however, the emissions penalty is set to zero. The major sources of energy consumption are the biomass acquisition process, transportation from supplier districts to biorefineries, bioethanol production, and transportation between biorefineries and demand zones. By considering these four energy consumers, the MILP accounts for the energy consumed in the switchgrass-to-bioethanol process. For the purpose of this paper, energy refers to diesel consumption as a major fuel for transportation modes, production facilities, and agricultural machinery. The diesel energy impact factor is 151.42 Megajoule (MJ) per gallon and a diesel price of $3.25 per gallon is chosen based on the on-highway diesel fuel price in the Midwest area of the US at the time of this study which leads to an energy cost of $0.0215 per MJ of energy (E.I.A., 2018; F. Zhang et al., 2017). This is the “Regular” ECF taken to quantify energy consumption. However, besides the Regular ECF, we considered other prices for penalizing energy usage to better analyze the impacts of energy on the proposed supply chain. The other different scenarios for ECF values are “No penalty”, “Reaction Point”, “Profit = $0”, and “Another Biorefinery Needed”. These are defined as for the scenarios used with the carbon tax in section 2.4.2. In our work, biorefineries are in charge of paying the penalties to the government for energy consumed during activities through the supply chain.

Table 2.7. Energy consumption and profit with different demand levels under different ECFs

		ECF				
		No Penalty	Reaction Point	Profit = $0	Regular	Another Biorefinery Needed
Demand (MGPY)	Values	$0	varied	varied	$0.0215	varied
150	Total profit	$70,735,060	$60,926,739 (ECF = $0.0004)	$0 (ECF = $0.0032)	$(393,511,221)	$(1,609,483,849) (ECF = $0.078)
	Energy (MJ)	24,631,063,008	21,537,344,071	21,537,344,071	21,537,344,071	20,248,379,593
300	Total profit	$141,873,566	$135,653,138 (ECF = $0.00014)	$0 (ECF = $0.0033)	$(795,544,890)	$(3,389,124,545) (ECF = $0.081)
	Energy (MJ)	44,489,135,416	43,595,413,313	43,595,413,313	43,595,413,313	42,339,964,254
450	Total profit	$209,761,577	$203,496,958 (ECF = $0.00009)	$0 (ECF = $0.0031)	$(1,266,990,598)	$(11,177,593,949) (ECF = $0.1658)
	Energy (MJ)	69,611,317,791	69,500,191,601	68,680,553,671	68,680,553,671	68,068,426,986
600	Total profit	$273,256,099	$264,158,559 (ECF = $0.00009)	$0 (ECF = $0.0028)	$(1,896,993,394)	No more biorefineries
	Energy (MJ)	101,089,408,308	100,941,239,825	100,941,239,825	100,941,239,825	-

Table 2.8. Impact of different energy cost factors on bioethanol plant land allocation decisions

		ECF				
		No Penalty	Reaction Point	Profit = $0	Regular	Another Biorefinery Needed
Demand (MGPY)	Bioethanol plant	$0	varied	varied	$0.0215	varied
150	Ward	✓	-	-	-	✓
	Grand Forks	-	-	-	-	-
	Richland	-	-	-	-	-
	Stutsman	-	✓	✓	✓	✓
300	Ward	✓	✓	✓	✓	✓
	Grand Forks	-	-	-	-	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓
450	Ward	✓	✓	✓	✓	✓
	Grand Forks	✓	✓	✓	✓	✓
	Richland	-	-	-	-	✓
	Stutsman	✓	✓	✓	✓	✓
600	Ward	✓	✓	✓	✓	✓
	Grand Forks	✓	✓	✓	✓	✓
	Richland	✓	✓	✓	✓	✓
	Stutsman	✓	✓	✓	✓	✓

In Table 2.7 and Table 2.8, along with four different cases for demand levels, we implemented five scenarios for pricing energy consumption to see how penalties for energy usage can change supply chain total profit, the total amount of energy consumption, and bioethanol plant siting decisions. In Table 2.7, unlike with the emissions penalty, the energy cost has a great contribution to the supply chain's biorefinery and demand zone assignment decisions. In this case, the model starts with Stutsman biorefinery instead of Ward when a penalty for energy use is considered. Moreover, for all demand levels, the maximum profit of the supply chain is positive only under "No Penalty" and "Reaction Point" ECF scenarios. The minimum ECFs which result in the supply chain reducing energy consumption ("Reaction Point" scenario) are $0.004,

$0.00014, $0.00009 and $0.00009 per MJ, respectively, for 150, 300, 450, and 600 MGPY bioethanol demand. The results of comparing the maximum profit of the supply chain when there is “No Penalty” for energy consumption and when “Reaction Point” ECF is implemented express that a desirable level of energy reduction is achieved with a decrease of 13.9%, 4.4%, 3%, and 3.3% in the economic objective under 150, 300, 450, and 600 MGPY demand levels, respectively. The ECFs that make the supply chain stop making a profit under 150, 300, 450, and 600 MGPY demand levels are $0.0032, $0.0033, $0.0031, and $0.0028 per MJ, respectively. In Table 2.9, we show how energy consumption by different consumers changes with different ECFs when demand is under 300 MGPY. The energy consumed in the transportation of switchgrass between suppliers and biorefineries is the main source of energy consumption. Imposing a “Reaction Point” ECF can decrease the amount of energy consumed in transporting both switchgrass and bioethanol while letting the supply chain make a profit.

Key results for the ECF are similar to for the emissions penalty with reductions coming in energy consumption coming from the trade-off between land rental cost and the ECF penalty, the reaction points were identified which reduce energy consumption but allow for a profitable supply chain, and a large enough ECF to result in opening a new plant also resulting in an unprofitable supply chain. One difference in the results for the ECF and the emissions penalty was that the Regular scenario for the ECF was unprofitable and reduced energy consumption but the Regular scenario for the emissions penalty was profitable and did not reduce emissions.

Table 2.9. Energy consumers reaction to different ECFs values at 300 MGPY demand level*

	ECF				
	No Penalty	Reaction Point	Profit = $0	Regular	Another Biorefinery Needed
Energy consumers	$0	$0.00014	$0.0033	$0.0215	$0.081
Biomass acquisition	831,235,619	831,235,619	831,235,619	831,235,619	831,235,619
Bioethanol production	4,145,999,997	4,145,999,997	4,145,999,997	4,145,999,997	4,145,999,997
Transport from supplier to biorefinery	34,930,956,349	34,111,318,419	34,111,318,419	34,111,318,419	34,278,618,010
Transport from biorefinery to demand zone	4,580,943,452	4,506,859,278	4,506,859,278	4,506,859,278	3,084,110,629
Total	44,489,135,416	43,595,413,313	43,595,413,313	43,595,413,313	42,339,964,254

* All energy values are in MJ units

2.4.4. Analysis with both emissions and energy consumption penalties

Addressing environmental and energy issues besides economic objectives would help our model to meet some aspects of sustainability. In order to see how imposing penalties simultaneously on both emissions and energy consumption affect the proposed supply chain, we considered the demand of 300 MGPY for further analysis as shown in Table 2.10 and Table 2.11. None of the “No Penalty”, “Regular”, “Reaction Point” and “Profit = $0” scenarios affect bioethanol plant siting decisions with a demand of 300 MGPY. This shows when demand is low (e.g. 150 MGPY in our study), the emissions and energy consumption penalties have high impacts on biorefinery siting while if the demand is high enough (e.g. more than 150 MGPY in our study), increasing the price of emissions and energy use penalties does not influence biorefinery allocation decisions until a very high penalty is considered one or both.

Table 2.10. Impact of different ECFs and carbon taxes on bioethanol plant land allocation at 300 MGPY demand level

		Carbon Tax ($/kg CO_2e)				
		No Penalty	Regular	Reaction Point	Profit = $0	Another Biorefinery Needed
ECF ($/MJ)	Bioethanol plant	$0	$0.1231	$0.22	$1.89	$280
No Penalty $0	Ward	✓	✓	✓	✓	✓
	Grand Forks	-	-	-	-	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓
Reaction Point $0.00014	Ward	✓	✓	✓	✓	✓
	Grand Forks	-	-	-	-	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓
Profit = $0 $0.0033	Ward	✓	✓	✓	✓	✓
	Grand Forks	-	-	-	-	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓
Regular $0.0215	Ward	✓	✓	✓	✓	✓
	Grand Forks	-	-	-	-	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓
Another Biorefinery Needed $0.081	Ward	✓	✓	✓	✓	✓
	Grand Forks	✓	✓	✓	✓	✓
	Richland	-	-	-	-	-
	Stutsman	✓	✓	✓	✓	✓

Table 2.11 shows the impact of different ECFs and carbon taxes on supply chain profit, energy use, and emissions with a demand of 300 MGPY. According to this table, the lowest possible emissions (74,431,385 kg CO_2e) occurs when “Another Biorefinery Needed” carbon tax is imposed, and the lowest energy consumption also occurs (42,339,964,254 MJ) when “Another Biorefinery Needed” ECF is applied. However, in these two cases, the supply chain is not profitable. There are two cases when the supply chain is profitable while penalizing emissions or energy consumption to achieve environmental benefits: (1) when there is no penalty for energy use but “Reaction Point” carbon tax for emissions; and (2) when there is no penalty for emissions but “Reaction Point” ECF for energy use. In the former policy, the “Reaction Point” carbon tax reduces emissions and energy use by 0.7% and 1.8%, respectively, while there is 11.7% reduction in profit. In the latter policy, the “Reaction Point” ECF decreases emissions and energy use by 0.7% and 2%, respectively, while there is a 4.4% reduction in profit. This means the best policy would be just to consider the “Reaction Point” ECF for energy consumption ($0.00014/MJ under 300 MGPY demand) since less economic compensation is required to achieve comparable environmental benefits compared to using a carbon tax.

Table 2.11. Impact of different ECFs and carbon taxes on total supply chain's profit, energy, and emissions at 300 MGPY demand level

		Carbon Tax				
		No Penalty	Regular	Reaction Point	Profit = $0 [b]	Another Biorefinery Needed
ECF	Values	$0	$0.1231	$0.22	$1.89	$280
No Penalty $0	Profit	$141,873,566	$132,601,966	$125,308,674	$0	$(20,799,938,779)
	Emissions [c]	75,317,633	75,317,633	74,791,924	74,791,924	74,431,385
	Energy [d]	44,489,135,416	44,489,135,416	43,669,497,445	43,669,497,445	42,595,469,330
Reaction Point $0.00014	Profit	**$135,653,138**	$126,445,922	$119,198,325	$(5,707,569)	$(3,959,758)
	Emissions	**74,794,603**	74,794,603	74,794,603	74,791,924	74,431,385
	Energy	**43,595,413,313**	43,595,413,313	43,595,413,313	43,669,497,445	42,595,469,330
Profit = $0 [a] $0.0033	Profit	$0	$(11,315,584)	$(18,563,181)	$(143,470,169)	$(20,940,503,828)
	Emissions	74,794,603	74,794,603	74,794,603	74,794,603	74,431,385
	Energy	43,595,413,313	43,595,413,313	43,595,413,313	43,595,413,313	42,595,469,330
Regular $0.0215	Profit	$(795,544,890)	$(804,752,106)	$(811,999,703)	$(936,906,691)	$(21,714,905,113)
	Emissions	74,794,603	74,794,603	74,794,603	74,794,603	74,434,064
	Energy	43,595,413,313	43,595,413,313	43,595,413,313	43,595,413,313	42,521,385,198
Another Biorefinery Needed $0.081	Profit	$(3,389,124,545)	$(3,398,312,054)	$(3,405,544,139)	$(3,530,183,780)	$(24,244,927,532)
	Emissions	74,634,515	74,634,515	74,634,515	74,634,515	74,434,064
	Energy	42,339,964,254	42,339,964,254	42,339,964,254	42,339,964,254	42,521,385,198

[a] the ECF that makes the supply chain stop from making a profit when the emission penalty is zero
[b] the emission penalty that makes the supply chain stop from making a profit when the ECF is zero
[c] the emissions are in kg CO_2e units
[d] the energy is in the MJ units

2.5. Conclusions

This research developed a two-stage modeling approach to investigate the economic and environmental factors of a switchgrass-to-bioethanol supply chain in the state of North Dakota. In the first stage, the potential locations of bioethanol plants were determined according to some geographical aspects. In the second stage, a MILP model was created. This optimization model aims to maximize the profit of supply chain by determining the optimal locations of bioethanol plant, and the optimal assignment of suppliers and demand zones for each plant such that transportation, carbon emissions, and energy consumption costs are minimized. Our study considers both in-state and out-of-state demand zones in North Dakota. The effects of different carbon tax rates, energy cost factors and bioethanol demand levels on the supply chain decisions (i.e., plant locations) were evaluated. According to the GIS analysis, four potential locations were chosen to build new cellulosic (switchgrass-based) bioethanol plants in North Dakota which served as inputs for the optimization model.

The results of the optimization model show that by setting the "Reaction Point" scenario for the carbon tax or ECF (scenarios with the minimum carbon tax or ECF which the supply chain starts to react), the supply chain starts reducing its emissions and energy consumption. The "Reaction Point" carbon taxes are \$1.06, \$0.22, and \$0.21 per kg CO_2e and the "Reaction Point" ECFs are \$0.004, \$0.00014, and \$0.00009 per MJ, respectively, for 150, 300, and 450 MGPY bioethanol demand levels. When the demand is 600 MGPY, there is no decrease in emissions since the supply chain is at its maximum capacity and there are no options to reduce emissions, however, setting a \$0.00009 per MJ penalty for energy consumption would result in the supply chain reducing energy consumption. If the demand is high enough (more than 150 MGPY in our study), the carbon tax or ECF does not have any effect on bioethanol siting decisions until a very high carbon tax which results in negative profit is imposed. Moreover, the results of this study illustrate that biomass transportation from suppliers to biorefineries and the transportation of bioethanol from biorefineries to demand zones are the important factors that control emissions and energy consumption for the supply chain. Another important point from the results is that when a carbon tax less than the “Reaction Point” scenario is set, the model assigns a supply location with cheaper land rental cost regardless of whether it is the closest to a biorefinery. However, if a “Reaction Point” carbon tax or ECF is applied, the model selects the supplier with the shortest path regardless of the land rental cost. Finally, considering both ECF and carbon tax simultaneously as the factors to control the emissions and energy use was also investigated. Our findings conclude that from a sustainability point of view, there is no need to penalize both emissions and energy use to get desirable environmental improvements. The best sustainable solution will be achieved when a “Reaction Point” ECF is set to penalize consumed energy. Under this scenario, emissions and energy use are decreased by 0.7% and 2%, respectively, while there is a 4.4% reduction in profit.

As future research, this study can be extended by considering other species of second-generation biomass feedstock rather than switchgrass while evaluating a bioethanol supply chain. Moreover, different types of biomass can be considered simultaneously to determine the most economical and sustainable approach to produce bioethanol. Future work can also emphasize incorporating the impacts of uncertainties, risks, or disruptions in the biomass bioethanol supply chain and bioethanol plant siting decisions.

3. SUSTAINABLE BIOMASS SUPPLY CHAIN NETWORK DESIGN WITH BIOMASS SWITCHING INCENTIVES FOR FIRST-GENERATION BIOETHANOL PRODUCERS[1]

3.1. Abstract

Sustainable energy requires renewable energy sources to reduce reliance on fossil fuels. As a renewable energy source, first-generation bioethanol has been produced from corn. However, the production of such a biofuel increases corn-based food prices resulting in serious food versus fuel debates. Financial incentives would motivate first-generation bioethanol producers switching to second-generation bioethanol production. This study investigates the effects of two financial incentives (incentive payments and emissions penalties) motivating first-generation bioethanol producers to use second-generation biomass. These financial incentives are integrated into linear programming models to maximize the profit of the bioethanol supply chains in the state of North Dakota. Numerical results indicate that first-generation bioethanol production is more efficient than the second-generation bioethanol. Hence, the social value of using corn as a source for food instead of fuel must be at least \$2.38/bushel. Furthermore, to switch from the first to the second-generation biofuel production, bioethanol producers must either receive at least an incentive payment of \$0.8495 per gallon of second-generation bioethanol or pay at least a penalty of \$3.2573

[1] The material in this chapter was co-authored by Seyed Ali Haji Esmaeili, Joseph Szmerekovsky, Ahmad Sobhani, Alan Dybing, and Tim O. Peterson. Seyed Ali Haji Esmaeili had primary responsibility for collecting data and analysis of the test system. Seyed Ali Haji Esmaeili was the primary developer of the model that are advanced here. Seyed Ali Haji Esmaeili also drafted and revised all versions of this chapter. This chapter appears in Energy Policy (Haji Esmaeili et al., 2020).

per Kg CO_2e emitted due to first-generation bioethanol production. The results of this study support policymaker decisions in developing incentive programs to promote sustainable second-generation bioethanol in the US.

3.2. Introduction

Given the increasing demand for energy, climate change, and environmental concerns over the use of fossil fuels, it is becoming important to find alternative renewable energy sources (Awudu & Zhang, 2012). One popular alternative is biofuels. Some sources, namely biomass, such as food crops, energy crops, and agriculture residues can be utilized in biofuel production. Biomass provides lower energy costs while emitting less CO_2e compared to fossil fuels (Mohamed Abdul Ghani et al., 2018). Bioethanol, as one sort of cellulosic biofuel, produced from lignocellulosic biomass feedstocks has shown vast potential as a renewable resource.

To encourage a shift from fossil fuels to biofuels, the Renewable Fuel Standard (RFS) was established by the US Congress in 2007 to support biofuel production (Halil I. Cobuloglu & Büyüktahtakın, 2015). The RFS mandates production of 36 billion gallons of biofuels annually by 2022 of which 21 billion gallons must be advanced biofuel, such as cellulosic (second-generation) bioethanol, while only 15 billion gallons can be corn (first-generation) ethanol (Luo & Miller, 2013). Currently, over 200 corn ethanol plants in the US are producing almost 15 billion gallons of corn-based bioethanol while there are less than ten cellulosic bioethanol plants producing around half-billion gallons per year (RFA, 2018). Accordingly, cellulosic bioethanol production is far behind the needs of the RFS (Bracmort, 2012) and the industry has been incapable of meeting its goals (Luo & Miller, 2013).

In contrast to the first-generation bioethanol, the second-generation bioethanol is produced from non-edible lignocellulosic-based biomass, such as agriculture residuals, dedicated energy crops (e.g., switchgrass) or woody materials. Corn stover, the agricultural residue from corn harvesting, is a popular agriculture residue for bioethanol production in the US from social, economic and environmental aspects as it allows land to be used for food production while still providing biomass for fuel production (Luo & Miller, 2013). Corn stover is considered in this study as a proxy for all sources of cellulosic ethanol to demonstrate the modeling framework and to be compared to corn ethanol production. Further, corn stover is a particularly attractive choice for analysis as corn is the primary first-generation feedstock for bioethanol production in the US. In addition to considering the social aspects of bioethanol production (food versus fuel debate), sustainability also requires that economic and environmental aspects of a supply chain be considered. Regarding this, our research aims to explore an efficient way to perform biomass supply chain network design (SCND) considering profit maximization and emissions minimization. We test the model using data from the state of North Dakota (ND), a primary producer of corn used for bioethanol production.

The objective of the paper is to evaluate and compare the economic and environmental effects of first-generation and second-generation bioethanol supply chains to assist policymakers in choosing the best policies to promote cellulosic bioethanol in the US. Specifically, it focuses on incentive schemes in the form of emissions penalties (i.e. carbon tax) and incentive payments for motivating the transition from the first to second-generation biofuel production. The importance of evaluating such incentives has been noted by Ge and Lei (2017). To that end, a linear programming model is developed to explore how the incentives impact the economic choice between first- and second-generation bioethanol production. Therefore, the boundaries of the analysis include only those factors that have a significant difference in corn and corn stover farming, transporting and processing. The competition between corn and corn stover as a biomass feedstock for bioethanol production is expected to be independent of exogenous factors. For this study, incentives for cellulosic bioethanol markets are explicitly addressed. To the best of our knowledge, this study is the first use of a linear programming model to make a comparison of first- and second-generation bioethanol supply chains. We also explore how the social value of using the land for food instead of fuel and the price of corn impact the value of switching from first to second-generation bioethanol production. Switching to the second-generation bioethanol production may support the social aspects in a way that stops using first-generation for biofuel production would let the edible biomass feedstock be sold to the food market leading to securing food security and supporting hunger issues in the world. Doing so would address the food versus fuel issues by fulfilling the concerns over the use of irrigation land for producing energy instead of food (Gonela, Zhang, & Osmani, 2015). Also, second-generation biomass production consumes fewer resources such as water and fertilizers (Charles, Ryan, Ryan, & Oloruntoba, 2007). In this study, we utilized corn stover as the residues of corn production for bioethanol production which helps corn farmers making more profit by selling corn stover besides corn leading to agricultural development, supporting the regional economy and nourishing the society. Making more profit would motivate investors to grow more biomass feedstocks resulting in creating more jobs and stimulating the economy of underdeveloped rural areas (J. Zhang et al., 2013).

The remainder of the paper is organized as follows. Section 3.3 contains the literature review of the study. Section 3.4 describes mathematical models. Sensitivity analysis, numerical findings and policy implications for conversion to second-generation bioethanol production are discussed in Section 3.5 and Section 3.6. Finally, Section 3.7 summarizes the study and provides opportunities for future research.

3.3. Background and literature review

Research on bioethanol producing from biomass has been growing recently because of its potential to become an alternative energy source that is both more economical and sustainable compared to fossil fuels. Awudu and Zhang (2013) developed a stochastic production planning model for corn-based ethanol biorefineries under bioethanol demand and price uncertainties. Mueller et al. (2011) studied the relation between food price and ethanol demand which shows a 3–30% contribution of ethanol demand in increasing food price. Their recommendation is to promote second-generation biofuels (e.g., cellulosic ethanol) that use non-edible biomass feedstocks. Regarding this, Osmani and Zhang (2013) explored a stochastic mixed-integer linear programming (SMILP) model for developing a second-generation bioethanol supply chain. They jointly considered uncertainties in biomass yield, biomass purchase price, bioethanol demand, and bioethanol price. Paulo et al. (2015) explored the advantages of mixed integer linear programming (MILP) model for designing residual forestry biomass to a bioelectricity supply chain. This study can help to specify the amount of biomass, the capacity, and location of energy facilities, and transportation modes selection. Their analysis demonstrated the positive contribution of the mathematical programming approach to achieve practical economic solutions. Additionally, Rabbani et al. (2018) designed a sustainable switchgrass-based bioenergy supply chain network incorporating conflicting economic, environmental and social objectives. The model was solved by applying two-stage algorithms to determine the appropriate strategical and tactical decisions concerning the preference of decision makers for suitable trade-offs among the sustainability factors. A common missing theme of these studies is the absence of comparison between first-generation and second-generation biomass network design both economically and environmentally. A few studies considered both first-generation and second-generation biomass simultaneously (known as hybrid generation). Gonela et al. (2015a) explored a hybrid generation bioethanol supply chain (HGBSC) considering different government-mandated sustainability standards to examine implementing first-generation and second-generation bioethanol plant configurations simultaneously including industrial symbiosis strategy.

Promoting sustainability concepts can make biomass bioethanol supply chain more competitive and comprehensive. While the definition of sustainability is broad, a triple bottom line approach that comprises economic, environmental and social aspects has been broadly accepted for sustainable development (e.g., Mota et al., 2015; Sobhani et al., 2019; Sobhani and Wahab, 2017). Thus, a substantial amount of research is conducted to design sustainable supply chains considering a variety of sustainability indicators. Tseng and Hung (2014) developed a strategic decision-making model for designing a sustainable apparel manufacturing supply chain network. The proposed model tries to improve supply chain operations and carbon emissions costs. The results illustrate that the regulation that forces enterprises to take carbon emission costs can considerably reduce carbon emissions. Gonela et al. (2015b) proposed a SMILP model to design an HGBSC that aims to maximize profit under Greenhouse Gas (GHG) emissions and irrigation land-use restrictions. The results imply that the design of HGBSC changes under different sustainability considerations.

The previous studies explored the sustainability aspects to streamline the biomass supply chain better. However, in terms of the social aspect of sustainability, most of the studies considered the number of jobs created by the supply chains in their modeling framework. In our study, to address the social issues of sustainability, we incorporate monetary incentives and monetized emissions for first-generation bioethanol producers to motivate them to switch their biomass input and production technologies to be compatible with second-generation biomass especially food crop residues. This sustainability modeling approach explores the trade-offs among the supply chain total profit, incentives, and emission prices which have not been considered in the previous literature. A study by Thompson and Meyer (2013) indicates that if biofuels are produced from food crop residues, then they may potentially decrease food prices due to the allocation of more land to food crop cultivation.

To help towards accomplishing more sustainable supply chains, it is necessary to explore cases of monetized incentives offered by the government to support the biomass bioethanol supply chain (Mohamed Abdul Ghani et al., 2018; Yousefi, Sobhani, Naeni, & Currie, 2019). In Norberg-Bohm (2000), it is indicated that government intervention seeks to promote the use of innovative technologies during the manufacture of commercial products to reduce emissions of polluters. Financial incentives are the opposite of taxes (such as carbon tax in this study), that is, an amount of money is given to companies for producing bioethanol from second-generation biomass versus imposing a carbon tax to force producers to reduce emissions. The government manifests its concerns with the environment by offering financial incentives (Kaboli Chalmardi & Camacho-Vallejo, 2019).

To meet sustainable energy independence global challenge, government intervention has been essential for supporting and promoting biomass conversion to produce renewable energy which is usually done through incentive programs such as the Biomass Crop Assistance Program (BCAP) which helps farmers to manage logistics activities for biomass feedstock (Mohamed Abdul Ghani et al., 2018). The government has also incentivized the use of renewable energy in many countries through different types of policies for each geographic location. For instance, Black et al. (2014) discovered that removing financial incentives for wind energy in the state of Idaho would result in reducing tax revenue along with decreases in state income and employment.

Government intervention through incentives can nurture the development of renewable energy that benefits our societies, economies, and the environment (Mohamed Abdul Ghani et al., 2018). Simsek and Simsek (2013) mentioned that the increase in renewable energy consumption all over the world has led to lessening dependency on fossil fuels and pollution reduction. In this work, they presented some incentive mechanisms and renewable energy policies that are implemented in Turkey.

Cohen et al. (2016) discussed two real cases that highlight the convenience of applying government subsidies for the use of green technologies. Notably, they used the US electric vehicle markets and solar panels to demonstrate the applicability of subsidies. Also, subsidies are applied in other countries to promote the use of wastewater treatment equipment in Indonesia, pollution control equipment in China, Taiwan, and the Philippines, energy-saving equipment in Korea, and pollution control activities in Thailand (Kaboli Chalmardi & Camacho-Vallejo, 2019). In other studies related to renewable energy incentives implementation, Cobuloglu and Büyüktahtakin (2015) developed a multi-objective mixed-integer optimization model to explore the competition and trade-offs between food production and biofuel using switchgrass and corn. The study is primarily conducted to address the food versus fuel issue and aims to improve operational and environmental costs regarding land allocations to food and energy crops. Their model reveals that switchgrass is more profitable than corn in cropland, while for production on marginal land, it needs the Conservation Research Program (CRP) incentives. Their study suggests managers and policymakers provide CRP incentives or to adjust sustainability factors, which restricts cropland availability for biofuel production, to ensure food security. In Nigeria, a biofuel policy and incentives were established to promote the bioenergy sector, and a review has been done by Ohimain (2013) to identify the policy gaps and provide recommendations. Cobuloglu and

Büyüktahtakin (2014) used mixed-integer optimization to formulate the economic and environmental benefits of switchgrass production, with incorporating incentives in their model. In their study, they considered the budget provided by the government for biomass production as an incentive for switchgrass cultivation on marginal lands. Recently, a study by Mohamed Abdul Ghani et al. (2018) dealt with the primary challenge confronted by many farmers which is whether leftover crops (corn stover) should be burned upon crop harvesting. They developed a large-scale linear program with the goal of maximizing profit with and without the emission cost which considers incentives for corn farmers to sell the leftover yield (corn stover) to bioethanol producers instead of burning it. Moreover, Kaboli Chalmardi and Camacho-Vallejo (2019) developed a bi-level programming approach to optimize a sustainable supply chain network design considering government intervention which offers financial incentives (subsidies) and encourages the supply chain's manager to use cleaner technologies. Their results show that an appropriate government's financial incentives strategy lead to decrease the environmental impact of the sustainable supply chain network design significantly.

From this literature review, it can be concluded that there is no work trying to formulate incentives and penalized emissions as financial levers to motivate existing corn ethanol producers to shift their production facilities to a cellulosic ethanol plant. In this regard, our paper tries to address this gap and introduces a profit maximization model with and without emissions penalties that consider the offer of financial incentives from the government to the supply chain's managers. Therefore, economic and environmental aspects of sustainable biomass network design are being considered explicitly. Our study allows corn bioethanol producers to make economic and environment-friendly management strategies so that they can optimally switch their technologies to use corn stover.

3.4. Methodology

This study aims to compare the existing first-generation (corn) biomass bioethanol supply chain (BBSC) with a proposed second-generation (corn stover) BBSC by developing two different models with and without emissions. Emissions are penalized with a carbon tax in this context. The main difference between first-generation and second-generation models is the cellulosic biorefinery technology transition cost along with different cost components associated with changing the biomass type. The supply chain network of both corn and corn stover bioethanol has three stages including suppliers, bioethanol plants, and demand zones. The biomass bioethanol supply chain network and the associated activities in each stage are shown in Figure 3.1. The biomass feedstock (including corn and corn stover) flows from the suppliers to the bioethanol plants (biorefineries) by trucks. Then the produced bioethanol in biorefineries either goes to in-state demand zones (by trucks) or to out-of-state demand zones by rail.

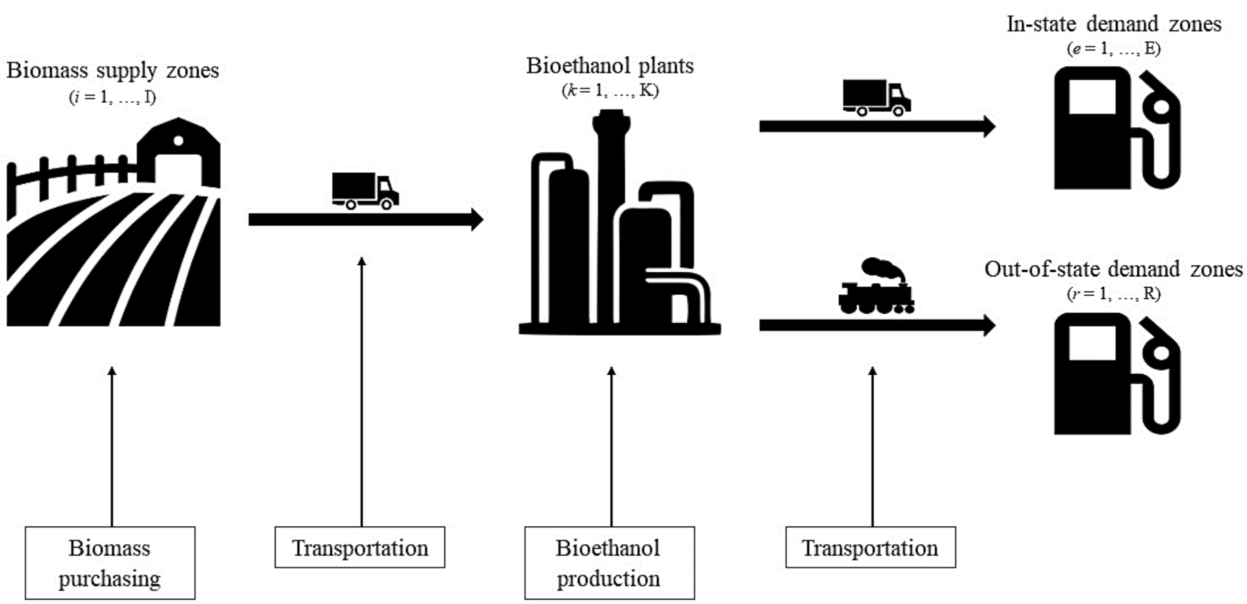


Figure 3.1. Biomass bioethanol supply chain network and the associated activities in each stage

The biofuel industry is a complex system including many decision-makers such as farmers and bioethanol producers (Luo & Miller, 2013). In our study, we make the following simplifying assumptions: (1) the bioethanol producers entirely use their capacity to produce bioethanol; (2) the biomass including corn (in bushels) and corn stover (in bales) are readily available at the edge of the farms and producers can purchase their required biomass with no significant additional equipment expenditures; (3) the capacity of first-generation bioethanol producers will remain unchanged after switching to second-generation compatible facilities; (4) the main cost component for corn ethanol producers to switch their production facilities to a cellulosic ethanol plant is as much as building a new cellulosic bioethanol plant; and (5) all bioethanol produced will be purchased by demand zones.

In this study, we develop two optimization models with two scenarios for each biomass feedstocks. The goals of the proposed models fold in four items in order to compare and capture the difference between corn bioethanol supply chain and corn stover (cellulosic) bioethanol supply chain with and without emissions. The framework of the given problem and the proposed methodology is shown in Figure 3.2.

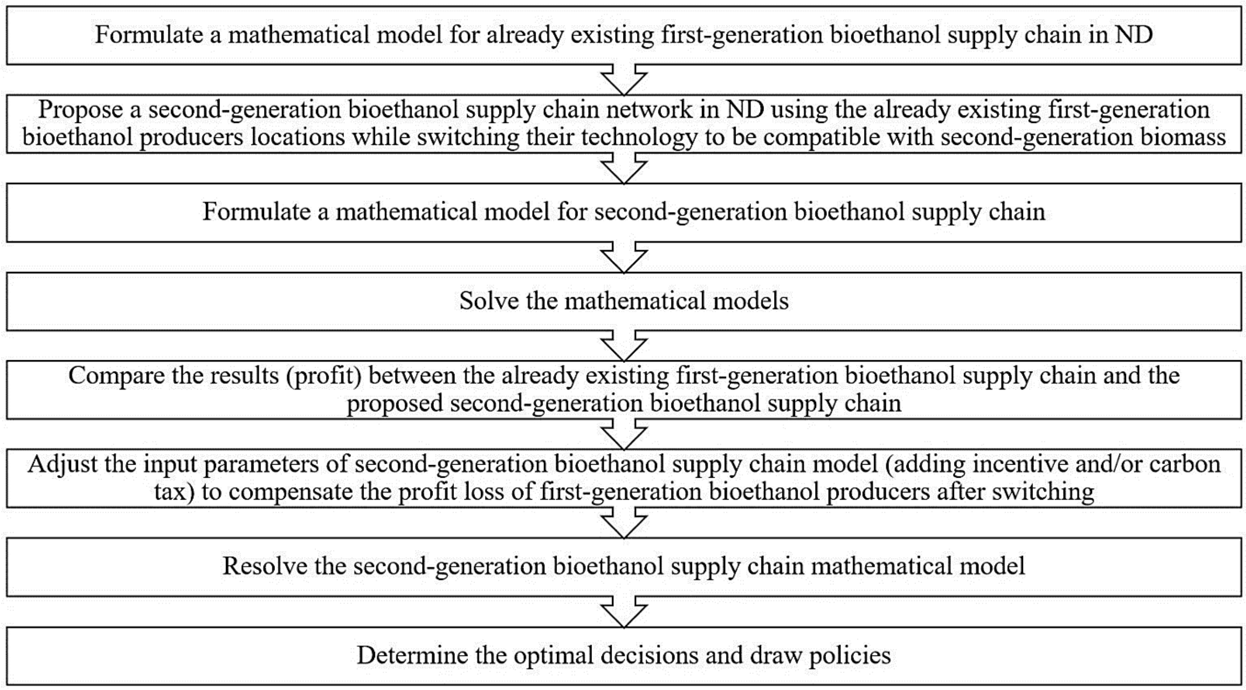


Figure 3.2. The framework of the proposed methodology

As shown in Figure 3.2, at first, two mathematical models of the existing first-generation bioethanol supply chain in ND are developed to maximize the profit of the corn bioethanol supply chain. The first mathematical model considers the revenue and cost items of the first-generation bioethanol supply chain without including emissions penalties. The second model includes the emissions penalty cost item. Developing these two distinctive models enables us to evaluate the effects of emission costs associated with the production, biomass acquisition, and transportation activities. Second, new mathematical formulations are proposed for the second-generation bioethanol supply chain. According to these formulations, the locations of second-generation biorefineries are the same as the ones used for first-generation biorefineries. The proposed formulations aim to maximize the profit of the second-generation bioethanol supply chain in ND with and without including emissions penalties as well as monetary incentive items for bioethanol producers to switch their facilities and use corn stover feedstock. According to the proposed methodology in Figure 3.2, the optimization models are solved. Different scenarios are evaluated to compare the maximized profits of the first- and second-generation bioethanol supply chains with and without the effects of carbon emission expenses. Furthermore, the monetary incentive parameters are changed to evaluate their effects on the profit of the second-generation supply chain. With respect to the different scenarios and associated results, the optimal decisions and policies are derived from the mathematical models and discussed from managerial implications.

3.4.1. First-generation supply chain profit optimization model without emissions penalty

The first objective function in Eq. (3.1) aims to maximize profit for corn bioethanol supply chain disregarding emissions. The first two elements in the objective function are the revenues coming from bioethanol and corn-based bioethanol co-product sales. The co-product of corn in bioethanol production is called Dried Distillers Grain (DDG). The remaining components are costs associated with the supply chain process such as corn purchase cost, transportation cost between suppliers and bioethanol plants, bioethanol production cost, and transportation cost between bioethanol plants and both in-state and out-of-state demand zones. Since bioethanol from corn is already produced in ND, there is no biorefinery construction/technology transition cost in corn-based optimization models. Notations used in this study are shown in Table 3.1.

Table 3.1. Sets, decision variables, and parameters for the models

Notation			
Indices/Sets			
I	Set of Suppliers, indexed by *i*	θ^s	Bioethanol conversion rate from corn stover (gallons/ton)
K	Set of biorefineries, indexed by *k*	6^s	Corn stover co-product (Lignin pallet) conversion rate (ton/gallon)
E	Set of in-state demand zones, indexed by *e*	γ^c	Transportation fixed cost of corn via truck ($/bushel)
R	Set of out-of-state demand zones, indexed by *r*	η^c	Transportation variable cost of corn via truck ($/bushel-mile)
Decision Variables		γ^s	Transportation fixed cost of corn stover via truck ($/ton)
Q_{ik}^c	Quantity of corn transported from supply area *i* to biorefinery *k* (bushel)	η^s	Transportation variable cost of corn stover via truck ($/ton-mile)
Q_{ke}^c	Quantity of bioethanol produced from corn transported from biorefinery *k* to in-state demand zone *e* (gallon)	γ^t	Transportation fixed cost of bioethanol via truck ($/gallon)
Q_{kr}^c	Quantity of bioethanol produced from corn transported from biorefinery *k* to out-of-state demand zone *r* (gallon)	η^t	Transportation variable cost of bioethanol via truck ($/gallon-mile)
Q^c	Quantity of co-product produced from corn (DDG) at biorefineries (ton)	γ^r	Transportation fixed cost of bioethanol via rail ($/gallon)
Q_{ik}^s	Quantity of corn stover transported from supply area *i* to biorefinery *k* (ton)	η^r	Transportation variable cost of bioethanol via rail ($/gallon)
Q_{ke}^s	Quantity of bioethanol produced from corn stover transported from biorefinery *k* to in-state demand zone *e* (gallon)	D_e	Annual bioethanol demand level at in-state demand zone *e* (gallon)
Q_{kr}^s	Quantity of bioethanol produced from corn stover transported from biorefinery *k* to out-of-state demand zone *r* (gallon)	D_r	Annual bioethanol demand level at out-of-state demand zone *r* (gallon)
Q^s	Quantity of co-product produced from corn stover (Lignin pallet) at biorefineries (ton)	e_s^{truck}	Emission factor of transporting corn stover via truck (Kg CO_2e /ton-mile)
Parameters		e_c^{truck}	Emission factor of transporting corn via truck (Kg CO_2e/ bushel-mile)
π	Bioethanol selling price ($/gal)	e_{be}^{truck}	Emission factor of transporting bioethanol via truck (Kg CO_2e/gallon-mile)
φ^c	Corn co-product (DDG) selling price ($/ton)	e_{be}^{rail}	Emission factor of transporting bioethanol via rail (Kg CO_2e/gallon-mile)
φ^s	Corn stover co-product (Lignin pallet) selling price ($/ton)	$e_c^{\text{acquisition}}$	Emission factor of corn acquisition (Kg CO_2e/bushel)
α^c	Selling price of corn ($/bushel)	$e_s^{\text{acquisition}}$	Emission factor of corn stover acquisition (Kg CO_2e/ton)
α^s	Selling price of corn stover ($/ton)	$e_c^{production}$	Emission factor of producing bioethanol from corn (Kg CO_2e/gallon)
ρ^c	Production cost of bioethanol at corn biorefinery ($/gallon)	$e_s^{production}$	Emission factor of producing bioethanol from corn stover (Kg CO_2e/gallon)
ρ^s	Production cost of bioethanol at corn stover biorefinery ($/gallon)	d_{ik}^c	Distance from corn supplier *i* to biorefinery *k* (mile)
ξ	Carbon tax / Environmental cost factor of emissions ($/Kg CO_2e)	d_{ke}^c	Distance from biorefinery *k* to in-state demand zone *e* when corn is used for bioethanol production (mile)

Table 3.1. Sets, decision variables, and parameters for the models (continued)

Notation			
Parameters			
f_k^b	The estimated annualized technology transition cost of biorefinery *k* ($)	d_{kr}^c	Distance from biorefinery *k* to out-of-state demand zone *r* when corn is used for bioethanol production (mile)
θ^c	Bioethanol conversion rate from corn (gallons/bushel)	d_{ik}^s	Distance from corn stover supplier *i* to biorefinery *k* (mile)
6^c	Corn co-product (DDG) conversion rate (ton/gallon)	d_{ke}^s	Distance from biorefinery *k* to in-state demand zone *e* when corn stover is used for bioethanol production (mile)
p_k^c	Capacity of corn biorefinery *k* (MGPY)	d_{kr}^s	Distance from biorefinery *k* to out-of-state demand zone *r* when corn stover is used for bioethanol production (mile)
p_k^s	Capacity of corn stover biorefinery *k* (MGPY)	Ω	Monetary incentive for second-generation bioethanol producers

The model is as follows:

$$\begin{aligned} Max\ Z_1^c = {} & \pi\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^c + \sum_{k\in K}\sum_{r\in R} Q_{kr}^c\right) + \varphi^c Q^c - \alpha^c \sum_{i\in I}\sum_{k\in K} Q_{ik}^c \\ & - \sum_{i\in I}\sum_{k\in K}(\gamma^c + \eta^c d_{ik}^c) Q_{ik}^c - \rho^c\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^c + \sum_{k\in K}\sum_{r\in R} Q_{kr}^c\right) \\ & - \sum_{k\in K}\sum_{e\in E}(\gamma^t + \eta^t d_{ke}^c) Q_{ke}^c - \sum_{k\in K}\sum_{r\in R}(\gamma^r + \eta^r d_{kr}^c) Q_{kr}^c \end{aligned} \tag{3.1}$$

Subject to constraints:

$$\sum_{k\in K} Q_{ik}^c \le a_i^c \qquad \forall i \in I \tag{3.2}$$

$$\theta^c \sum_{i\in I} Q_{ik}^c = \sum_{e\in E} Q_{ke}^c + \sum_{r\in R} Q_{kr}^c \qquad \forall k \in K \tag{3.3}$$

$$6^c\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^c + \sum_{k\in K}\sum_{r\in R} Q_{kr}^c\right) = Q^c \tag{3.4}$$

$$\sum_{e\in E} Q_{ke}^c + \sum_{r\in R} Q_{kr}^c \le p_k^c \qquad \forall k \in K \tag{3.5}$$

$$\sum_{k\in K} Q_{ke}^{c} = D_e \quad \forall e \in E \tag{3.6}$$

$$\sum_{k\in K} Q_{kr}^{c} = D_r \quad \forall r \in R \tag{3.7}$$

$$Q^{c} \geq 0 \tag{3.8}$$

$$Q_{ik}^{c} \geq 0 \quad \forall i \in I, \forall k \in K \tag{3.9}$$

$$Q_{ke}^{c} \geq 0 \quad \forall k \in K, \forall e \in E \tag{3.10}$$

$$Q_{kr}^{c} \geq 0 \quad \forall k \in K, \forall r \in R \tag{3.11}$$

Eq. (3.2) is the supply constraint which ensures the amount of corn purchased from supply areas to not exceed the maximum corn available in each ASDs. Eq. (3.3) is the material flow constraint for corn-to-bioethanol process showing the corn coming from suppliers to bioethanol plants are converted to bioethanol going out to demand zones. Eq. (3.4) is the conversion of corn-based bioethanol co-product (DDG) production. Eq. (3.5) guarantees the amount of bioethanol produced in biorefineries (bioethanol plants) does not exceed the biorefineries capacities. Moreover, Eq. (3.6) is the in-state demand fulfillment constraint and Eq. (3.7) addresses out-of-state demand. Also, Eqs. (3.8) - (3.11) are non-negativity constraints.

3.4.2. First-generation supply chain profit optimization model with emission penalty

The objective function in Eq. (3.12) considers emissions for the first-generation supply chain and penalizes them with a cost of ξ. Also, Eq. (3.13) shows the total amount of emissions produced in the corn-based bioethanol supply chain. Corn-to-bioethanol activities such as corn acquisition, corn transportation via truck, bioethanol production, bioethanol transportation from bioethanol plants to demand zones have been considered as emissions sources in the first-generation supply chain. For the given objective function in Eq. (3.12), the same constraints used for the first objective function (Eq. (3.1)) are also considered.

$$Max\ Z_2^c = Z_1^c - \xi\ .Z_e^c \tag{3.12}$$

$$\begin{aligned} Z_e^c \ = \ e_c^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^c + \ e_c^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^c Q_{ik}^c + \ e_c^{production} \Bigg(\sum_{k \in K} \sum_{e \in E} Q_{ke}^c \\ + \sum_{k \in K} \sum_{r \in R} Q_{kr}^c \Bigg) + \ e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^c Q_{ke}^c + e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^c Q_{kr}^c \end{aligned} \tag{3.13}$$

Subject to constraints (3.2) – (3.11).

3.4.3. Second-generation supply chain profit optimization model without emission penalty

The second-generation supply chain modeling is similar to the first-generation supply chain model where corn stover and its associated parameters are replaced with corn. However, in the corn stover model, since the current bioethanol producers need to switch their facilities to be compatible with cellulosic biomass, the biorefinery technology transition cost is included in corresponding models. Also, to motivate corn ethanol producers to switch, monetary incentives are considered in second-generation (corn stover) biomass models.

$$\begin{aligned} Max\ Z_1^s = (\pi + \Omega) \Bigg(\sum_{k \in K} \sum_{e \in E} Q_{ke}^s + \sum_{k \in K} \sum_{r \in R} Q_{kr}^s \Bigg) + \varphi^s Q^s - \alpha^s \sum_{i \in I} \sum_{k \in K} Q_{ik}^s \\ - \sum_{i \in I} \sum_{k \in K} (\gamma^s + \eta^s d_{ik}^s) Q_{ik}^s - \sum_{k \in K} f_k^b - \rho^s \Bigg(\sum_{k \in K} \sum_{e \in E} Q_{ke}^s + \sum_{k \in K} \sum_{r \in R} Q_{kr}^s \Bigg) \\ - \sum_{k \in K} \sum_{e \in E} (\gamma^t + \eta^t d_{ke}^s) Q_{ke}^s - \sum_{k \in K} \sum_{r \in R} (\gamma^r + \eta^r d_{kr}^s) Q_{kr}^s \end{aligned} \tag{3.14}$$

Subject to constraints:

$$\sum_{k \in K} Q_{ik}^s \leq a_i^s \qquad \forall i \in I \tag{3.15}$$

$$\theta^s \sum_{i \in I} Q_{ik}^s = \sum_{e \in E} Q_{ke}^s + \sum_{r \in R} Q_{kr}^s \qquad \forall k \in K \tag{3.16}$$

$$6^s\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^s + \sum_{k\in K}\sum_{r\in R} Q_{kr}^s\right) = Q^s \tag{3.17}$$

$$\sum_{e\in E} Q_{ke}^s + \sum_{r\in R} Q_{kr}^s \leq p_k^s \quad \forall k \in K \tag{3.18}$$

$$\sum_{k\in K} Q_{ke}^s = D_e \quad \forall e \in E \tag{3.19}$$

$$\sum_{k\in R} Q_{kr}^s = D_r \quad \forall r \in R \tag{3.20}$$

$$Q^s \geq 0 \tag{3.21}$$

$$Q_{ik}^s \geq 0 \quad \forall i \in I, \forall k \in K \tag{3.22}$$

$$Q_{ke}^s \geq 0 \quad \forall k \in K, \forall e \in E \tag{3.23}$$

$$Q_{kr}^s \geq 0 \quad \forall k \in K, \forall r \in R \tag{3.24}$$

The objective function in Eq. (3.14) aims to maximize profit for corn stover bioethanol supply chain disregarding emissions. The model tries to maximize the revenues coming from bioethanol and corn-stover-based bioethanol co-product (which is called lignin pallet) sales while seeking to minimize corn stover purchase cost, production cost, and transportation costs. Besides the above cost elements, the biorefinery technology transition cost for corn biorefineries to switch to a cellulosic (second-generation) biorefinery is also considered as a fixed cost. In our study, it is assumed that all existing corn biorefineries switch together to cellulosic (second-generation) bioethanol plants if incentivized enough by the government. Also, in Eq. (3.14) Ω is the incentive that will be assigned to each gallon of bioethanol production only if the producers switch their facilities and use corn stover feedstock.

Eqs. (3.15) - (3.24) express the constraints of the objective function. Eq. (3.15) ensures the amount of corn stover purchased cannot exceed the amount of corn stover available in supply areas. Eq. (3.16) is the flow balance between suppliers, bioethanol plants, and demand zones. Eq. (3.17) shows the conversion of corn stover bioethanol co-product (lignin pallet) production. Eq. (3.18) indicates the amount of bioethanol produced in cellulosic bioethanol plants does not exceed the bioethanol plant capacities. Also, Eqs. (3.19) and (3.20) assure that the volume of bioethanol produced in cellulosic bioethanol plants fulfills the in-state and out-of-state demands. Finally, constraints (3.21) to (3.24) present the non-negativity constraints.

3.4.4. Second-generation supply chain profit optimization model with emission penalty

The objective function in Eq. (3.25) tries to consider a carbon tax (ξ) for emissions producing in the second-generation (corn stover) supply chain. Also, the total amount of emissions produced in the corn-stover-based bioethanol supply chain is formulated in Eq. (3.26). the corn-stover-to-bioethanol activities such as corn stover acquisition, corn stover transportation via truck, bioethanol production, bioethanol transportation from bioethanol plants to in-state demand zones via truck and to out-of-state demand zones via rail have been considered as emissions sources in the second-generation supply chain. For the given objective function in Eq. (3.25), the same constraints used for the objective function in Eq. (3.14) are also considered.

$$Max\ Z_2^s = Z_1^s - \xi\ .Z_e^s \tag{3.25}$$

$$\begin{aligned} Z_e^s \ = \ e_s^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^s + e_s^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^s Q_{ik}^s + e_s^{production} \Bigg(\sum_{k \in K} \sum_{e \in E} Q_{ke}^s \\ + \sum_{k \in K} \sum_{r \in R} Q_{kr}^s \Bigg) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^s Q_{ke}^s + e_{br}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^s Q_{kr}^s \end{aligned} \tag{3.26}$$

Subject to constraints (3.15) – (3.24).

3.5. Data and case study

This study examines monetary incentives as a gain in revenue for producing ethanol from second-generation biomass and considers carbon taxes for penalizing emissions as revenue losses resulting from first-generation bioethanol supply chains. However, we also considered penalties for emissions coming from the second-generation supply chain to better compare first-generation and second-generation models. To validate our study, we considered ND as one of the leading states in terms of corn production. Out of 53 counties, there are 34 counties that have corn farms producing almost 443 million gallons of bioethanol each year (ND Studies Energy Curriculum, 2019). These counties have been divided into nine Agricultural Statistical Districts (ASDs) serving as both corn and corn stover suppliers (including NE, EC, SE, NC, CENTRAL, SC, NW, WC, and SW). Distances from ASDs to biorefineries are calculated by taking the average of distances between the middle of counties located in each ASD (which produces corn and corn stover) and biorefineries. Also, there are already five biorefineries in ND (including Red Trail Energy, Blue Flint Ethanol, Dakota Spirit AgEnergy, Tharaldson Ethanol, and Guardian Hankinson) that are producing ethanol from corn which have also been considered as the locations for second-generation (cellulosic) biorefineries. For comparison, we consider the same capacities of the current first-generation facilities for the new cellulosic biorefineries where there is no need for new labors. Figure 3.3 shows the ASDs as suppliers and bioethanol plants in ND for both first-generation and second-generation bioethanol supply chains.

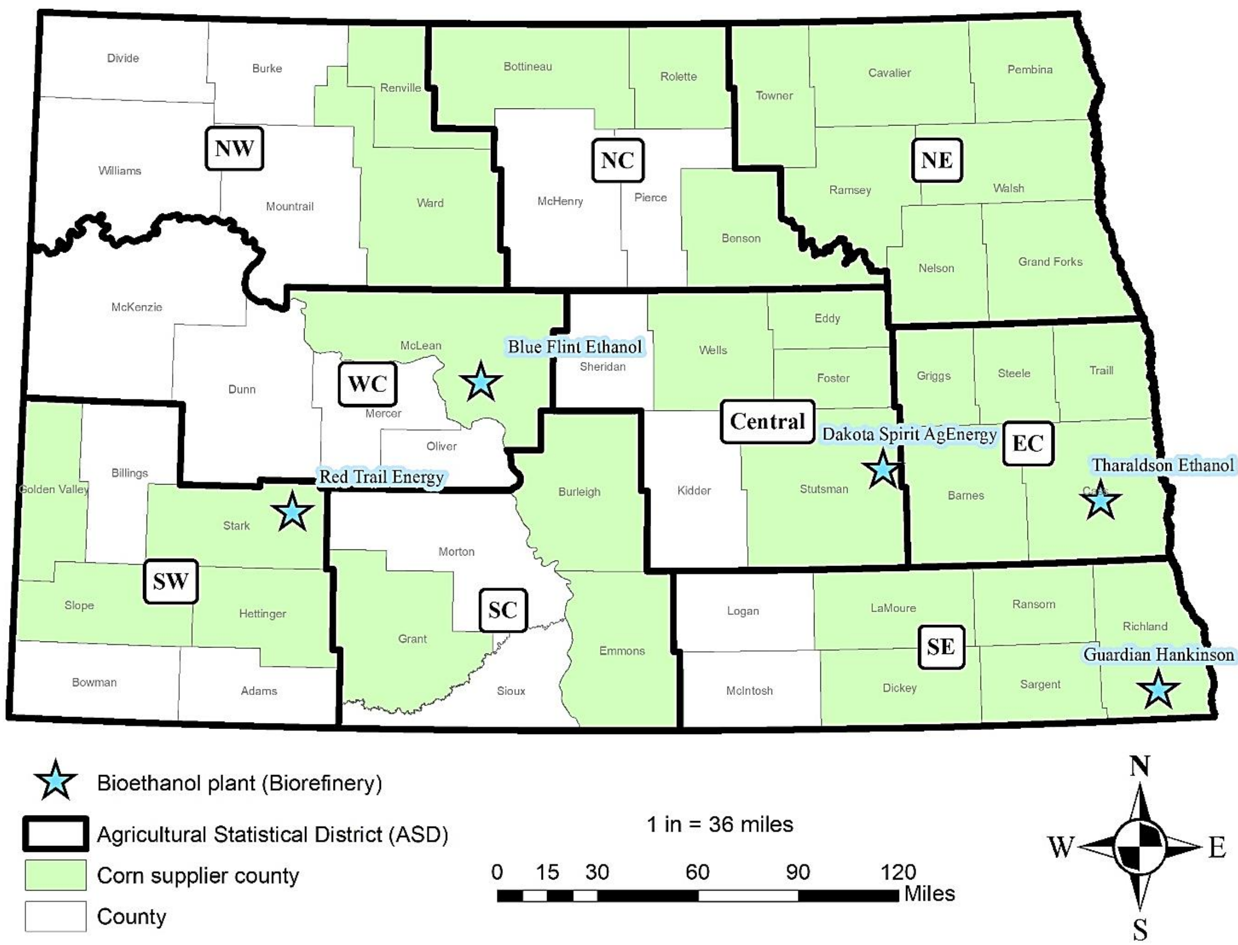


Figure 3.3. Agricultural statistical districts (ASDs) and bioethanol plants (biorefineries) in ND

The in-state and out-of-state demand zones are shown in Figure 3.4. According to the interviews and conversations with bioethanol professions and producers in ND (Blue Flint - Midwest Ag Energy, Guardian Energy LLC, Tharaldson Ethanol, 2019), there are six in-state demand zones including Fargo, Grand Forks, Jamestown, Bismarck, Dickinson, and Minot which have fuel racks where bioethanol is blended with gasoline. These demand zones are all located in the ND state where all biorefineries are also located in. Truck based transportation is used for delivering in-state bioethanol. Also, there are four out-of-state demand zones including Houston (TX), Los Angeles (CA), Portland (OR), and Seattle (WA). Railway transportation is used for delivering out-state bioethanol. Considering out-of-state demand zones makes our case study more realistic which would result in better and more reliable results for policymakers to rely on. In this study, the total annual bioethanol demand is set to 443 million gallons per year (MGPY) which is equal to the total bioethanol produced by current biorefineries in ND. About 10 percent of the ND state annual bioethanol production is sold within the state (shipped by truck) and the other 90 percent is shipped by rail to other states (ND Studies Energy Curriculum, 2019). Considering the amount of bioethanol sold to in-state and out-of-state demand zones, the demand associated with each demand zone is assigned according to their population.

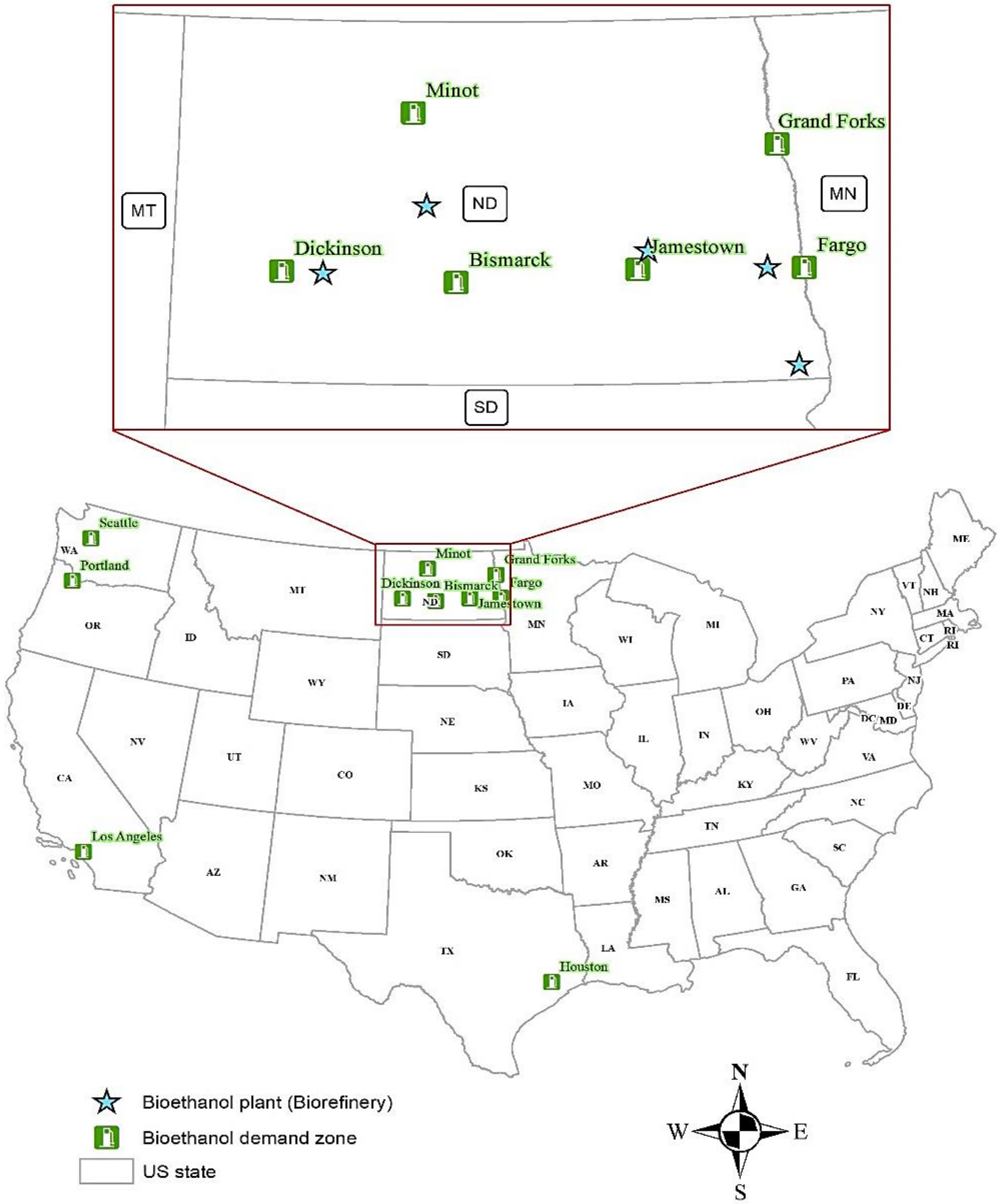


Figure 3.4. In-state and out-of-state demand zones

Table 3.2 shows total corn and corn stover availability for each ASD in ND. To estimate corn stover availability, we multiplied the available corn in bushel by corn stover yield rate (0.028) (Mohamed Abdul Ghani et al., 2018). Also, Table 3.3 presents the current operating corn biorefineries in ND with their bioethanol production capacities. The annualized biorefinery technology transition cost for corn biorefineries to switch to a cellulosic (second-generation) biorefinery is varied based on the production capacity. In our study, it is assumed that the biorefinery technology transition cost is as much as constructing a new cellulosic biorefinery where the revenue from corn-based facility salvage sale compensates the total cost associated with production loss during the switching process. The annualized fixed capital cost for a 50 MGPY (p_r) cellulosic biorefinery with biorefinery life of 20 years and interest rate of 5% is $42 M ($f^r$) (Osmani & Zhang, 2013) while for other biorefineries, the annual fixed construction cost (f^b) with the capacity p_k has been calculated based on Eq. (3.27), where β is a scaling factor which is set to 0.8 (Dunnett, Adjiman, & Shah, 2008). The estimated annualized biorefinery technology transition costs (f_k^b) in our proposed models regarding their production capacities are shown in Table 3.4. The other related data used in this chapter can be found in Appendix A2.

$$f^b = f^r(\frac{p_k}{p_r})^\beta \tag{3.27}$$

Table 3.2. Biomass feedstocks availability[1]

Agricultural Statistical District (ASD)	Available corn (thousand bushels)	Available corn stover (ton)
SE	161,291	4,608,314
EC	101,297.6	2,894,217
NE	48,071	1,373,457
SC	24,905	711,571
CENTRAL	57,930	1,655,143
NC	12,312	351,771
SW	3,744	106,971
WC	6,138	175,371
NW	3,529	100,829

[1] (Mohamed Abdul Ghani et al., 2018; State Agriculture Overview, 2018)

Table 3.3. List of ND biorefineries with their production capacities[1]

Biorefinery	City	Production Capacity (MGPY)
Blue Flint Ethanol	Underwood, ND	65
Dakota Spirit AgEnergy	Spiritwood, ND	68
Red Trail Energy	Richardton, ND	50
Tharaldson Ethanol	Casselton, ND	130
Guardian Hankinson	Hankinson, ND	130

[1] (ND Studies Energy Curriculum, 2019)

Table 3.4. The estimated annualized biorefinery technology transition cost for corn biorefineries to switch to a cellulosic (second-generation) biorefinery regarding their production capacities

Biorefinery	Production Capacity (MGPY)	Estimated Annualized Biorefinery Technology Transition Cost
Blue Flint Ethanol	65	$51.81 M
Dakota Spirit AgEnergy	68	$53.71 M
Red Trail Energy	50	$42 M
Tharaldson Ethanol	130	$90.2 M
Guardian Hankinson	130	$90.2 M

3.6. Results and discussion

Different numerical analyses completed here to compare the economic and environmental consequences of first-generation and second-generation bioethanol supply chains. First, the cost items of both bioethanol supply chains resulted from the implementation of the profit optimization models are reviewed. Then, the effects of different incentives that biorefineries can be received from the government to switch from the first generation (corn-based) biorefinery technology to the second generation (corn-stover-based) one are evaluated This section also studies the impacts of emissions penalties as carbon taxes on both supply chains. The contribution of both carbon taxes and monetary incentives are numerically evaluated for both bioethanol supply chains. Finally, the impacts of different corn purchase prices are studied to realize how the market itself can motivate corn ethanol producers to switch their technology without any incentives. To set up realistic scenarios, the parameters of the profit optimization models (Eqs. (3.1) - (3.26)) are estimated according to the empirical-based literature listed in Appendix A2. The optimization problems were solved via OpenSolver 2.9.0 using CBC (COIN-OR Branch-and-Cut) optimization engine (Mason, 2012; OpenSolver, 2018).

For the purpose of this study, emissions refer to carbon dioxide equivalent (CO_2e) as a term for describing different GHGs in a common unit. The environmental cost per unit of CO_2e (Kg of CO_2e) is imposed on the emitters as a carbon tax. The "Regular" carbon tax per Kg of CO_2e, which is adapted in this study and taken as the emission cost, is \$0.1231 based on the estimation of environmental costs of CO_2 emissions (Nguyen & Gheewala, 2008; Sobhani & Wahab, 2017). However, besides the Regular carbon tax, we considered other prices for penalizing emissions to better analyze the impacts of emissions on the proposed supply chain. In our study, biorefineries, as the leader of our proposed SBSC, are in charge of paying the penalties to the government for emissions coming from all activities through the supply chain.

The optimal assignment of supply zones and demand zones to both first-generation and second-generation biorefineries with either considering or disregarding emission cost is shown in Table 3.5. There is no difference between corn and corn stover bioethanol supply chains network design since suppliers and demand zones for each biorefinery are similar. Dakota Spirit AgEnergy, Tharaldson, and Hankinson Renewable Energy biorefineries are located in Central, EC, SE districts where they supply their required biomass from the same districts they are operating. On the other hand, Blue Flint Ethanol and Red Trail Energy biorefineries are located in WC and SW districts which the available necessary biomass is not sufficient in these districts to supply these biorefineries solely; Thus, they need more biomass from other districts to meet their required production level. According to the optimization models' output, the SC district is the main supplier for Blue Flint Ethanol and Red Trail Energy biorefineries with 46% and 79% supply fulfillment respectively which means 46% of the Blue Flint Ethanol biorefinery need is supplied from SC district and similarly, 79% of the Red Trail Energy biorefinery need is also supplied from SC district. According to Table 3.5, the demand for Portland, Minot, and Bismarck can be fully met by Blue Flint Ethanol biorefinery while only 76% of Seattle demand is fulfilled with this facility. Likewise, Dakota Spirit AgEnergy addresses 46% and 100% of Houston and Jamestown demands respectively. The Los Angeles demand is mainly met by Tharaldson biorefinery (54%) followed by Hankinson Renewable Energy (27%) and Red Trail Energy (19%). The remaining of Seattle (24%) and Houston (54%) demands are addressed by Red Trail Energy and Hankinson Renewable Energy biorefineries, respectively. Also, the demand of Dickinson can be fully satisfied by Red Trail Energy, and in the same way, Fargo and Grand Forks demand by Tharaldson Ethanol. These results are remarkable since they show there is no need for any changes in the network design of corn bioethanol producers to switch their technology to a corn-stover-based biorefinery.

Table 3.5. Optimal assignment of supply zones and demand zones to both first-generation and second-generation biorefineries

Supplier districts (% of supply fulfillment)	Biorefinery	Out-of-state demand zone (% of demand fulfillment)	In-state demand zone (% of demand fulfillment)
SC (46%), CENTRAL (12%), WC (26%), NW (15%)	Blue Flint Ethanol	Portland (100%), Seattle (76%)	Minot (100%), Bismarck (100%)
CENTRAL (100%)	Dakota Spirit AgEnergy	Houston (46%)	Jamestown (100%)
SC (79%), SW (21%)	Red Trail Energy	Los Angeles (19%), Seattle (24%)	Dickinson (100%)
EC (100%)	Tharaldson Ethanol	Los Angeles (54%)	Fargo (100%), Grand Forks (100%)
SE (100%)	Hankinson Renewable Energy	Houston (54%), Los Angeles (27%)	-

With respect to the selected supply and demand zones for the given biorefineries, Figure 3.5 shows the optimal transportation, biomass purchase, bioethanol production, emission, and biorefinery technology transition costs estimated for the first-generation and second-generation bioethanol supply chains. In general, the emission cost (with Regular carbon tax) has the minimum contribution to the total cost of both bioethanol supply chains. It is as equal as 1.9% and 1.4% of the total cost of the first-generation and second-generation bioethanol supply chains, respectively. Without carbon tax effects, the corn-based bioethanol supply chain will have an annual total cost of $742.22 M. From this amount, the biomass purchase cost has the maximum contribution with 61.8% cost share ($458.82 million (M)) while the bioethanol production cost is in the second rank with 25.7% cost contribution ($190.49 M) followed by transportation cost ($92.9 M). By including carbon emission expenses (with Regular carbon tax), the total cost of the corn-based supply chain increases to $756.44 M (1.92% growth). The carbon tax incurs an expense of $14.2 M paid for the amount of carbon emitted due to corn acquisition, bioethanol production, and transportation activities.

In comparison with the first-generation (corn-based) bioethanol supply chain, the total cost of the second-generation (corn-stover-based) supply chain shows a growth of 50.7% ($1.119 B) without including carbon emissions expenses. This growth occurs mainly due to the biorefinery technology transition expenses, bioethanol production cost, and transportation expenses. Changing biorefinery technology to produce bioethanol from corn stover incurs an annualized capital cost equal to $327.9 M. This extra cost has around 29.3% contribution to the total cost of the supply chain. Furthermore, by changing the biorefinery technology, the bioethanol production cost increases from $190.49 M (production from corn) to $398.7 M (production from corn stover). Accordingly, the transportation cost increases from $92.9 to $144.6 M due to higher expenses of corn stover transport compared to corn. Although the road networks for transporting corn and corn stover are similar, the costs associated with corn stover transportation as bales rather than bushels (corn container) are higher. Moreover, more units of corn stover are needed compared to corn to produce the same amount of bioethanol. On the other hand, the biomass purchase cost for corn stover dramatically decreases from $458.82 M to $247.3 M (-54%) compared with corn. This is due to the price of corn stover ($45/ton (Maung & Gustafson, 2011)) which is much cheaper than corn ($103.57/ton (GRAINS COUNCIL, 2019)) or $2.9/bushel (State Agriculture Overview, 2018)) since corn stover is the leftover of the corn harvesting process. By including carbon tax effects, the total cost of the second-generation bioethanol supply chain increases by 1.4%. In compared with the first-generation bioethanol supply chain, the corn-stover-based supply chain emits more CO_2e (see Figure 3.6) causing the emission cost to be increased by 10.56% (from $14.2 M to $15.7 M).

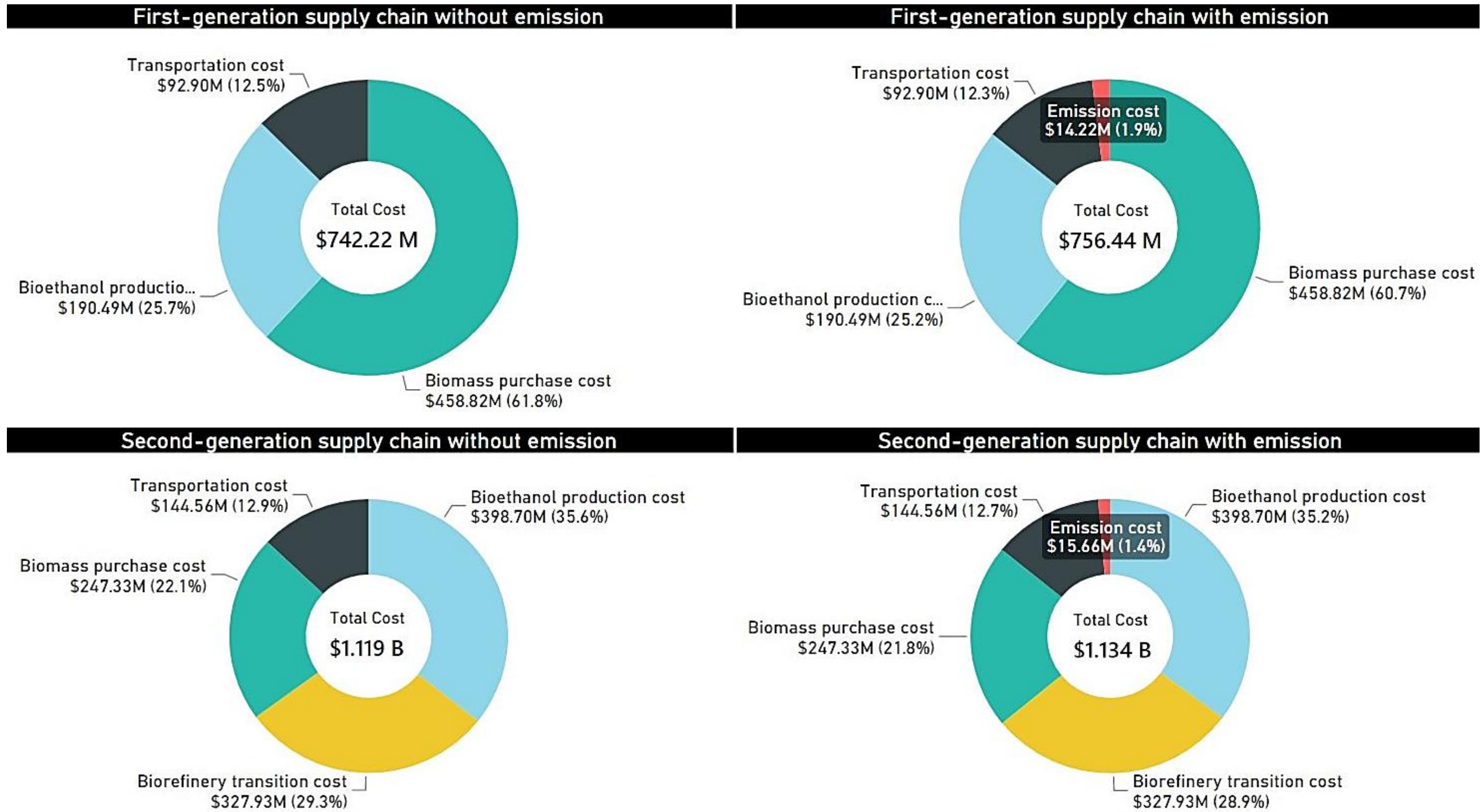


Figure 3.5. Cost breakdown of both first-generation and second-generation supply chains (Regular carbon tax considered for emission cost)

Figure 3.6 shows how much emissions are coming from four different sources of emissions in corn and corn stover bioethanol supply chains. The amount of emissions emitted by the corn stover bioethanol plant is lesser than emitted by the corn ethanol plant, but surprisingly, the total emissions of the corn stover bioethanol supply chain is higher than that of the corn bioethanol supply chain (a 10.1% difference). According to Figure 3.6, the emissions produced in bioethanol transportation from bioethanol plants to demand zones is the main source of emissions in both corn-based and corn-stover-based bioethanol supply chains. This happens mainly because 90% of the bioethanol produced in biorefineries goes to out-of-state demand zones and the distances between biorefineries and demand zones are significantly high. Also, since the bioethanol demand is equal (443 MGPY) for both supply chains, they produce emissions equally from biorefineries to demand zones. The second main source of emissions is due to biomass transportation from suppliers to bioethanol plants. According to Figure 3.6, more emissions are produced in corn stover transportation compared to corn. This is due to two reasons: (a) The emission factor for transporting a ton of corn stover (0.1103 Kg CO_2e/ton-mile) is higher than the emission factor of transporting a ton of corn bushels (0.0028 Kg CO_2e/bushel-mile or 0.1 Kg CO_2e/ton-mile) because the same amount of corn stover occupies more space compared to corn due to the fact that corn stover is shipped in a bale form while corn is shipped in bushels, and (b) more corn stover biomass is needed to produce the same amount of bioethanol compared to corn biomass feedstock. In our study, 5.5 M tons of corn stover is required to produce 443 MGPY bioethanol while to produce the same amount of bioethanol, 4.43 M tons (158.21 M bushels) of corn is needed. Also, the emissions of corn stover acquisition are somewhat higher than those for corn acquisitions since corn stover is the leftover of corn harvesting and more corn stover is needed to satisfy the bioethanol production requirement.

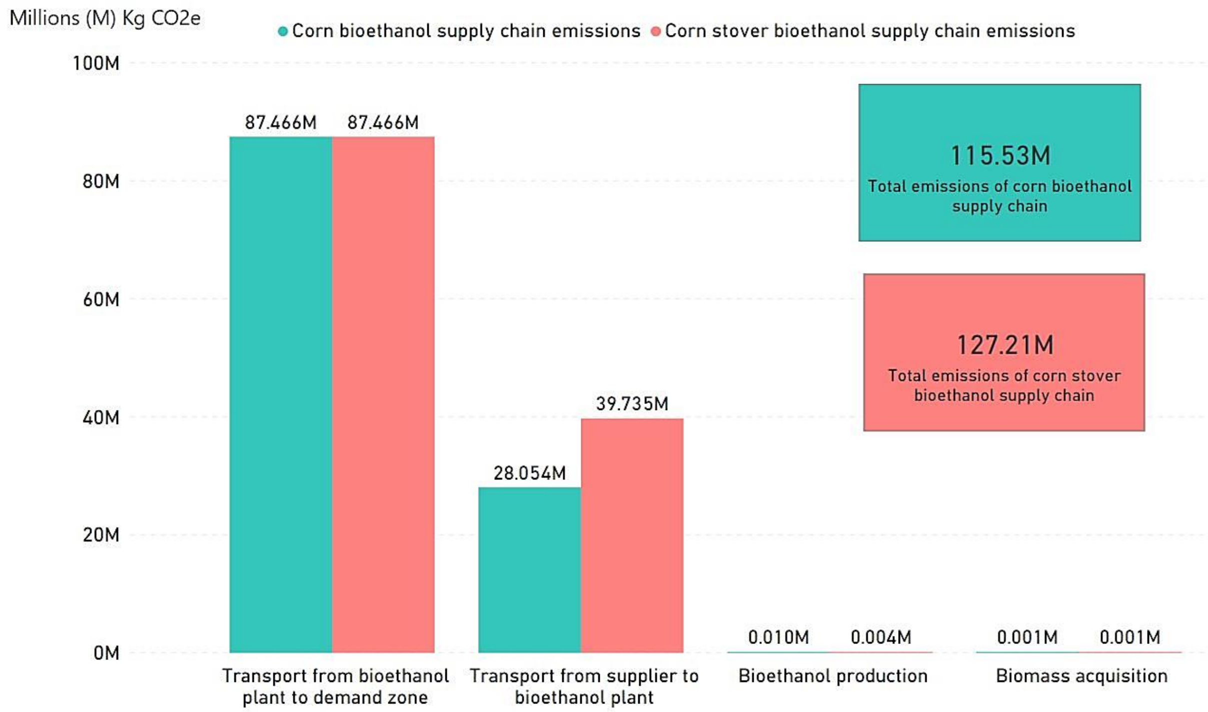


Figure 3.6. Emissions volume in Kg CO_2e comparison of corn bioethanol supply chain vs. corn stover bioethanol supply chain

Table 3.6 shows the profit comparison when the carbon tax is considered for penalizing emissions of both first-generation and second-generation bioethanol supply chains. Different scenarios for carbon tax values are developed including "Without" ($0 carbon tax) and "Regular" ($0.1231 carbon tax). Also, we developed a scenario called "$0 profit at first-generation supply chain" where the corn supply chain stops making profits along with a scenario called "$0 profit at second-generation supply chain" where the corn stover supply chain stops making profits. The results show that by increasing the price of the carbon tax, the total amount of emissions is not reduced and constant through different carbon tax pricing scenarios. In other words, the emissions penalty is just a fixed cost added to the model since the total annual of bioethanol is equal to the total capacity of biorefineries. The profit of both first-generation and second-generation models starts to decrease when the price of carbon tax increases. The highest carbon tax that can be offered to a second-generation supply chain is \$3.1034 and \$6.6742 to a first-generation supply chain per kg of CO_2e emissions.

Table 3.6. Profit comparison with different carbon tax scenarios

	Carbon Tax			
	Without	Regular	\$0 profit at second-generation supply chain	\$0 profit at first-generation supply chain
	\$0	\$0.1231	\$3.1034	\$6.6742
Profit of first-generation supply chain	\$771.07 M	\$756.85 M	\$412.54 M	\$0
Profit of second-generation supply chain	\$394.77 M	\$379.12 M	\$0	\$(454.23 M)

Without using direct monetary incentives, a carbon tax may play a role to motivate biorefineries to switch to the corn-stover-based technologies. In this regard, different carbon tax rates can be applied for the first-generation (corn-based) bioethanol supply chains. Table 3.7 shows the emission penalty (carbon tax) analysis for the first-generation bioethanol supply chain according to the impact of different carbon taxes on second-generation bioethanol supply chain profit. This table shows if \$0, \$0.1231, and \$3.1034 carbon taxes applied to second-generation bioethanol supply chain, then at least how much carbon tax should be imposed on first-generation bioethanol producers to make them switch their technologies to the second-generation-based production technology because they make a lower profit if they refuse to switch. Without any carbon tax for the second-generation supply chain, the government can charge the first-generation supply chain by \$3.2573 per Kg CO_2e causing both supply chains to have the same profit level. By increasing the second-generation supply chain carbon tax to \$0.1231 per Kg CO_2e, the carbon tax of the first-generation supply chain should increase to \$3.3928 per Kg CO_2e to reach the same profit level for both supply chains. By setting the carbon tax rate to \$3.1034 per kg CO_2e for the second-generation supply chain (where it stops making profit), the government should charge the first-generation supply chain by at least \$6.6742 (+215% more than the second-generation carbon tax) to force (motivate) them to switch to the second-generation (corn-stover-based) bioethanol technology. In these scenarios, the government does not pay any monetary incentives to the second-generation producers, whereas, as an alternative, it takes money as a penalty from first-generation bioethanol producers if they deny switching. Therefore, imposing higher emission penalties on current corn ethanol producers while offering a lower carbon tax to second-generation bioethanol producers would be a promising lever to motive bioethanol producers to use second-generation biomass since if they continue producing bioethanol from corn, they make less profit compared to cellulosic bioethanol producers. Therefore, the best option here would be to offer at least \$3.2573 carbon tax to first-generation bioethanol producers while \$0 (no penalty) to second-generation bioethanol producers to motive first-generation bioethanol producers to switch.

Table 3.7. Emission penalty analysis for first-generation supply chain

	Carbon Tax for second-generation supply chain		
	Without	Regular	$0 profit at second-generation supply chain
	$0	$0.1231	$3.1034
Minimum carbon tax for first-generation supply chain to switch	$3.2573	$3.3928	$6.6742
Profit of first-generation supply chain after paying higher emission penalty (first-generation profit = second-generation profit)	$394.77 M	$379.12 M	$0

Table 3.8 demonstrates the effects of monetary incentives on the profit level of the first-generation and second-generation bioethanol supply chains with and without carbon tax penalties. The incentive is paid by the government to bioethanol producers only if they use second-generation biomass (corn stover in our study). Second-generation biorefineries receive the incentive for each gallon of bioethanol they produce. Therefore, the higher the production capacity, the more incentive the bioethanol producers get. The performance indicator to compare first-generation and second-generation bioethanol producers is the total maximum profit of each supply chain. Without a monetary incentive, biorefineries will have \$771.07 M profit when they use their existing corn-based (first-generation) biorefinery technology to produce bioethanol. This annual profit is 95.3% higher than the situation if biorefineries change their technology to produce bioethanol from corn stover (\$394.77 M). According to Table 8, at least \$0.8495 per gallon (the equalizer incentive) required to cover extra expenses due to changing the biorefinery technology to a cellulosic (second-generation) one. This incentive makes the profit of switched second-generation supply chain equal to their profit before switching (first-generation supply chain).

Clearly, if the government aims to penalize emissions while incentivizing first-generation bioethanol producers to use second-generation biomass, they should offer incentives more than \$0.8495. In general, including the carbon tax in the supply chain optimization models reduces the profit of both corn and corn-stover-based supply chains. Since the corn-stover-based supply chain emits more CO_2e (see Figure 3.6), initiating the carbon tax policy increases the profit differences existing between first-generation and second-generation bioethanol supply chains. Therefore, state or federal governments should pay more monetary incentives to equalize (balance) the profit of the two supply chains. This monetary incentive gains different values (\$ per gallon) to equalize the profit of the corn-stover-based bioethanol supply chain with the corn-based one according to different carbon tax rates. By comparing Table 3.6 and 3.8 findings, with a \$0 carbon tax per Kg CO_2e, the first-generation (corn-based) bioethanol supply chain reaches \$376.31 M more profit than the second-generation bioethanol supply chain to fulfill the same annual demand. Therefore, biorefineries need \$0.8495 per bioethanol gallon to have the same profit if they switch to corn-stover-based biorefinery technology. By increasing the emission tax to \$0.1231 per Kg CO_2e (Regular scenario for a carbon tax), the "profit difference" between the corn-based bioethanol supply chain and the corn stover one becomes as equal as \$377.74 M. In this case, in comparison with the first-generation bioethanol supply chain, biorefineries need at least \$0.8527 (+0.38% growth) per gallon incentive to have the same profit after changing their biorefinery technologies to the cellulosic (corn-stover-based) one. If a \$3.1034 carbon tax is imposed, the second-generation supply chain stops making profits and a minimum of \$0.9312 (9.62% growth compared to the case when no carbon tax is offered) is needed to match the supply chain profit and motive corn ethanol producers to switch. Also, if \$6.6742 carbon tax is applied which prevent the first-generation supply chain from making profits, a minimum of \$1.0253 incentive (20.69% growth compared to the case when no carbon tax is offered) per gallon of bioethanol is required to make the second-generation supply chain start making profits. It is important to notice that this incentive is the minimum monetary benefits that biorefineries require to switch from corn-based biorefinery technology to the corn-stover-based one and gain the same profit level.

Table 3.8. Incentive analysis with the same carbon tax for both first-generation and second-generation models

	Carbon Tax			
	Without	Regular	$0 profit at second-generation supply chain	$0 profit at first-generation supply chain
	$0	$0.1231	$3.1034	$6.6742
Minimum incentive for first-generation bioethanol producers to switch	$0.8495	$0.8527	$0.9312	$1.0253
Profit of second-generation supply chain after receiving incentives	$771.07 M	$756.85 M	$412.54 M	$0

The numerical analysis so far considered how incentives and carbon taxes can motivate corn bioethanol producers to switch their technology to a cellulosic one so they can utilize corn stover as their biomass feedstock in which the purchase price of corn was constant and equals to \$2.9/bushel (State Agriculture Overview, 2018). Obviously, the corn price which is determined by the market can change the profit of the corn-based (first-generation) supply chain. Figure 3.7 shows the impact of different corn prices on technology switching decisions without considering carbon tax. In this case, if all factors and parameters in the corn-stover-based (second-generation) bioethanol supply chain remains unchanged (such as corn stover price, bioethanol price, etc.), the corn price can play a role as a motivator for corn bioethanol producers to consider other biomass feedstocks (corn stover in our study) without government intervention. With the current price of corn in ND (\$2.9/bushel by the time of this study), which is shown in Figure 3.7 as the BASE scenario, the corn bioethanol supply chain profit is higher than corn stover bioethanol supply chain by \$376.31 M. However, if the corn price goes more than \$5.28/bushel (82% growth compared to the BASE scenario), the profit of the proposed second-generation (corn stover) bioethanol supply chain will be higher than the existing corn bioethanol supply chain which can be encouraging for corn ethanol producers to switch their technology. This means the social value of corn for not using it as a source for fuel and using it for food instead is \$2.38/bushel (\$5.28 - \$2.9). Consequently, if the corn price reaches more than \$5.28/bushel, it is not both economically and socially reasonable to use corn for fuel (bioethanol) production. This situation is possible to occur since, for instance, the corn price in August 2012 got close to \$8/bushel (National Agricultural Statistics Service, USDA, Agricultural Prices, 2019). At last, the break-even point of the corn bioethanol supply chain is when the corn price is \$7.77/bushel (168% growth compared to the BASE scenario) which stops the current corn bioethanol supply chain from making profits.

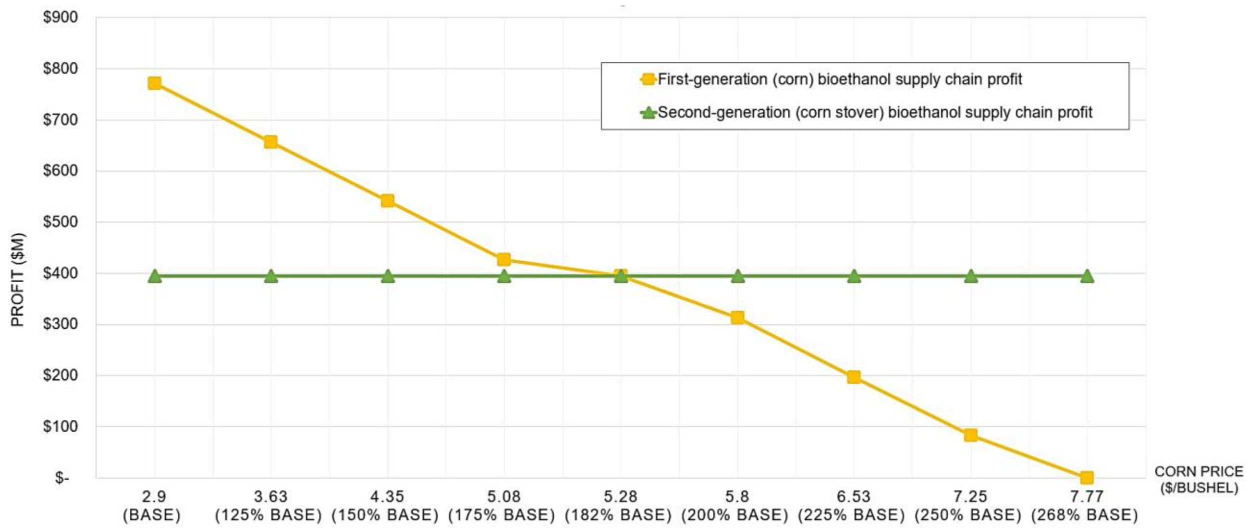


Figure 3.7. First-generation and second-generation profit comparison with different corn prices

In this study, we analyzed how much incentive the US government should pay or how much carbon tax should be imposed to motivate/force first-generation bioethanol producers to switch their technology to second-generation ones. At present, new policies are being enacted and previous legislation is consequently modified by different countries for the biofuel market (Carriquiry, Du, & Timilsina, 2011). In the US, the Energy Independence and Security Act (EISA) of 2007 specified a tax credit of $1.01/gallon for second-generation bioethanol, while a lower tax credit of $0.45/gallon for first-generation bioethanol (Carriquiry et al., 2011). These credits were active until the end of 2017 and expired since then ("RFA - Tax Policy", 2019). This is the reason that the current tax credits (incentives) are not considered in this study, however, since the US Congress aims to extend the biofuel tax credits again for 2020 ("Ethanol Producer Magazine", 2019), we conducted an analysis by considering the previous tax credits that have been offered. According to Table 3.9, with considering the tax credits, the current first-generation bioethanol producers still require a $0.2895/gallon monetary incentive to switch or a $1.1099/Kg of CO_2e carbon tax should be imposed on them.

Table 3.9. The effects of tax credits on supply chain profits, minimum incentives, and carbon tax

	Without tax credit	With tax credit
First-generation bioethanol supply chain profit	\$771.07 M	\$970.42 M
Second-generation bioethanol supply chain profit	\$394.77 M	\$842.2 M
Minimum incentive to switch (without emissions penalties)	\$0.8495/gallon	\$0.2895/gallon
Minimum carbon tax to switch (without incentive payments)	\$3.2573/Kg of CO_2e	\$1.1099/Kg of CO_2e

So far, we have considered the summation of the maximum capacity of all biorefineries as the annual demand level (443 MGPY). In Figure 3.8, we investigated how different demand levels with current production capacities would affect the minimum incentive payments for current corn-based biorefineries to switch to a corn-stover-based biorefinery without considering emissions penalties. Demand levels lower than 443 MGPY are considered here since the current existing biorefineries are not able to produce more than that. According to results, as the demand decreases, more incentive is required to compensate the profit loss of existing first-generation bioethanol producers. With the current demand level (443 MGPY as the BASE scenario), the minimum needed incentive to switch is \$0.8495 per gallon of bioethanol, while the highest required incentive should be paid when the demand is set at 10% of the current demand level (44.3 MGPY) which the minimum incentive is \$7.5004 per gallon. In this analysis, with all different demand levels, the first-generation bioethanol supply chain is profitable, however, the second-generation bioethanol supply chain stops making profits when the demand reduces to 199.2 MGPY (44.9% of the BASE demand level).

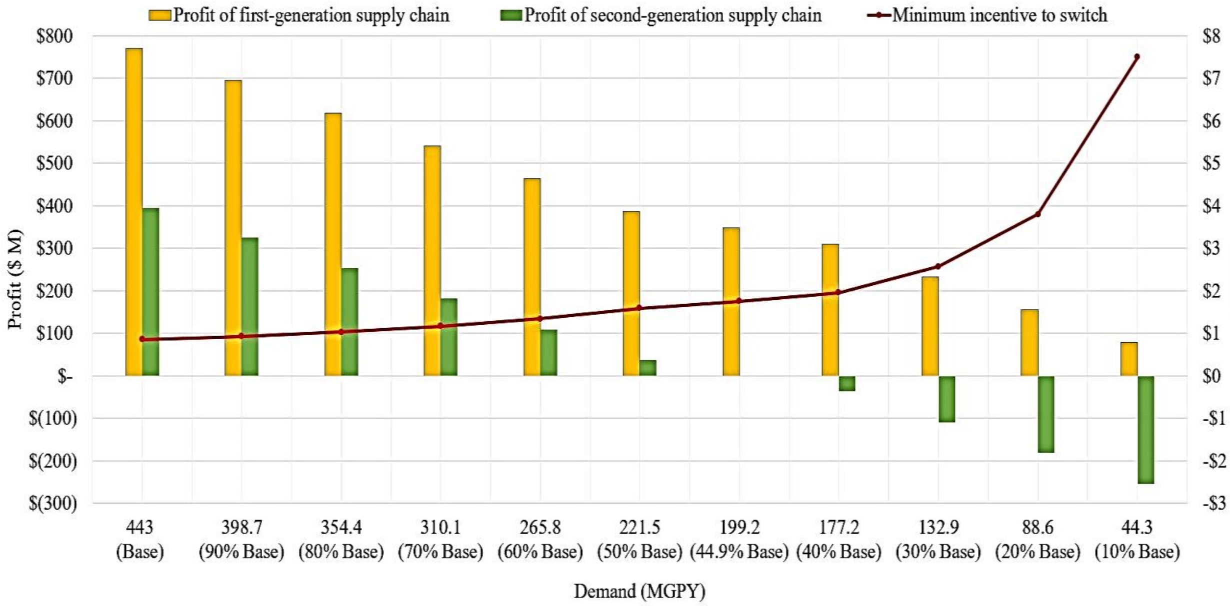


Figure 3.8. The effects of demand variation on the incentive payments

In this study, it is assumed that the capacity of first-generation bioethanol producers will remain unchanged after switching to second-generation compatible facilities. In Figure 3.9, we investigate the scenarios in which the capacities of the new switched second-generation biorefineries are increased compared to their previous production capacities disregarding emissions penalties. It is assumed that the extra bioethanol that is produced will be purchased by the demand zones. Also, since the first-generation bioethanol producers already exist, their profit ($771.07 M) remains unchanged under the 443 MGPY demand level and production capacity (BASE scenario). According to this analysis, as the production capacity of second-generation biorefineries increases, the profit of the second-generation bioethanol supply chain raises from $394.77 M to $694.78 M where the summation of biorefineries' capacities and their demand are set at 750 MGPY (169.3% of the BASE scenario) because there are five biorefineries in the state of ND and the maximum capacity for second-generation biorefineries that have been commercialized is 150 MGPY (Kou & Zhao, 2011). Also, as the production capacities and the profit of the second-generation bioethanol supply chain increase, the minimum incentive required to switch decreases from $0.8495 to $0.1017 per gallon of bioethanol production.

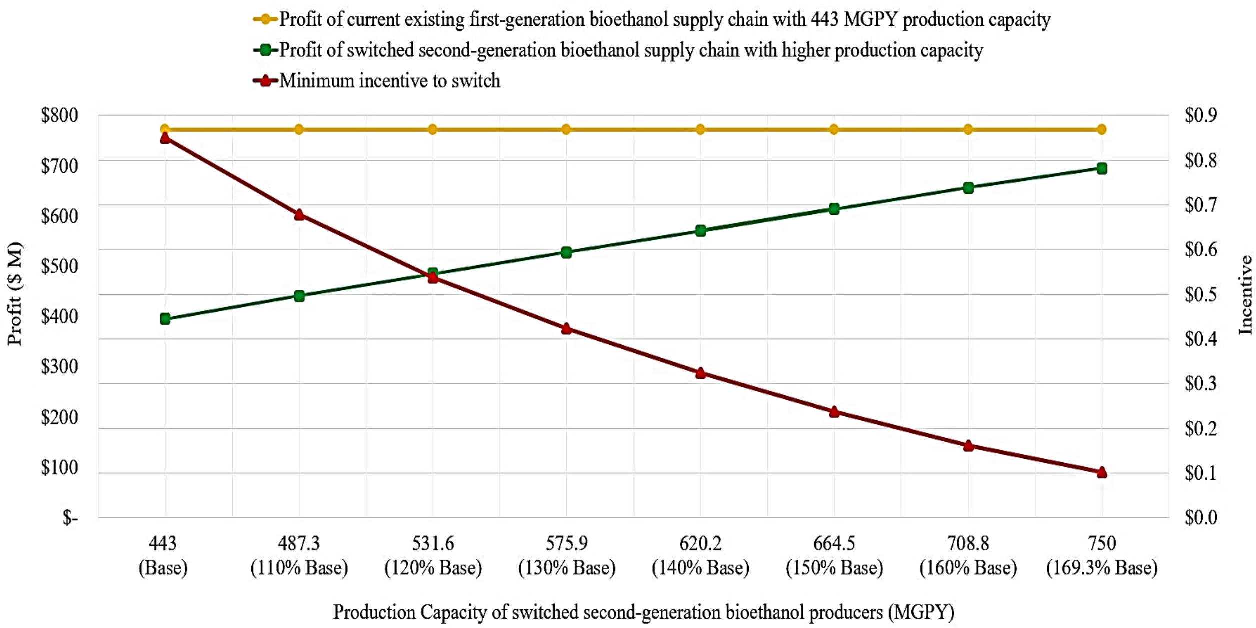


Figure 3.9. Incentive analysis with higher production capacities for the switched second-generation bioethanol producers disregarding emissions penalties

3.7. Conclusions and policy implications

Designing sustainable biomass supply chain networks requires a balance between economic, environmental, and social objectives. The RFS indicates that 21 out of 36 billion gallons of biofuels annually should be advanced biofuel, such as cellulosic (second-generation) bioethanol, while only 15 billion gallons can be corn (first-generation) bioethanol. The cellulosic biorefineries in the US are producing less than half-billion gallons per year which are far behind the requirements of the RFS. Therefore, stimulating and motivating the existing first-generation bioethanol producers to switch their production technologies to a cellulosic one would be a great policy. In this case, the government intervention on incentivizing these bioethanol producers is essential due to the expenses and costs coming from the technology transition. To do so, two types of financial motivations can be considered by policymakers: (a) carbon tax and (b) monetary incentives per gallon of bioethanol produced from the second-generation biomass. This study addressed economic and environmental goals of sustainable biomass supply chains explicitly by profit maximization and emissions minimization while meeting their social objectives implicitly via considering monetary incentives for bioethanol producers to use the second-generation biomass instead of the first-generation to support food security. The main contribution of this paper is designing the BBSC network which helps to investigate the impacts of monetary incentives and emissions penalties on motivating existing first-generation (corn-based) bioethanol producers to change their production technology. In this study, the performance indicator to compare existing corn bioethanol producers and proposed second-generation biorefineries is the total maximum profit of their supply chains. The comparison between first-generation and second-generation supply chains was explored with and without financial incentives and emissions penalties.

Different numerical analysis is conducted to compare the economic and environmental aspects of first-generation and second-generation bioethanol supply chains. Accordingly, the trade-offs between incentives and emission penalties and their effects on both supply chain profit levels were investigated. In comparison with the first-generation bioethanol supply chain, the total cost of the second-generation supply chain displays the growth of 50.7% (from $742.22 M to $1.119 B) mainly due to the biorefinery technology transition expenses and bioethanol production cost which economically makes the current corn-based bioethanol supply chain a better option. However, the biomass purchase cost for corn stover (second-generation) noticeably decreases from $458.82 M to $247.3 M compared with corn since corn stover is the leftover of the corn harvesting process, hence it is relatively cheaper. Considering penalties for carbon emissions shows that the emission cost (with Regular $0.1231 carbon tax per Kg CO_2e) has the minimum contribution to the total cost of both bioethanol supply chains:1.9% and 1.4% cost share for the first-generation and second-generation bioethanol supply chains. Carbon tax analysis indicates that \$3.1034 and \$6.6742 per kg of CO_2e are the highest carbon tax rates that can be imposed on the second-generation and the first-generation supply chains. Any tax rates above these numbers would make the supply chains not profitable. Carbon emission analysis also concludes that although the corn-stover-based bioethanol plants emit less CO_2e than corn-based biorefineries, the total amount of emissions of corn stover bioethanol supply chain is higher than corn bioethanol supply chain (10.1% growth). This finding surprisingly makes the corn bioethanol supply chain more sustainable when the optimal assignment of supply and demand zones is similar for both first-generation and second-generation bioethanol supply chains. For this reason, policymakers must impose higher carbon tax rate on the first-generation bioethanol supply chain. Changing the location and production capacity of biorefineries may improve the sustainability of the second-generation bioethanol supply chain that can be an interesting future research topic.

Without carbon emissions penalty, the annual profit of corn-based supply chain (\$771.71 M) is 95.3% higher than the situation if biorefineries change their technology to produce bioethanol from corn stover (\$394.77 M). Therefore, without monetary incentives, biorefineries are not interested in such technology changes. The minimum incentive required is \$0.8495 per gallon of bioethanol. This incentive will cost the government by \$376.31 M in a year (by considering 443 MGPY demand level) which is equal to the difference in first-generation and second-generation supply chain profits when no incentives are considered. By considering a carbon tax of \$0.1231 per Kg CO_2e (Regular scenario for the carbon tax), first-generation biorefineries need at least \$0.8527 (+0.38% growth) per gallon incentive to have the same profit after switching their biorefinery technologies to the cellulosic (corn-stover-based) one. This analysis looks like a trading for the government since they take money from second-generation bioethanol plants as a penalty for emissions to make them produce fewer emissions if they network design is not at its optimal level, while on the other hand, the government offer monetary incentives to second-generation bioethanol producers to compensate their profit loss due to technology transition.

Investigating the impact of corn prices on the corn-based bioethanol supply chain shows that without any monetary incentive and carbon tax policies, the corn price has an upper threshold of $5.28 per bushel resulting in a lower profit for corn stover bioethanol supply chain compared with the existing corn bioethanol supply chain. This threshold sets the minimum social value of corn for not using it as a source of producing fuel and using it for food instead to $2.38/bushel (Figure 3.7). If the corn price passes the threshold of $5.28/bushel, the profit of the corn-based bioethanol supply chain becomes lower than the corn-stover-based one. Therefore, it is not both economically and socially reasonable to use corn for fuel (bioethanol) production. The break-even point of the corn bioethanol supply chain is when the corn price is $7.77/bushel (168% growth compared to the BASE scenario with $2.9/bushel corn price) which stops the current corn bioethanol supply chain from making profits.

The results of analyzing the effects of tax credits on minimum incentives and carbon tax indicate that if the US Congress aims to extend its previous biofuel tax credits ($1.01/gallon for second-generation bioethanol and $0.45/gallon for first-generation bioethanol), the current first-generation bioethanol producers still require $0.2895/gallon monetary incentives to switch or a carbon tax of $1.1099/ Kg of CO_2e should be imposed on them. Also, sensitivity analysis on the effects of demand variation on the incentive payments indicates that as the demand decreases, more incentive is required to compensate the profit loss of existing first-generation bioethanol producers. Also, it specifies that under all different demand levels, the first-generation bioethanol supply chain is profitable, however, the second-generation bioethanol supply chain stops making profits when the demand reduces to 199.2 MGPY (44.9% of the BASE 443 MGPY demand level). Finally, sensitivity analysis is conducted to provide insights for investigating the scenarios in which the capacities of the new switched second-generation biorefineries are increased compared to their previous production capacities. According to this analysis, as the production capacity of second-generation biorefineries increases, the profit of the second-generation bioethanol supply chain increases from $394.77 M to $694.78 M where the summation of biorefineries' capacities and their demand are increased from 443 MGPY (BASE scenario) to 750 MGPY (169.3% of the BASE scenario). Besides, as the production capacities and the profit of the second-generation bioethanol supply chain increase, the minimum incentive required to switch decreases from $0.8495 to $0.1017 per gallon of bioethanol production.

As future research, a similar analysis can be implemented for other second-generation biomass feedstocks and the findings can be compared with corn stover. Incorporating the impacts of uncertainties, risks, or disruptions in the BBSC or setting societal objectives such as the number of jobs created can also be addressed through developing multi-objective mathematical modeling in future research. Lastly, as a future direction for research, other types of incentive policies such as an annual fixed incentive or declining year by year incentive can be taken into account to broaden the scope of this study.

4. FIRST-GENERATION VS. SECOND-GENERATION: A MARKET INCENTIVES ANALYSIS FOR BIOETHANOL SUPPLY CHAINS WITH CARBON POLICIES

4.1. Abstract

Increasing demand for energy, the food versus fuel debate, and competitive market pressure for environmental sustainability are driving bioethanol supply chain decision-makers to use second-generation biomass feedstocks and reduce carbon emissions. Currently, most biomass supply chains use edible first-generation feedstocks to produce bioethanol, therefore incentivizing them to switch to a non-edible second-generation feedstock seems necessary and motivating in this context. Implementing various carbon policy mechanisms to curb carbon emissions and address sustainability issues plays a vital role in planning bioethanol supply chains as well as determining the total carbon footprint across the supply chain. In this context, this research proposes a quantitative optimization model for designing and planning biomass bioethanol supply chains considering monetary incentives. The model is developed further by investigating the impact of four different carbon policies including carbon tax, carbon cap, carbon cap-and-trade, and carbon offset policies on the supply chain decisions. Also, the proposed model compares a first-generation (corn) and two different second-generation (corn stover and switchgrass) bioethanol supply chain networks to identify a better alternative for first-generation bioethanol producers. The presented methodology is implemented by applying a case study for the state of North Dakota to derive more realistic results and policies.

4.2. Introduction

The increasing demand for energy, high reliance on non-renewable fuel sources in the transportation sector, and environmental concerns over the consumption of fossil fuels have motivated researchers to find alternative renewable energy sources. Biofuels, such as bioethanol, utilize renewable biomass feedstocks which have shown great potential to be promising alternatives to fossil fuels. Biomass is a key renewable energy source because that can potentially offer lower environmental impacts in terms of CO_2e emissions compared to fossil fuels (Hendricks et al., 2016). The Renewable Fuel Standard (RFS) was established by the US Congress in 2007 to encourage a shift from fossil fuels to biofuels (Halil I. Cobuloglu & Büyüktahtakın, 2015). The RFS mandates production of 36 billion gallons of biofuels annually by 2022 of which 21 billion gallons must be advanced biofuel, such as cellulosic (second-generation) bioethanol, while only 15 billion gallons can be produced from food crops (first-generation) such as corn (Luo & Miller, 2013). At present, there are over 200 corn bioethanol plants in the US that produce almost 15 billion gallons of corn-based bioethanol. In contrast, there are less than ten cellulosic bioethanol plants producing around half-billion gallons per year (RFA, 2018). Hence, cellulosic bioethanol production is far behind the requirements of the RFS (Bracmort, 2012) leading to concerns over the use of irrigation land for producing energy instead of food (Gonela, Zhang, & Osmani, 2015). First-generation bioethanol production from food crops has also raised multiple concerns such as food versus fuel debates and environmental sustainability (Osmani & Zhang, 2017). Accordingly, researchers and practitioners have recently focused on second-generation (cellulosic) biomass feedstocks especially agriculture residues such as corn stover and energy crops such as switchgrass. Regarding this, our research aims to explore an existing corn-based bioethanol supply chain and investigate the potential for a shift in its' production technology influenced by motivatinal incentives to use second-generation biomass either corn stover or switchgrass. A comparison is made to find out the better second-generation biomass alternative for corn in terms of profit maximization to produce bioethanol.

In addition to the economic viability, the negative impacts of human activity on the environment and society have become manifest which motivated different studies to address them (Keramati, Lu, Sobhani, & Haji Esmaeili, 2020; Mota et al., 2015; Sobhani & Wahab, 2017; Sobhani et al., 2019). As a result, along with the economic performance, emissions minimization is also considered in this study by exploring four different carbon policies to determine which policy results in better environmental performance. Also, since the existing corn bioethanol producers are already operating, the production of second-generation bioethanol would be less profitable due to the technology transition costs. Therefore, to motivate first-generation bioethanol producers to switch their biomass input and production technologies to be compatible with second-generation biomass, we incorporate monetary incentives (subsidies) to compensate for their profit loss because of the transition. Government intervention through incentives is essential to promote sustainable biomass conversion (Mohamed Abdul Ghani et al., 2018) especially in our case study to promote utilizing second-generation biomass and support food security.

Research on bioethanol production from biomass has been rising recently owing to its potential to turn out to be a more economical and sustainable alternative energy source compared to fossil fuels. Mueller et al. (2011) explored the relationship between food price and bioethanol demand showing a 3–30% contribution of bioethanol demand in increasing food prices. Their study recommended promoting second-generation biofuels that use non-edible biomass feedstocks. Osmani and Zhang (2013) developed a stochastic mixed-integer linear programming model for a second-generation bioethanol supply chain while considering uncertainties in the biomass purchase price, biomass yield, bioethanol price, and bioethanol demand. Gonela et al. (2015a) designed a hybrid generation bioethanol supply chain considering different government-mandated sustainability standards to investigate implementing first-generation and second-generation bioethanol plant configurations simultaneously considering industrial symbiosis strategy. In none of these studies, motivating first-generation bioethanol producers through incentives to switch their production technology to a second-generation one is addressed. In a study done by Mohamed Abdul Ghani et al. (2018), monetary incentives are considered for corn farmers to sell the leftover yield (corn stover) to bioethanol producers instead of burning it to promote second-generation bioethanol production. Additionally, Kaboli Chalmardi and Camacho-Vallejo (2019) explored a bi-level program to optimize a sustainable supply chain network design considering financial incentives (subsidies) offered by the government and encourages the supply chain's manager to use cleaner technologies. Their results represent that suitable government incentives lead to reduce the environmental impact of the supply chain significantly, however, none of these studies have considered incentives to encourage bioethanol producers to stop using first-generation biomass. A recent study by Haji Esmaeili et al. (2020) is the only study that attempted to use incentives and emissions penalties (carbon tax policy) as levers to motivate existing corn-based bioethanol producers to shift their production facilities to a corn-stover-based bioethanol plant. Our study is inspired by their work, however, it tries to compare corn-based bioethanol supply chain with more than one second-generation biomass feedstock (namely corn stover and switchgrass) and strives to implement different carbon restriction policies (four carbon policies) instead of one.

The increase in greenhouse gas (GHG) emissions which have resulted in climate change and environmental issues has led policymakers to introduce restrictive environmental regulations. Many countries introduced various carbon emissions reduction policies mainly including carbon tax, carbon cap, cap-and-trade, and carbon offset policies to curb the total amount of carbon emissions (Mohammed et al., 2017). There are very few studies that have considered all of these four carbon policies together in their modeling. Palak et al. (2014) analyzed the impacts of carbon regulatory mechanisms on supplier and transportation mode selection decisions in a woody biomass biofuel supply chain. Their model accounts for transportation and inventory storage activities emissions which shows the significant impact of carbon policies on the supply chain's costs and emissions. In another study, Mohammed et al. (2017) proposed an optimization model for design and planning a general closed-loop supply chain network with carbon footprint consideration under different uncertainties. Motivated by their work, our study aims to consider carbon tax, carbon cap, cap-and-trade, and carbon offset policies to compare first-generation (corn) and second-generation (corn stover and switchgrass) bioethanol supply chains through profit maximization and emissions minimization while also taking these four carbon policies as levers to stimulate first-generation bioethanol producers to switch their technology to a cellulosic one. Therefore, our study takes the advantages of using monetary incentives and four carbon policies as motivators to facilitate the transition of first-generation bioethanol producers to second-generation by developing a mixed-integer linear program (MILP) model to design a sustainable biomass supply chain network for the state of North Dakota as the case study to derive more realistic results and policies.

The remainder of the paper is organized as follows: Section 4.3 contains the proposed problem and model; The results and corresponding discussions are presented in Section 4.4; finally, Section 4.5 summarizes the study and provides managerial policies.

4.3. Material and methods

4.3.1. Problem statement

This study aims to compare an existing first-generation (corn) biomass bioethanol supply chain (BBSC) with two proposed second-generation (corn stover and switchgrass) BBSCs while considering four different carbon policies for emissions and monetary incentives only for bioethanol producers if they use second-generation biomass. We propose three supply chain networks to analyze how policymakers can incentivize first-generation bioethanol producers to switch their technology and biomass supply from first-generation to second-generation and to investigate which type of second-generation biomass is a better alternative to corn both economically and environmentally. All three supply chain networks and the associated activities in each stage are shown in Figure 4.1. There are three stages for each supply chain network including suppliers, bioethanol plants, and demand zones. The biomass feedstock flows from the suppliers to the bioethanol plants (biorefineries) by trucks. Then the produced bioethanol in biorefineries either goes to in-state demand zones by trucks or to out-of-state demand zones by rail. The main difference between first-generation (corn) and second-generation (corn stover and switchgrass) supply chains is the cellulosic biorefinery technology transition cost. In our study, since the corn bioethanol supply chain is already in operation, there is no biorefinery construction cost or technology transition cost. However, since we try to motivate these corn bioethanol producers to switch their technology to use either corn stover or switchgrass, there is a cost for this transition. Also, in our model, when corn and corn stover are being used, the biorefinery producers purchase the feedstock from farmers while when switchgrass is the input biomass, they must rent the land to cultivate the switchgrass, and harvest it on their own. It would be beneficial for bioethanol producers to know whether it is more beneficial to outsource their biomass acquisition or not.

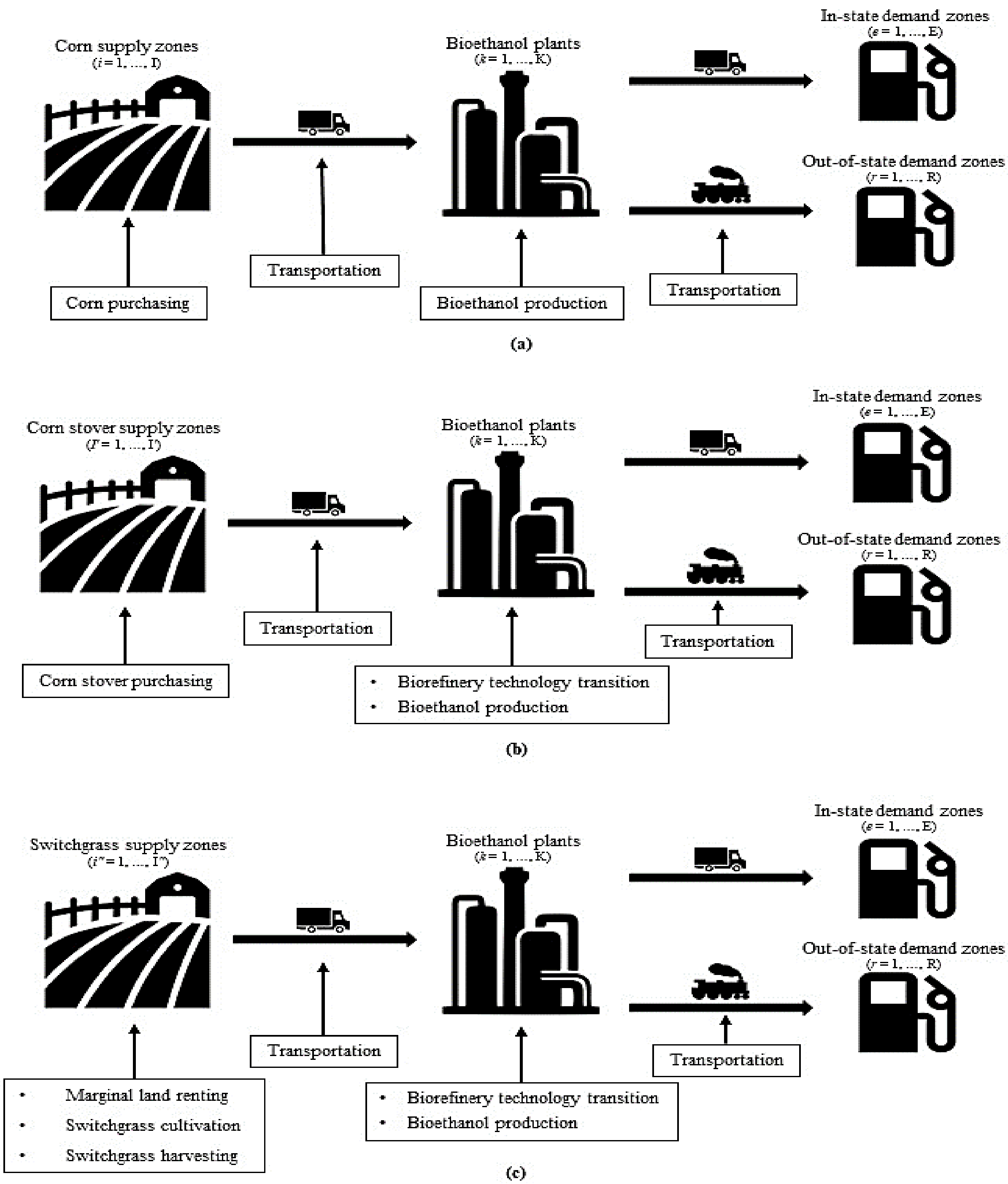


Figure 4.1. Corn (a), corn stover (b), and switchgrass (c) bioethanol supply chain networks and the associated activities in each stage

To validate our study, we considered North Dakota (ND) as one of the leading states in corn production. There are 53 counties in ND that have been divided into nine Agricultural

Statistical Districts (ASDs) serving as suppliers (including NE, EC, SE, NC, CENTRAL, SC, NW, WC, and SW). Also, there are already five bioethanol plants in ND (including Red Train Energy, Blue Flint Ethanol, Dakota Spirit AgEnergy, Tharaldson Ethanol, and Guardian Hankinson) that are producing almost 443 million gallons of bioethanol each year from corn which have been considered as the existing first-generation bioethanol producers and the potential locations for second-generation (cellulosic) biorefineries. For comparison, we consider the same capacities of the current first-generation facilities for the new switched-technology cellulosic biorefineries, where there is no need for new labors. Figure 4.2 shows the ASDs as suppliers and bioethanol plants in ND for both first-generation and second-generation bioethanol supply chains.

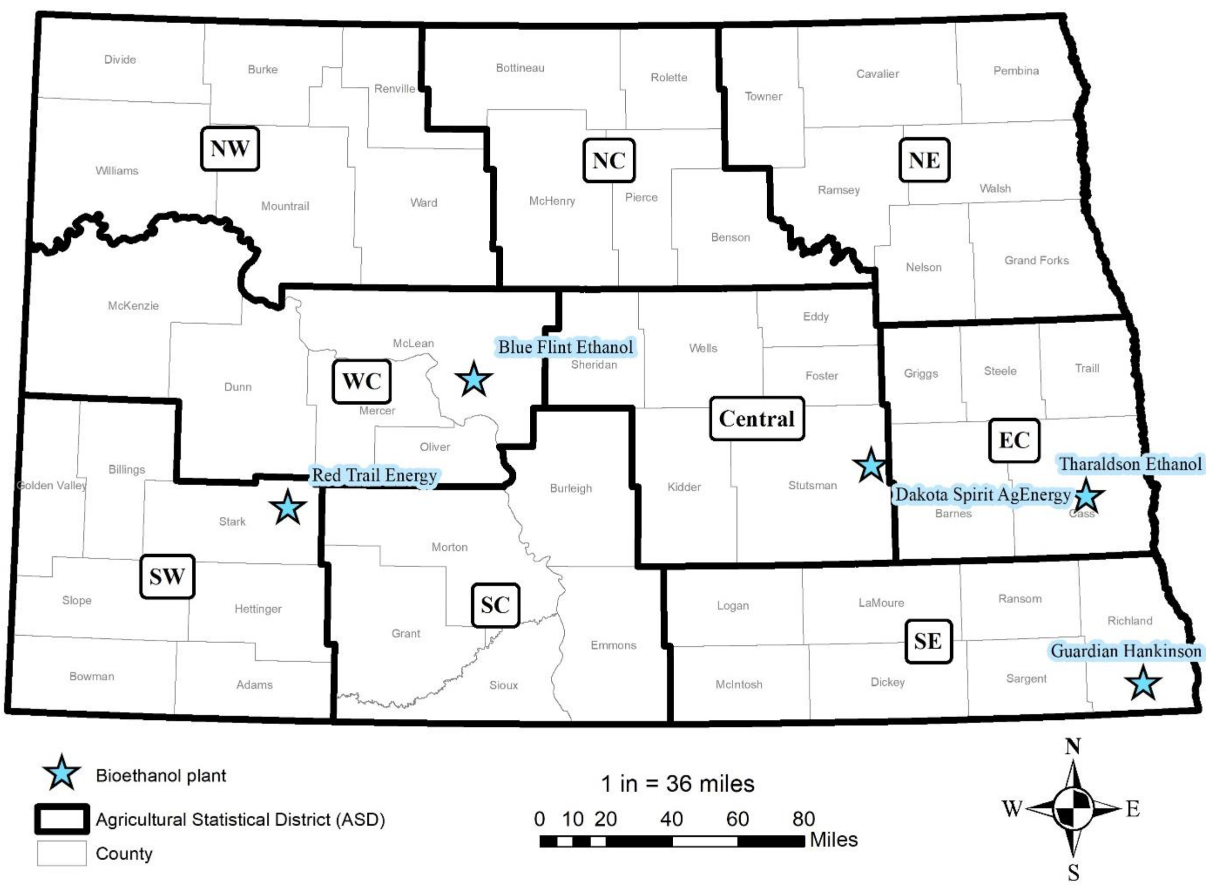


Figure 4.2. Agricultural statistical districts (ASDs) and bioethanol plants (biorefineries) in ND

The bioethanol produced in ND is sold not only within the state but also to other states in the US. Thus, we divided the bioethanol demand zones into two categories that are referred as “in-state” and “out-of-state” demand zones. With respect to the interviews with bioethanol experts in ND, there are six in-state demand zones including Fargo, Grand Forks, Jamestown, Bismarck, Dickinson, and Minot which have fuel racks, where bioethanol is blended with gasoline. These demand zones are all located in ND. Moreover, there are four out-of-state demand zones including Houston (TX), Los Angeles (CA), Portland (OR), and Seattle (WA). Considering the out-of-state demand zones makes our case study more realistic for policymakers to rely on. Around 10 percent of ND bioethanol production is sold within the state (shipped by truck) and the other 90 percent is shipped by rail to other states (ND Studies Energy Curriculum, 2019). The demand of each zone is assigned proportionally based on its population. The in-state and out-of-state demand zones are shown in Figure 4.3. The price of bioethanol is set to \$1.4 per gallon which is the average of the selling price of bioethanol from January 2015 to May 2019 in some of the US Midwest states including Iowa, Illinois, South Dakota, and Nebraska where ND is also located (Johanns, 2019).

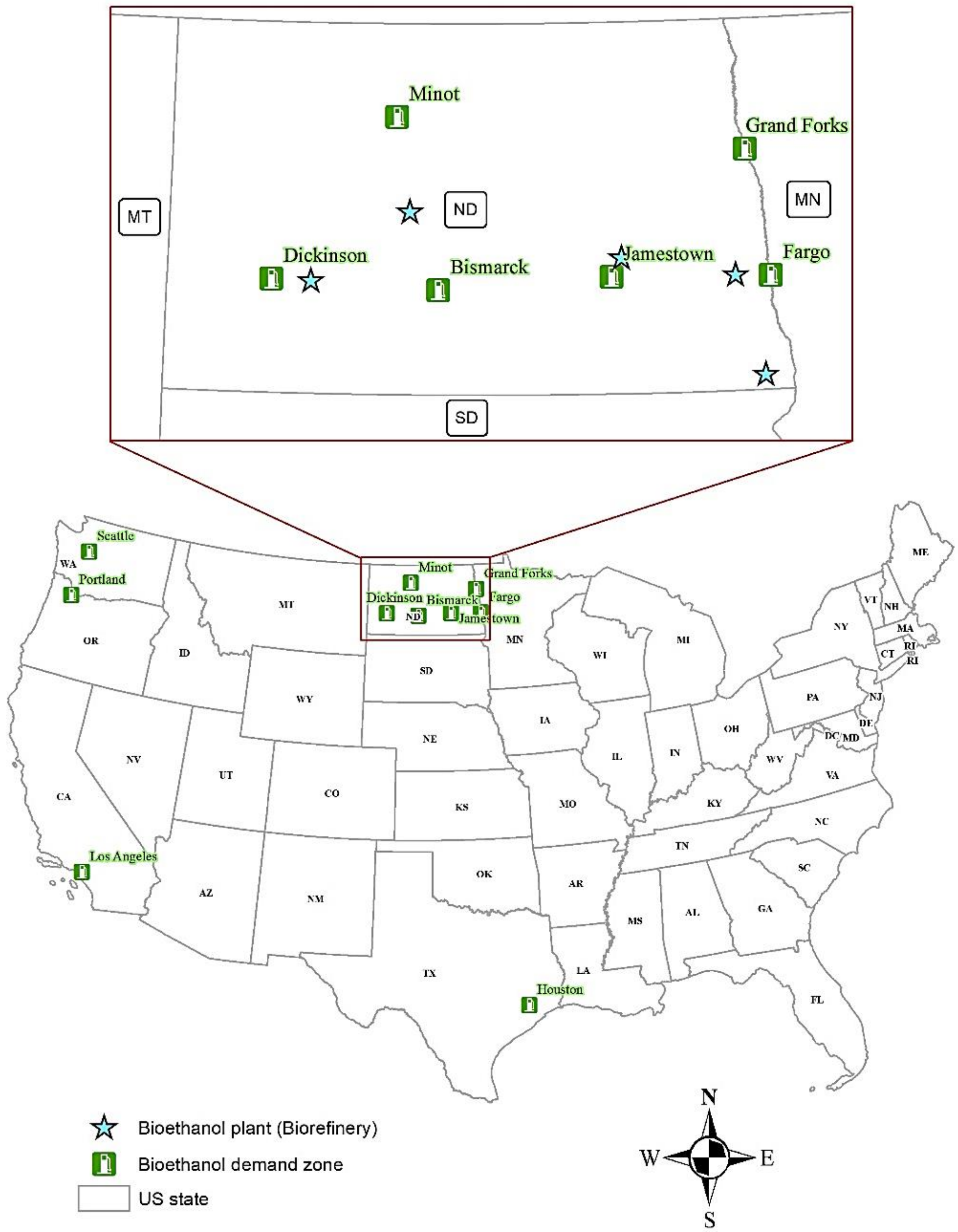


Figure 4.3. In-state and out-of-state demand zones

Total corn and corn stover availability for each ASD in ND is shown in Table 4.1. The available corn in bushels is multiplied by corn stover yield rate (0.028) to estimate the corn stover availability (Mohamed Abdul Ghani et al., 2018). Also, Table 4.1 shows the total marginal land available for switchgrass cultivation along with marginal land rental cost in ND. According to the

United States Department of Agriculture, in the state of ND, cropland accounted for 69.1%, pastureland 26.1%, and marginal land (other uses) 4.8% of the total 15.89 million hectares of farmland under cultivation (NASS Census of Agriculture, 2019). This study only considers marginal land for switchgrass cultivation which totals around 0.76 million hectares. Using marginal land for switchgrass cultivation prevents competition for land used for humans and animals. Moreover, since marginal lands have not been used for any commercial activities so far, there is no published marginal land rental cost available. Thus, we considered pastureland rental cost for each supply zone as the cost for renting marginal lands per hectare (ha).

Table 4.1. Biomass feedstocks availability and marginal land rental cost

	Agricultural Statistical District (ASD)								
	SE	EC	NE	SC	CENTRAL	NC	SW	WC	NW
Available corn (thousand bushels) [a]	161,291	101,297.6	48,071	24,905	57,930	12,312	3,744	6,138	3,529
Available corn stover (ton)	4,608,314	2,894,217	1,373,457	711,571	1,655,143	351,771	106,971	175,371	100,829
Available marginal land (ha) [b]	76,229	74,394	195,229	65,442	84,683	88,533	45,013	75,253	102,370
Marginal land rental cost ($/ha) [c]	$67.95	$49.42	$40.77	$45.71	$49.42	$39.54	$35.83	$34.59	$24.71

[a] (Mohamed Abdul Ghani et al., 2018; NASS Census of Agriculture, 2019)
[b] (NASS Census of Agriculture, 2019)
[c] (NASS Statistics by State, 2019)

The current operating corn-based bioethanol plants in ND, their bioethanol production capacities, and their estimated annualized biorefinery technology transition costs (f_k^b) are presented in Table 4.2. The annualized biorefinery technology transition cost required to switch to a second-generation biorefinery is varied according to the production capacity of biorefineries. In this study, it is assumed that the biorefinery technology transition cost is as much as constructing a new cellulosic biorefinery where the revenue from corn-based biorefinery salvage sales compensates the total cost related to production loss during the switching process. The annualized fixed capital cost of a cellulosic biorefinery (f^r) with 50 million gallons per year (MGPY) production capacity (p_r) with biorefinery life of 20 years and interest rate of 5% is \$42 million (Osmani & Zhang, 2013), while for biorefineries with other capacities, the annual fixed construction cost (annualized biorefinery technology transition in this study (f_k^b)) with the capacity p_k has been calculated based on the Eq. (4.1), where β is a scaling factor which is set to 0.8 (Dunnett et al., 2008).

$$f_k^b = f^r (\frac{p_k}{p_r})^\beta \tag{4.1}$$

Table 4.2. List of ND biorefineries with their production capacities and estimated annualized biorefinery technology transition costs

Biorefinery	Production Capacity (MGPY) [a]	Estimated annualized biorefinery technology transition cost
Blue Flint Ethanol	65	\$51,808,852
Dakota Spirit AgEnergy	68	\$53,713,125
Red Trail Energy	50	\$42,000,000
Tharaldson Ethanol	130	\$90,204,451
Guardian Hankinson	130	\$90,204,451

[a] (ND Studies Energy Curriculum, 2019)

4.3.2. Methodology

In this study, we develop three mixed-integer linear programming (MILP) models with five carbon scenarios (including no carbon policy, carbon tax, carbon cap, cap-and-trade, and carbon offset) for each biomass feedstock, namely corn, corn stover, and switchgrass to maximize the total supply chains profit, minimize the emissions in the supply chain, and optimally design the supply chain network. To better address sustainability issues, we implement four different carbon policies in addition to the base model for each biomass feedstock in which carbon emission consideration is excluded.

4.3.2.1. Corn-based bioethanol supply chain (CBSC) model with no carbon policy

This section presents the base model for the CBSC which disregards emissions. The objective function in Eq. (4.2) aims to maximize the CBSC profit. The first two elements in the objective function are the revenues coming from bioethanol and corn-based bioethanol co-product sales which is called Dried Distillers Grain (DDG). The remaining elements are costs related to the supply chain process such as corn purchasing cost, corn transportation cost between suppliers and bioethanol plants, bioethanol production cost, and bioethanol transportation cost between biorefineries and both in-state and out-of-state demand zones. In this study, the bioethanol plants are responsible for bioethanol transport but not for bioethanol co-products; thus, the transportation cost and emissions of bioethanol co-products are not considered. Table 4.3 shows the notations used in this study and the input parameters are presented in Table A3 in Appendix A.

Table 4.3. Sets, decision variables, and parameters for the models

Notation			
Indices/Sets		*Parameters*	
I	Set of corn suppliers, indexed by i	γ^c	Transportation fixed cost of corn via truck ($/bushel)
I'	Set of corn suppliers, indexed by i'	η^c	Transportation variable cost of corn via truck ($/bushel-mile)
I''	Set of corn suppliers, indexed by i''	γ^s	Transportation fixed cost of corn stover via truck ($/ton)
K	Set of biorefineries, indexed by k	η^s	Transportation variable cost of corn stover via truck ($/ton-mile)
E	Set of in-state demand zones, indexed by e	γ^g	Transportation fixed cost of switchgrass via truck ($/bushel)
R	Set of out-of-state demand zones, indexed by r	η^g	Transportation variable cost of switchgrass via truck ($/bushel-mile)
Decision Variables		γ^t	Transportation fixed cost of bioethanol via truck ($/gallon)
Q^c_{ik}	Quantity of corn transported from supply area i to biorefinery k (bushel)	η^t	Transportation variable cost of bioethanol via truck ($/gallon-mile)
Q^c_{ke}	Quantity of bioethanol produced from corn transported from biorefinery k to in-state demand zone e (gallon)	γ^r	Transportation fixed cost of bioethanol via rail ($/gallon)
Q^c_{kr}	Quantity of bioethanol produced from corn transported from biorefinery k to out-of-state demand zone r (gallon)	η^r	Transportation variable cost of bioethanol via rail ($/gallon)
Q^c	Quantity of co-product produced from corn (DDG) at biorefineries (ton)	D_e	Annual bioethanol demand level at in-state demand zone e (gallon)
$Q^s_{i'k}$	Quantity of corn stover transported from supply area i' to biorefinery k (ton)	D_r	Annual bioethanol demand level at out-of-state demand zone r (gallon)
Q^s_{ke}	Quantity of bioethanol produced from corn stover transported from biorefinery k to in-state demand zone e (gallon)	e_s^{truck}	Emission factor of transporting corn stover via truck (kg CO_2e /ton-mile)
Q^s_{kr}	Quantity of bioethanol produced from corn stover transported from biorefinery k to out-of-state demand zone r (gallon)	C_c^{cap}	Carbon cap for corn bioethanol supply chain (kg CO_2e)
Q^s	Quantity of co-product produced from corn stover (lignin pallet) at biorefineries (ton)	C_s^{cap}	Carbon cap for corn stover bioethanol supply chain (kg CO_2e)
$Q^g_{i''k}$	Quantity of switchgrass transported from supply area i'' to biorefinery k (bushel)	C_g^{cap}	Carbon cap for switchgrass bioethanol supply chain (kg CO_2e)
Q^g_{ke}	Quantity of bioethanol produced from switchgrass transported from biorefinery k to in-state demand zone e (gallon)	p^+	Buying price of one kg of carbon (CO_2e) in the carbon market ($)
Q^g_{kr}	Quantity of bioethanol produced from switchgrass transported from biorefinery k to out-of-state demand zone r (gallon)	p^-	Selling price of one kg of carbon (CO_2e) in the carbon market ($)
Q^g	Quantity of co-product produced from switchgrass (lignin pallet) at biorefineries (ton)	p^0	Carbon (CO_2e) price per unit offset ($)
Y_k^c	1 if a corn-based biorefinery is activated at location k; 0 otherwise	λ^g	Mean yield rate of switchgrass (tons/ha)

Table 4.3. Sets, decision variables, and parameters for the models (continued)

Notation			
Decision Variables			
Y_k^s	1 if a corn-stover-based biorefinery is activated at location k; 0 otherwise	v^g	Cultivation cost of switchgrass (\$/ha)
Y_k^g	1 if a switchgrass-based biorefinery is activated at location k; 0 otherwise	h^g	Harvesting cost of (square bale) switchgrass (\$/ha)
e_c^+	Number of carbon credits purchased when corn is the feedstock	$r_{i''}$	Marginal land rental cost at supply zone i'' (\$/ha)
e_c^-	Number of carbon credits sold when corn is the feedstock	$a_{i''}^g$	Available marginal land at supply zone i'' (ha)
e_s^+	Number of carbon credits purchased when corn stover is the feedstock	p_k^c	Capacity of corn-based biorefinery k (MGPY)
e_s^-	Number of carbon credits sold when corn stover is the feedstock	p_k^s	Capacity of corn-stover-based biorefinery k (MGPY)
e_g^+	Number of carbon credits purchased when switchgrass is the feedstock	p_k^g	Capacity of switchgrass-based biorefinery k (MGPY)
e_g^-	Number of carbon credits sold when switchgrass is the feedstock	e_c^{truck}	Emission factor of transporting corn via truck (kg CO_2e/ bushel-mile)
Parameters		e_s^{truck}	Emission factor of transporting corn stover via truck (kg CO_2e/ ton-mile)
π	Bioethanol selling price (\$/gal)	e_g^{truck}	Emission factor of transporting switchgrass (Kg CO_2e/ton-mile)
φ^c	Corn-based bioethanol co-product (DDG) selling price (\$/ton)	e_{be}^{truck}	Emission factor of transporting bioethanol via truck (kg CO_2e/gallon-mile)
φ^s	Corn-stover-based bioethanol co-product (lignin pallet) selling price (\$/ton)	e_{be}^{rail}	Emission factor of transporting bioethanol via rail (kg CO_2e/gallon-mile)
φ^g	Switchgrass-based bioethanol co-product (lignin pallet) selling price (\$/ton)	$e_c^{\text{acquisitio}}$	Emission factor of corn acquisition (kg CO_2e/bushel)
α^c	Selling price of corn (\$/bushel)	$e_s^{\text{acquisitio}}$	Emission factor of corn stover acquisition (kg CO_2e/ton)
α^s	Selling price of corn stover (\$/ton)	$e_g^{acquisitio}$	Emission factor of switchgrass acquisition (kg CO_2e/ton)
f_k^b	The estimated annualized technology transition cost of biorefinery k (\$)	$e_c^{productio}$	Emission factor of producing bioethanol from corn (kg CO_2e/gallon)
Ω	Monetary incentive for second-generation bioethanol producers	$e_s^{productio}$	Emission factor of producing bioethanol from corn stover (kg CO_2e/gallon)
ρ^c	Production cost of bioethanol at corn biorefinery (\$/gallon)	$e_g^{productio}$	Emission factor of producing bioethanol from switchgrass (kg CO_2e/gallon)
ρ^s	Production cost of bioethanol at corn stover biorefinery (\$/gallon)	d_{ik}^c	Distance from corn supplier i to biorefinery k (mile)
ρ^g	Production cost of bioethanol at switchgrass biorefinery (\$/gallon)	d_{ke}^c	Distance from biorefinery k to in-state demand zone e when corn is used for bioethanol production (mile)
θ^c	Bioethanol conversion rate from corn (gallons/bushel)	d_{kr}^c	Distance from biorefinery k to out-of-state demand zone r when corn is used for bioethanol production (mile)

Table 4.3. Sets, decision variables, and parameters for the models (continued)

Notation			
Parameters			
6^c	Corn-based co-product (DDG) conversion rate (ton/gallon)	$d^s_{i'k}$	Distance from corn stover supplier i' to biorefinery k (mile)
θ^s	Bioethanol conversion rate from corn stover (gallons/ton)	d^s_{ke}	Distance from biorefinery k to in-state demand zone e when corn stover is used for bioethanol production (mile)
6^s	Corn-stover-based co-product (Lignin pallet) conversion rate (ton/gallon)	d^s_{kr}	Distance from biorefinery k to out-of-state demand zone r when corn stover is used for bioethanol production (mile)
θ^g	Bioethanol conversion rate from switchgrass (gallons/ton)	$d^g_{i''k}$	Distance from switchgrass supply zone i'' to biorefinery k (miles)
6^g	Switchgrass-based co-product (lignin pallet) conversion rate at biorefineries (tons/gallon)	d^g_{ke}	Distance from biorefinery k to in-state demand zone e when switchgrass is used for bioethanol production (miles)
ξ	Carbon tax / Environmental cost factor of emissions (\$/kg CO_2e)	d^g_{kr}	Distance from biorefinery k to out-of-state demand zone r when switchgrass is used for bioethanol production (miles)

The model is as follows:

$$Max\ Z_1^c = \pi\left(\sum_{k\in K}\sum_{e\in E} Q^c_{ke} + \sum_{k\in K}\sum_{r\in R} Q^c_{kr}\right) + \varphi^c Q^c - \alpha^c \sum_{i\in I}\sum_{k\in K} Q^c_{ik}$$

$$- \sum_{i\in I}\sum_{k\in K}(\gamma^c + \eta^c d^c_{ik})Q^c_{ik} - \rho^c\left(\sum_{k\in K}\sum_{e\in E} Q^c_{ke} + \sum_{k\in K}\sum_{r\in R} Q^c_{kr}\right) \quad (4.2)$$

$$- \sum_{k\in K}\sum_{e\in E}(\gamma^t + \eta^t d^c_{ke})Q^c_{ke} - \sum_{k\in K}\sum_{r\in R}(\gamma^r + \eta^r d^c_{kr})Q^c_{kr}$$

Subject to constraints:

$$\sum_{k\in K} Q^c_{ik} \le a^c_i \qquad \forall i \in I \quad (4.3)$$

$$\theta^c \sum_{i\in I} Q^c_{ik} = \sum_{e\in E} Q^c_{ke} + \sum_{r\in R} Q^c_{kr} \qquad \forall k \in K \quad (4.4)$$

$$6^c\left(\sum_{k\in K}\sum_{e\in E} Q^c_{ke} + \sum_{k\in K}\sum_{r\in R} Q^c_{kr}\right) = Q^c \quad (4.5)$$

$$\sum_{e \in E} Q_{ke}^{c} + \sum_{r \in R} Q_{kr}^{c} \leq p_k^c Y_k^c \quad \forall k \in K \tag{4.6}$$

$$\sum_{k \in K} Q_{ke}^{c} = D_e \quad \forall e \in E \tag{4.7}$$

$$\sum_{k \in K} Q_{kr}^{c} = D_r \quad \forall r \in R \tag{4.8}$$

$$Y_k = \{0,1\} \quad \forall k \in K \tag{4.9}$$

$$Q^c \geq 0 \tag{4.10}$$

$$Q_{ik}^{c} \geq 0 \quad \forall i \in I, \forall k \in K \tag{4.11}$$

$$Q_{ke}^{c} \geq 0 \quad \forall k \in K, \forall e \in E \tag{4.12}$$

$$Q_{kr}^{c} \geq 0 \quad \forall k \in K, \forall r \in R \tag{4.13}$$

Eqs. (4.3) - (4.13) shows the constraints of the CBSC base model. Eq. (4.3) is the supply constraint which ensures that the amount of corn purchased from suppliers cannot exceed the maximum corn available. Eq. (4.4) is the material flow constraint presenting the corn coming from suppliers to biorefineries that are converted to bioethanol going out to demand zones. Eq. (4.5) shows the conversion of corn-based bioethanol co-product (DDG) production. Eq. (4.6) guarantees the amount of bioethanol produced in biorefineries (if activated) does not exceed their production capacities. Also, Eq. (4.7) displays the in-state demand fulfillment and Eq. (4.8) addresses out-of-state bioethanol demand. Moreover, Eqs. (4.9) - (4.13) indicate the nature and non-negativity of variables used in the model. The models are solved via OpenSolver 2.9.0 using the CBC (COIN-OR Branch-and-Cut) optimization engine (Mason, 2012; OpenSolver, 2018).

4.3.2.2. CBSC model with carbon tax policy

This policy incurs a financial penalty per unit of emitted CO_2e. The objective function in Eq. (4.14) considers emissions for the CBSC and penalizes them with a carbon tax (ξ). Eq. (4.15) indicates the total amount of emissions emitted in the CBSC. The emissions sources that have been considered in this supply chain include corn-to-bioethanol operations such as corn acquisition, corn transportation via truck, bioethanol production, bioethanol transportation from bioethanol plants to demand zones. For the given objective function in Eq. (4.14), the same constraints used for CBSC based model are also considered.

$$Max\ Z_2^c = Z_1^c - \xi\ .Z_e^c \tag{4.14}$$

$$Z_e^c = e_c^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^c + e_c^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^c Q_{ik}^c + e_c^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^c + \sum_{k \in K} \sum_{r \in R} Q_{kr}^c \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^c Q_{ke}^c + e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^c Q_{kr}^c \tag{4.15}$$

Subject to constraints (4.3) – (4.13).

4.3.2.3. CBSC model with carbon cap policy

Under this policy, the supply chain is allowed to emit a limited amount of CO_2e emissions. Regarding this, a carbon cap (C_c^{cap}) is referred to the imposed carbon allowance on the CBSC.

$$Max\ Z_3^c = Z_1^c \tag{4.16}$$

Subject to constraints (4.3) – (4.13) and

$$e_c^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^c + e_c^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^c Q_{ik}^c + e_c^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^c + \sum_{k \in K} \sum_{r \in R} Q_{kr}^c \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^c Q_{ke}^c + e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^c Q_{kr}^c \leq C_c^{cap} \tag{4.17}$$

4.3.2.4. CBSC with carbon cap-and-trade policy

A cap-and-trade policy has a carbon cap; however, it allows trading of the carbon allowance. The supply chain players can sell the unused amount of carbon emissions or purchase additional carbon emission credits. In the objective function presented in Eq. (18), e_c^+ and e_c^- are two variables representing the amount of bought and sold carbon credits in the CBSC.

$$Max\ Z_4^c = Z_1^c - (p^+ e_c^+ - p^- e_c^-) \tag{4.18}$$

Subject to constraints (4.3) – (4.13) and

$$\begin{aligned} e_c^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^c + e_c^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^c Q_{ik}^c + e_c^{production} \Bigg(\sum_{k \in K} \sum_{e \in E} Q_{ke}^c \\ + \sum_{k \in K} \sum_{r \in R} Q_{kr}^c \Bigg) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^c Q_{ke}^c + e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^c Q_{kr}^c + e_c^- \\ \leq C_c^{cap} + e_c^+ \end{aligned} \tag{4.19}$$

4.3.2.5. CBSC model with carbon offset policy

A carbon offset policy is the same as the cap-and-trade policy where the supply chain cannot sell the unused carbon emission credits. This means the supply chain can buy carbon credit but cannot make further profits by selling the unused carbon credit.

$$Max\ Z_5^c = Z_1^c - p^0 e_c^+ \tag{4.20}$$

Subject to constraints (4.3) – (4.13) and

$$\begin{aligned} e_c^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^c + e_c^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^c Q_{ik}^c + e_c^{production} \Bigg(\sum_{k \in K} \sum_{e \in E} Q_{ke}^c \\ + \sum_{k \in K} \sum_{r \in R} Q_{kr}^c \Bigg) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^c Q_{ke}^c + e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^c Q_{kr}^c \\ \leq C_c^{cap} + e_c^+ \end{aligned} \tag{4.21}$$

4.3.2.6. Corn-stover-based bioethanol supply chain (CSBSC) model with no carbon policy

The CSBSC modeling is similar to the CBSC model where corn stover and its associated parameters are replaced with corn. However, in the CSBSC model, since the current bioethanol producers need to switch their facilities to be compatible with corn stover (cellulosic) biomass, the biorefinery technology transition cost is included in corresponding models. Also, to motivate corn bioethanol producers to switch, monetary incentives are considered in CSBSC models.

$$\begin{aligned} Max\ Z_1^s = {} & (\pi + \Omega)\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^s + \sum_{k\in K}\sum_{r\in R} Q_{kr}^s\right) + \varphi^s Q^s - \alpha^s \sum_{i\in I}\sum_{k\in K} Q_{ik}^s \\ & - \sum_{i\in I}\sum_{k\in K}(\gamma^s + \eta^s d_{ik}^s) Q_{ik}^s - \sum_{k\in K} f_k^b Y_k \\ & - \rho^s\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^s + \sum_{k\in K}\sum_{r\in R} Q_{kr}^s\right) - \sum_{k\in K}\sum_{e\in E}(\gamma^t + \eta^t d_{ke}^s) Q_{ke}^s \\ & - \sum_{k\in K}\sum_{r\in R}(\gamma^r + \eta^r d_{kr}^s) Q_{kr}^s \end{aligned} \tag{4.22}$$

Subject to constraints:

$$\sum_{k\in K} Q_{ik}^s \leq a_i^s \qquad \forall i \in I \tag{4.23}$$

$$\theta^s \sum_{i\in I} Q_{ik}^s = \sum_{e\in E} Q_{ke}^s + \sum_{r\in R} Q_{kr}^s \qquad \forall k \in K \tag{4.24}$$

$$6^s\left(\sum_{k\in K}\sum_{e\in E} Q_{ke}^s + \sum_{k\in K}\sum_{r\in R} Q_{kr}^s\right) = Q^s \tag{4.25}$$

$$\sum_{e\in E} Q_{ke}^s + \sum_{r\in R} Q_{kr}^s \leq p_k^s Y_k^s \qquad \forall k \in K \tag{4.26}$$

$$\sum_{k\in K} Q_{ke}^s = D_e \qquad \forall e \in E \tag{4.27}$$

$$\sum_{k \in R} Q_{kr}^{s} = D_r \quad \forall r \in R \tag{4.28}$$

$$Y_k = \{0,1\} \quad \forall k \in K \tag{4.29}$$

$$Q^{s} \geq 0 \tag{4.30}$$

$$Q_{ik}^{s} \geq 0 \quad \forall i \in I, \forall k \in K \tag{4.31}$$

$$Q_{ke}^{s} \geq 0 \quad \forall k \in K, \forall e \in E \tag{4.32}$$

$$Q_{kr}^{s} \geq 0 \quad \forall k \in K, \forall r \in R \tag{4.33}$$

The objective function in Eq. (4.22) intends to maximize the CSBSC profit while disregarding emissions. The model maximizes the revenues coming from bioethanol and corn-stover-based bioethanol co-product (lignin pallet) sales while minimizing corn stover purchasing cost, production cost, and transportation costs. Along with these cost elements, the biorefinery technology transition cost for corn biorefineries to switch to a cellulosic (second-generation) biorefinery is also considered. Moreover, in Eq. (4.22), Ω is the incentive that will be assigned to each gallon of bioethanol production only if the corn-based bioethanol producers switch their facilities and use corn stover as the feedstock.

Eqs. (4.23) - (4.33) present the constraints of the objective function. Eq. (4.23) shows the supply constraint in which the amount of corn stover purchased cannot exceed the amount of available corn stover in supply areas. In Eq. (4.24), the flow balance between suppliers, bioethanol plants, and demand zones is ensured. The conversion of corn stover bioethanol co-product (lignin pallet) production is illustrated in Eq. (4.25). Eq. (4.26) indicates the amount of bioethanol produced in biorefineries cannot exceed the biorefineries' capacities. Eqs. (4.27) and (4.28) guarantee that the volume of bioethanol produced in biorefineries fulfills the in-state and out-of-state bioethanol demands. At last, Eqs. (4.29) - (4.33) present the nature of the variables.

4.3.2.7. CSBSC model with carbon tax policy

In this model, the objective function in Eq. (4.34) maximizes the CSBSC profit while the emissions produced in this supply chain is penalized with a carbon tax (ξ). The total amount of emissions produced in this supply chain is formulated in Eq. (4.35). The emissions sources include the corn-stover-to-bioethanol activities such as corn stover acquisition, corn stover transportation via truck, bioethanol production, bioethanol transportation from bioethanol plants to in-state demand zones via truck and to out-of-state demand zones via rail. The same constraints used for the objective function in Eq. (4.22) are also considered for the given objective function in Eq. (4.34).

$$Max\ Z_2^s = Z_1^s - \xi\ .Z_e^s \tag{4.34}$$

$$\begin{aligned} Z_e^s \ = \ e_s^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^s + e_s^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^s Q_{ik}^s + e_s^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^s \right. \\ \left. + \sum_{k \in K} \sum_{r \in R} Q_{kr}^s \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^s Q_{ke}^s + e_{br}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^s Q_{kr}^s \end{aligned} \tag{4.35}$$

Subject to constraints (4.23) – (4.33).

4.3.2.8. CSBSC model with carbon cap policy

The modeling of this section is similar to the CSBSC base model but with an additional constraint which set a maximum limit for carbon emissions (C_s^{cap}).

$$Max\ Z_3^s = Z_1^s \tag{4.36}$$

Subject to constraints (4.23) – (4.33) and

$$e_s^{acquisition}\sum_{i\in I}\sum_{k\in K}Q_{ik}^s + e_s^{truck}\sum_{i\in I}\sum_{k\in K}d_{ik}^s Q_{ik}^s + e_s^{production}\left(\sum_{k\in K}\sum_{e\in E}Q_{ke}^s + \sum_{k\in K}\sum_{r\in R}Q_{kr}^s\right) + e_{be}^{truck}\sum_{k\in K}\sum_{e\in E}d_{ke}^s Q_{ke}^s + e_{br}^{rail}\sum_{k\in K}\sum_{r\in R}d_{kr}^s Q_{kr}^s \leq C_s^{cap} \quad (4.37)$$

4.3.2.9. CSBSC model with carbon cap-and-trade policy

As mentioned before, under this policy, the supply chain allows trading its carbon allowance. In the objective function presented in Eq. (4.38), e_s^+ and e_s^- are two variables representing the amount of bought and sold carbon credits in the CSBSC.

$$Max\ Z_4^s = Z_1^s - (p^+ e_s^+ - p^- e_s^-) \quad (4.38)$$

Subject to constraints (4.23) – (4.33) and

$$e_s^{acquisition}\sum_{i\in I}\sum_{k\in K}Q_{ik}^s + e_s^{truck}\sum_{i\in I}\sum_{k\in K}d_{ik}^s Q_{ik}^s + e_s^{production}\left(\sum_{k\in K}\sum_{e\in E}Q_{ke}^s + \sum_{k\in K}\sum_{r\in R}Q_{kr}^s\right) + e_{be}^{truck}\sum_{k\in K}\sum_{e\in E}d_{ke}^s Q_{ke}^s + e_{br}^{rail}\sum_{k\in K}\sum_{r\in R}d_{kr}^s Q_{kr}^s + e_s^- \leq C_s^{cap} + e_s^+ \quad (4.39)$$

4.3.2.10. CSBSC model with carbon offset policy

The modeling in this section tries to maximize the CSBSC profit and minimize its emissions by setting a carbon cap (C_s^{cap}) while the carbon market allows the supply chain to purchase carbon credits with a price of p^0.

$$Max\ Z_5^s = Z_1^s - p^0 e_s^+ \quad (4.40)$$

Subject to constraints (4.23) – (4.33) and

$$e_s^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^s + e_s^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^s Q_{ik}^s + e_s^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^s \right.$$

$$\left. + \sum_{k \in K} \sum_{r \in R} Q_{kr}^s \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^s Q_{ke}^s + e_{br}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^s Q_{kr}^s \tag{4.41}$$

$$\leq C_s^{cap} + e_s^+$$

4.3.2.11. Switchgrass-based bioethanol supply chain (SBSC) model with no carbon policy

This model formulates the SBSC model to explore how corn can be replaced by switchgrass as the biomass feedstock to produce bioethanol. The objective function in Eq. (4.42) maximizes the SBSC profit. The first two elements in the objective function are supply chain revenues coming from two final products' sales: bioethanol and switchgrass-based bioethanol co-product (lignin pallets). Other cost elements in the objective function respectively present the marginal land rental cost for switchgrass cultivation, switchgrass cultivation cost, harvesting cost of switchgrass, transportation cost of switchgrass, biorefinery capital cost, biorefinery production cost, transportation cost of bioethanol via truck to in-state demand zones, and transportation cost of bioethanol via rail to out-of-state demand zones.

$$Max\ Z_1^g = (\pi + \Omega) \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^g + \sum_{k \in K} \sum_{r \in R} Q_{kr}^g \right) + \varphi^g Q^g - \sum_{i \in I} \sum_{k \in K} \frac{r_i}{\lambda^g} Q_{ik}^g$$

$$- \frac{v^g}{\lambda^g} \sum_{i \in I} \sum_{k \in K} Q_{ik}^g - \frac{h^g}{\lambda^g} \sum_{i \in I} \sum_{k \in K} Q_{ik}^g - \sum_{i \in I} \sum_{k \in K} (\gamma^g + \eta^g d_{ik}^g) Q_{ik}^g$$

$$- \sum_{k \in K} f_k^b Y_k - \rho^g \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^g + \sum_{k \in K} \sum_{r \in R} Q_{kr}^g \right) \tag{4.42}$$

$$- \sum_{e \in E} \sum_{k \in K} (\gamma^t + \eta^t d_{ke}^g) Q_{ke}^g - \sum_{k \in K} \sum_{r \in R} (\gamma^r + \eta^r d_{kr}^g) Q_{kr}^g$$

Subject to constraints:

$$\sum_{k\in K} Q_{ik}^{g} \leq \lambda_g a_i^g \qquad \forall i \in I \tag{4.43}$$

$$\theta^g \sum_{i\in I} Q_{ik}^{g} = \sum_{e\in E} Q_{ke}^{g} + \sum_{r\in R} Q_{kr}^{g} \qquad \forall k \in K \tag{4.44}$$

$$6^g \left(\sum_{k\in K} \sum_{e\in E} Q_{ke}^{g} + \sum_{k\in K} \sum_{r\in R} Q_{kr}^{g} \right) = Q^g \tag{4.45}$$

$$\sum_{e\in E} Q_{ke}^{g} + \sum_{r\in R} Q_{kr}^{g} \leq p_k^g Y_k^g \qquad \forall k \in K \tag{4.46}$$

$$\sum_{k\in K} Q_{ke}^{g} = D_e \qquad \forall e \in E \tag{4.47}$$

$$\sum_{k\in K} Q_{kr}^{g} = D_r \qquad \forall r \in R \tag{4.48}$$

$$Y_k = \{0,1\} \qquad \forall k \in K \tag{4.49}$$

$$Q^g \geq 0 \tag{4.50}$$

$$Q_{ik}^{g} \geq 0 \qquad \forall i \in I, \forall k \in K \tag{4.51}$$

$$Q_{ke}^{g} \geq 0 \qquad \forall k \in K, \forall e \in E \tag{4.52}$$

$$Q_{kr}^{g} \geq 0 \qquad \forall k \in K, \forall r \in R \tag{4.53}$$

The constraints of the objective function in Eq. (4.42) are presented in Eqs. (4.43) - (4.53). Eq. (4.43) ensures the amount of switchgrass harvested at area *i* cannot be more than the maximum switchgrass available to be harvested on marginal lands for each supply zone. The material flow constraint for switchgrass-to-bioethanol is given in Eq. (4.44) and switchgrass to bioethanol co-product (lignin pallet) is presented in Eq. (4.45). The capacity constraints of biorefineries and whether they should be constructed are explored in Eq. (4.46). The demand fulfillment of in-state demand zones is assured in Eq. (4.47). Similarly, Eq. (4.48) indicates the demand fulfillment for out-of-state demand zones. Finally, Eqs. (4.49) - (4.53) illustrate the nature and non-negativity of variables.

4.3.2.12. SBSC model with carbon tax policy

The SBSC emissions are penalized with a cost of ξ (carbon tax) in Eq. (4.54) to minimize carbon emissions while the profit is maximized. The emissions sources in the SBSC have been formulated in Eq. (4.55) including emission emitted from switchgrass acquisition, bioethanol production, and switchgrass and bioethanol transportation.

$$Max\ Z_2^g = Z_1^g - \xi\ .Z_e^g \tag{4.54}$$

$$\begin{aligned} Z_e^g &= e_g^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^g + e_g^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^g Q_{ik}^g \\ &+ e_g^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^g + \sum_{k \in K} \sum_{r \in R} Q_{kr}^g \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^g Q_{ke}^g \\ &+ e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^g Q_{kr}^g \end{aligned} \tag{4.55}$$

Subject to constraints (4.43) – (4.53).

4.3.2.13. SBSC model with carbon cap policy

In this model, the carbon emissions in the SBSC are also restricted by an imposed carbon can cap (C_g^{cap}). The objective function is in Eq. (4.56) and the constraints are in Eqs. (4.43) – (4.53) and Eq. (4.57).

$$Max\ Z_3^g = Z_1^g \tag{4.56}$$

Subject to constraints (4.43) – (4.53) and

$$e_g^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^g + e_g^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^g Q_{ik}^g$$
$$+ e_g^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^g + \sum_{k \in K} \sum_{r \in R} Q_{kr}^g \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^g Q_{ke}^g \qquad (4.57)$$
$$+ e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^g Q_{kr}^g \leq C_g^{cap}$$

4.3.2.14. SBSC model with carbon cap-and-trade policy

The SBSC model with a carbon cap-and-trade policy is formulated in this section. The supply chain is allowed to emit more than the prescribed carbon cap (C_g^{cap}) but it would be penalized by p^+; however, the supply chain would be rewarded if emits less than the carbon cap.

$$Max\ Z_4^g = Z_1^g - (p^+ e_g^+ - p^- e_g^-) \qquad (4.58)$$

Subject to constraints (4.43) – (4.53) and

$$e_g^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^g + e_g^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^g Q_{ik}^g$$
$$+ e_g^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^g + \sum_{k \in K} \sum_{r \in R} Q_{kr}^g \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^g Q_{ke}^g \qquad (4.59)$$
$$+ e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^g Q_{kr}^g + e_g^- \leq C_g^{cap} + e_g^+$$

4.3.2.15. SBSC model with carbon offset policy

The SBSC model with carbon offset policy is presented in this section. p^0 denotes the carbon price per unit offset and e_g^+ denotes the number of carbon credits purchased in the SBSC.

$$Max\ Z_5^g = Z_1^g - p^0 e_g^+ \qquad (4.60)$$

Subject to constraints (4.43) – (4.53) and

$$
\begin{aligned}
e_g^{acquisition} \sum_{i \in I} \sum_{k \in K} Q_{ik}^g + e_g^{truck} \sum_{i \in I} \sum_{k \in K} d_{ik}^g Q_{ik}^g \\
+ e_g^{production} \left(\sum_{k \in K} \sum_{e \in E} Q_{ke}^g + \sum_{k \in K} \sum_{r \in R} Q_{kr}^g \right) + e_{be}^{truck} \sum_{k \in K} \sum_{e \in E} d_{ke}^g Q_{ke}^g \\
+ e_{be}^{rail} \sum_{k \in K} \sum_{r \in R} d_{kr}^g Q_{kr}^g \leq C_g^{cap} + e_g^+
\end{aligned}
\tag{4.61}
$$

4.4. Results and discussion

This section explores important observations related to the design and planning of first-generation and second-generation bioethanol supply chains' maximum profit, incentive payment, and carbon emissions related decisions while considering various carbon policies. To investigate the impact of incentive payments and carbon emission policies on the design of a biomass-to-bioethanol supply chain, a real case study is used.

4.4.1. Results without carbon policies consideration

The optimal cost elements of the three supply chains are presented in Figure 4.4. According to this figure, the existing CBSC has the lowest total cost compared to the proposed CSBSC and SBSC since there is no biorefinery technology transition cost for the corn-based supply chain, however, the biomass acquisition cost is higher for CBSC. The costs associated with corn-stover-based and switchgrass-based biorefineries (transition and production costs) have the cost-share among other cost elements (65% and 71% respectively) which emphasizes the importance of biorefineries in the bioethanol supply chains. Also, the results show that among CSBSC and SBSC, SBSC has a lower total cost mainly due to the lower supply cost of switchgrass.

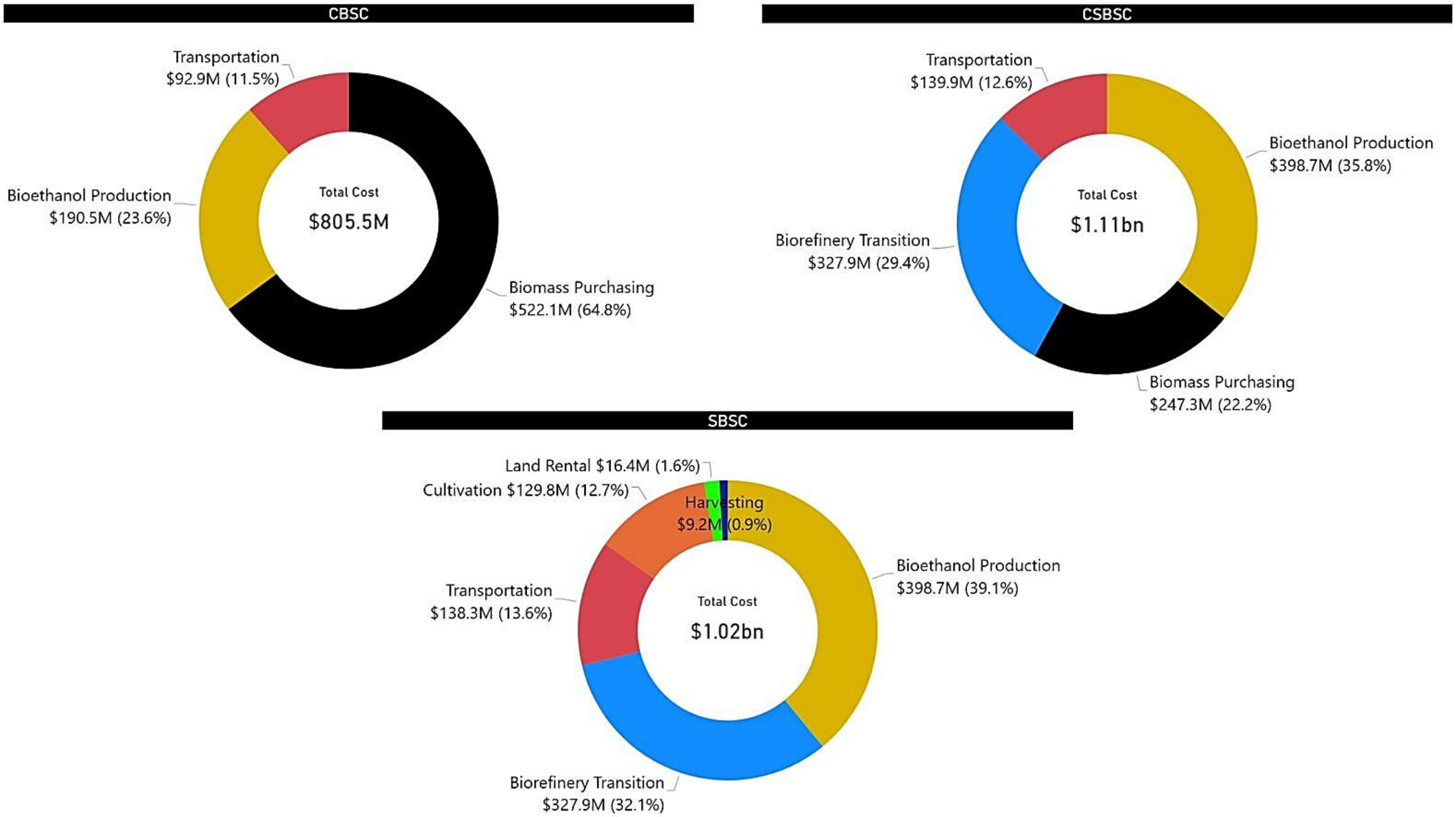


Figure 4.4. Total cost breakdown of CBSC, CSBSC, and SBSC

Various valuable information can be driven from Table 4.4 where it compares the maximum profit and emissions of the three supply chains and shows the minimum incentive to switch from CBSC to CSBSC or SBSC considering two different demand levels. The summation of the maximum capacity of all biorefineries (443 MGPY) is considered as the base scenario demand level, besides considering 75% of the base scenario demand level (332.25 MGPY) to analyze the supply chains when they are not at their full capacity levels. This allows the supply chains to be flexible in choosing optimal network designs. According to Table 4.4, the existing first-generation bioethanol supply chain makes higher profits and generates less emissions compared to second-generation bioethanol supply chains, making it a better option both economically and environmentally. Producing more emissions in second-generation bioethanol supply chains is due to two main reasons: (a) the emissions factor for transporting a ton of corn stover or switchgrass (second-generation biomass) is higher than the emissions factor for transporting corn bushels (firs-generation biomass) because the same amount of corn stover or switchgrass biomass occupies more space compared to corn due to the fact that corn stover and switchgrass are shipped in a bale form while corn is shipped in bushels, and (b) more corn stover or switchgrass biomass is needed compared to corn biomass feedstock to produce the same amount of bioethanol. However, as discussed before, using first-generation biomass brings various social issues which need to be addressed by switching to a second-generation one. In this case, switching to an SBSC is a better option both economically and environmentally than CSBSC which makes the switchgrass a better alternative for corn rather than corn stover to be utilized for bioethanol production. At the base demand level, to switch from CBSC to CSBSC and SBSC, a minimum incentive of \$0.7632/gallon and \$0.5517/gallon of bioethanol are required respectively to compensate the profit loss resulting from technology transition. Similarly, at the 75% of the base demand level, a minimum incentive of \$0.8462/gallon and \$0.6308/gallon are needed to switch from CBSC to CSBSC and SBSC. This indicates that SBSC requires fewer incentives compared to SCBSC to be paid by the government to first-generation bioethanol producers. Also, as the demand decreases, more incentive payments are required and vice versa.

Table 4.4. Maximum profit, minimum incentive to switch, and emissions of the three supply chains without carbon policies under two demand levels

Demand	Values	CBSC	CSBSC	SBSC
443 MGPY (base)	Maximum Profit (\$M)	348.96	10.88	104.54
	Incentive (\$/gallon)	-	0.7632	0.5517
	Profit with incentive (\$M)	-	348.96	348.96
	Emissions (M Kg CO_2e)	115.53	127.21	126.08
332.25 MGPY (75% base)	Maximum Profit (\$M)	263.68	(17.47)	54.09
	Incentive (\$/gallon)	-	0.8462	0.6308
	Profit with incentive (\$M)	-	263.68	263.68
	Emissions (M Kg CO_2e)	82.97	91.73	88.98

4.4.2. Results of carbon tax policy

Carbon tax policy impacts on profit, emissions, and required incentives are investigated in Table 4.5. For the rest of the paper, 75% of the base scenario demand level (332.25 MGPY) is considered for analysis, which permits the supply chains to be flexible in choosing optimal network designs. According to Table 4.5, the existing CBSC does not react to carbon taxes even when it stops making profits. This occurs because the network design of the CBSC is optimized and the supply chain is not able to find a better network design. The highest carbon tax that can be imposed on the current CBSC is \$3.178/Kg CO_2e, otherwise, the supply chain stops making profits. The minimum carbon tax that can be imposed on the CSBSC is \$1.329/Kg CO_2e to make the supply chain reacts and decreases its' emissions, however, it loses 698% of its' profit only to reduce its' emissions by 0.94% which is not reasonable and profitable. The same situation happens for the

SBSC where a carbon tax rate of $18.747/Kg CO_2e causes a decrease in emissions by 0.70%, however, the supply chain would not be profitable anymore (3084% profit loss).

Table 4.5. Carbon tax policy impacts on profit, emissions, and incentive

Carbon tax	Values	CBSC	CSBSC	SBSC
No carbon tax	Maximum Profit ($M)	$263.68	$(17.47)	$54.09
	Incentive ($/gallon)	-	$0.8462	$0.6308
	Profit with incentive ($M)	-	$263.68	$263.68
	Emissions (M Kg CO_2e)	82.97	91.73	88.98
$0 profit carbon tax	Maximum Profit ($M)	$0	$(17.47)	$0
	Carbon tax ($/Kg CO_2e)	$3.178	-	$0.608
	Emissions without carbon tax (M Kg CO_2e)	82.97	91.73	88.98
	Emissions with carbon tax (M Kg CO_2e)	82.97	-	88.98
Reactive carbon tax	Maximum Profit ($M)	No reaction	$(139.39)	$(1,614.04)
	Difference in profit (%)	No reaction	-698%	-3084%
	Carbon tax ($/Kg CO_2e)	No reaction	$1.329	$18.747
	Emissions without carbon tax (M Kg CO_2e)	82.97	91.73	88.98
	Emissions with carbon tax (M Kg CO_2e)	No reaction	90.87	88.36
	Difference in emissions (%)	No reaction	-0.94%	-0.70%
	Incentive ($/gallon)	-	$1.2131	$5.6515
	Profit with incentive ($M)	-	$263.68	$263.68

4.4.3. Results of carbon cap policy

In Table 4.6, the carbon cap policy impacts on profit, incentive payments, as well as emissions are investigated. When there is no carbon cap for emissions (base case), CBSC, CSBSC, and SBSC are producing 82.97, 91.73, and 88.98 M Kg CO_2e respectively. When a 1% reduction in emissions is desired (99% of base carbon cap), the CBSC model is unable to find a solution (network design) to address this target, however, CSBSC and SBSC could reduce their emissions by losing 59% and 98% of their maximum profits. In this case, higher incentives are also required to motivate corn-based bioethanol producers to switch. When a 2% reduction in emissions is imposed (98% of base carbon cap), both CBSC and SBSC are incapable of finding a feasible solution for their network, however, the CSBSC is able to find a solution to follow the new carbon cap by losing 299% of its' maximum profit which makes the supply chain not profitable. When a 3% or higher reduction in total emissions are targeted, there are no feasible network designs for all supply chains since they are optimally designed by the mathematical models.

Table 4.6. Carbon cap policy impacts on profit, emissions, and incentive

Carbon cap	Values	CBSC	CSBSC	SBSC
No carbon cap (base)	Maximum Profit ($M)	$263.68	$(17.47)	$54.09
	Incentive ($/gallon)	-	$0.8462	$0.6308
	Profit with incentive ($M)	-	$263.68	$263.68
	Emissions (M Kg CO_2e)	82.97	91.73	88.98
99% of base carbon cap	Maximum Profit ($M)	No Feasible Solution (NFS)	$(27.85)	$1.17
	Difference in profit (%)	NFS	-59%	-98%
	Emissions without carbon cap (M Kg CO_2e)	82.97	91.73	88.98
	Carbon cap (M Kg CO_2e)	82.14	90.81	88.09
	Emissions with carbon tax (M Kg CO_2e)	NFS	89.91	88.09
	Incentive ($/gallon)	-	$0.8774	$0.7901
	Profit with incentive ($M)	-	$263.68	$263.68
98% of base carbon cap	Maximum Profit ($M)	NFS	$(69.76)	NFS
	Difference in profit (%)	-	-299%	-
	Emissions without carbon cap (M Kg CO_2e)	82.97	91.73	88.98
	Carbon cap (M Kg CO_2e)	81.31	89.9	87.2
	Emissions with carbon tax (M Kg CO_2e)	NFS	89.71	NFS
	Incentive ($/gallon)	-	$1.0036	-
	Profit with incentive ($M)	-	$263.68	-
97% of base carbon cap	Maximum Profit ($M)	NFS	NFS	NFS
	Difference in profit (%)	-	-	-
	Emissions without carbon cap (M Kg CO_2e)	82.97	91.73	88.98
	Carbon cap (M Kg CO_2e)	80.48	88.98	86.31
	Emissions with carbon tax (M Kg CO_2e)	NFS	NFS	NFS
	Incentive ($/gallon)	-	-	-
	Profit with incentive ($M)	-	-	-

4.4.4. Results of carbon cap-and-trade policy

By implementing the carbon cap-and-trade policy, the supply chain has the flexibility to buy and sell carbon allowance in the carbon market. This policy can be executed by a regulatory body or with the help of a trading market for carbon emissions, in which supply chains are able to buy and sell the right to emit (Choudhary, Sarkar, Settur, & Tiwari, 2015). The CBSC performance under the cap-and-trade policy is presented in Figure 4.5. Although different carbon caps and buying/selling carbon price are imposed, the volume of emissions emitted in the CBSC is constant. Therefore, as the carbon cap decreases, the supply chain starts to buy carbon allowance to be operatable and hence the total profit keeps decreasing.

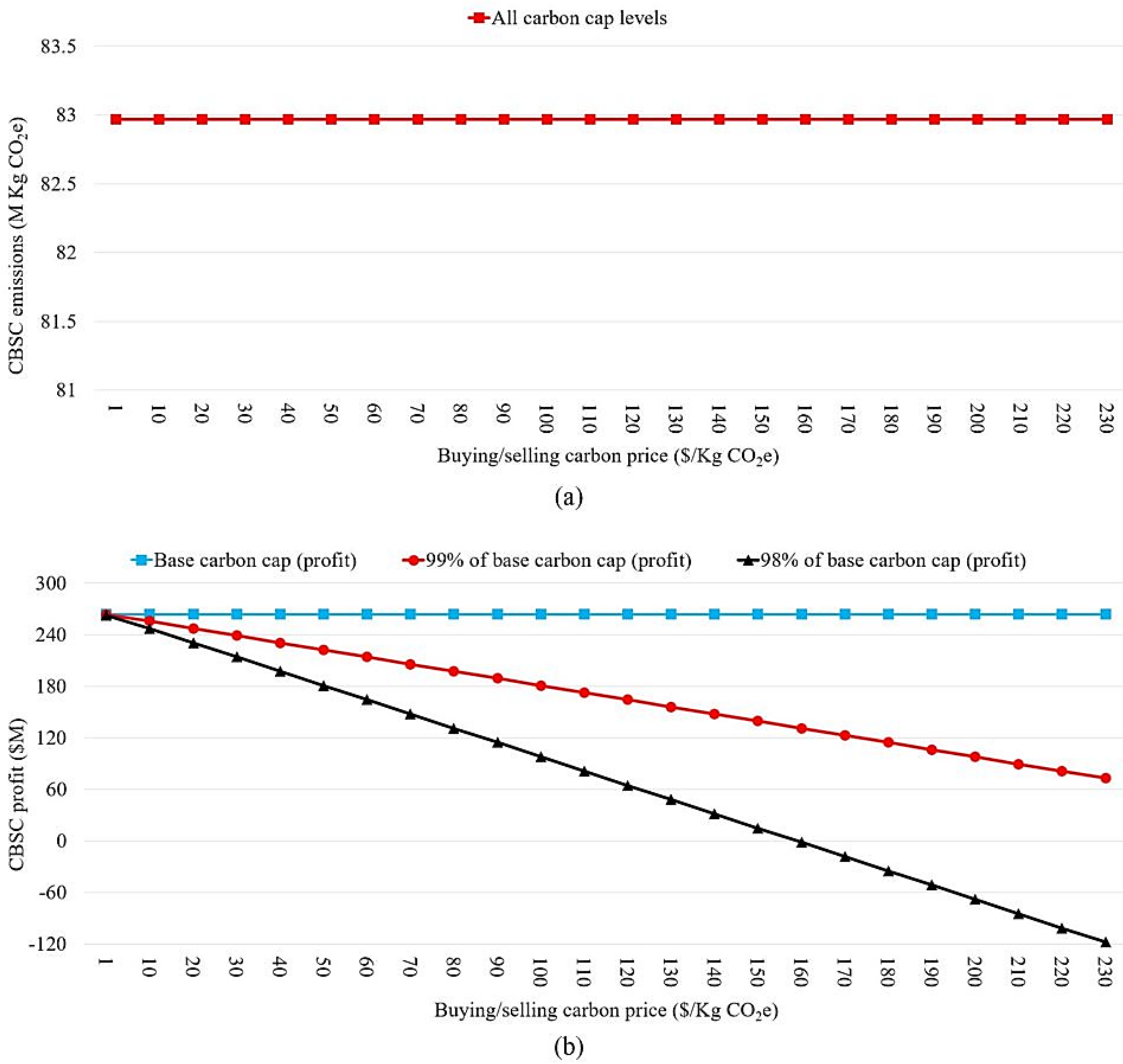
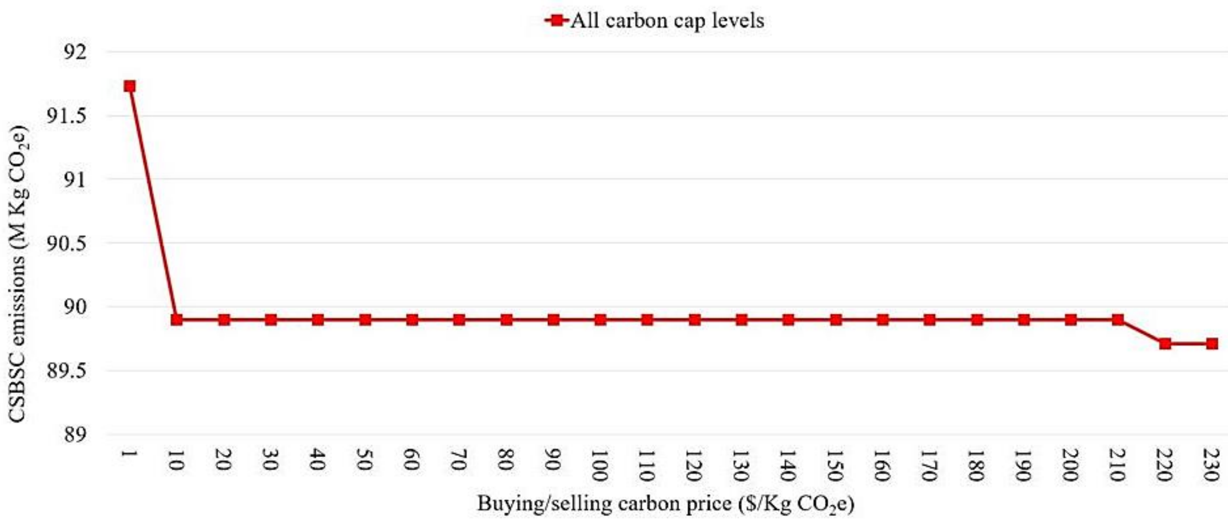


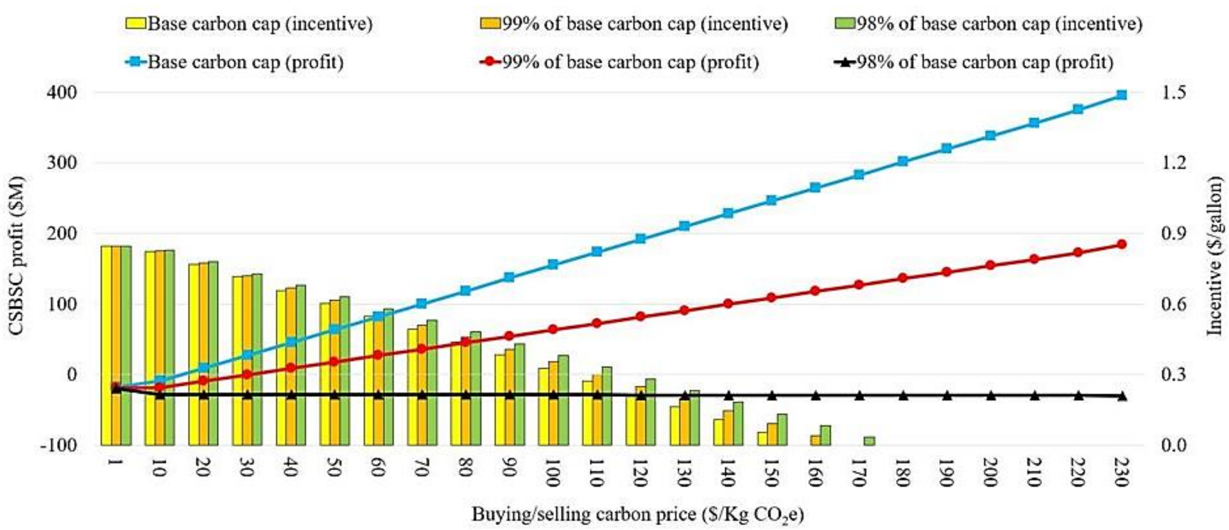
Figure 4.5. Emissions (a) and profit (b) of CBSC under the cap-and-trade policy

Next, we investigate the CSBSC performance under the cap-and-trade policy in Figure 4.6. Under all carbon cap levels, the supply chain produces the same volume of emissions. First, a decrease in supply chain's emissions happens (when the carbon market price is \$10/M Kg CO_2e) by choosing other suppliers and producers compared to the initial network design, then another drop in emissions occurs (when the carbon market price is \$220/M Kg CO_2e) when the supply chain adds a new biorefinery to the initial network design. The initial network design activates four biorefineris, namely Blue Flint Ethanol, Tharaldson Ethanol, Guarduan Hankinson, and Red Trail Energy, but when the carbon market price is \$10/M Kg CO_2e, the model replaces Red Trail Energy with Dakota Spirit AgEnergy. Also, when the carbon market price is \$220/M Kg CO_2e, all five biorefineries are actived to fulfill the model requirements.

When there is no carbon cap or 1% reduction in emissions (99% of base carbon cap) is imposed, as the buying/selling carbon price increases, the supply chain starts to be a carbon seller and hence the total profit increases; Also, less incentive is required to switch from using corn to corn stover for bioethanol production. When a 2% reduction in emissions (98% of base carbon cap) is imposed, the supply chain is not profitable and starts to buy carbon credits since it cannot reduce its' emissions by 2%.



(a)



(b)

Figure 4.6. Emissions (a), profit, and required incentive (b) of CSBSC under the cap-and-trade policy

Our next analysis focuses on SBSC performance under the cap-and-trade policy which is presented in Figure 4.7. The first decrease in supply chain's emissions occurs (when the carbon market price is \$20/M Kg CO_2e) by choosing other suppliers and producers compared to the initial network design, then a second drop in emissions happens (when the carbon market price is \$100/M Kg CO_2e) by adding a new biorefinery to the initial network design. When the carbon price increases, the total supply chain's profit increases when there is no carbon cap (base level) and when there is a 98% carbon cap level, the total supply chain's profit decreases and the supply chain is not profitable anymore. When a 1% reduction in emissions (99% of the base carbon cap) is desired, the supply chain profit does not change significantly as the carbon price increases. This would be a great policy both economically and environmentally since the supply chain remains profitable and a decrease in emissions is achieved.

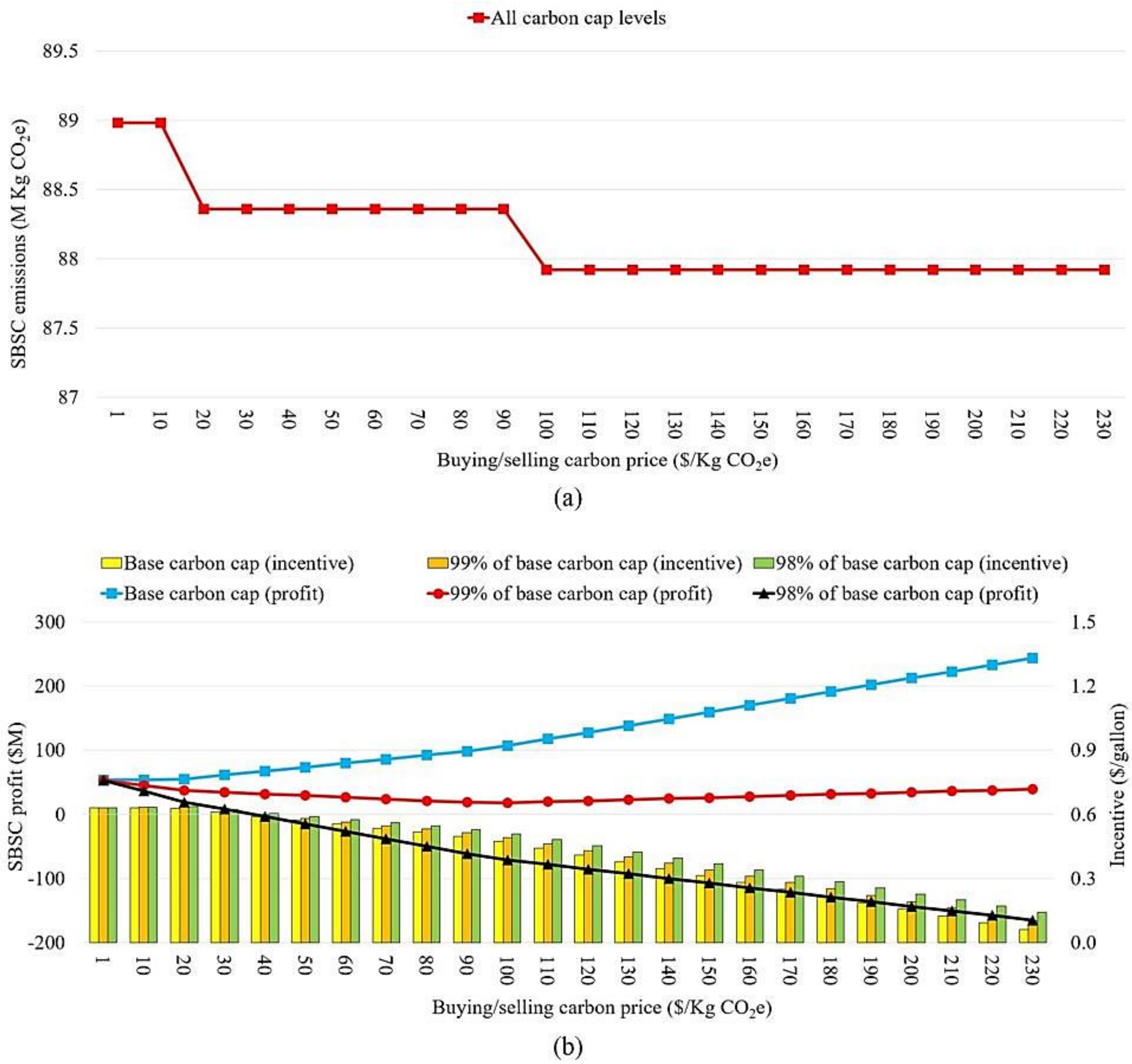


Figure 4.7. Emissions (a), profit, and required incentive (b) of SBSC under the cap-and-trade policy

4.4.5. Results of carbon offset policy

The CBSC, CSBSC, SBSC performances under carbon offset policy are shown in Figure 4.8, Figure 4.9, and Figure 4.10 respectively. In all three supply chains, when a reduction in emissions is targeted (1% or 2% reduction from the base carbon cap), the total profit of the supply chains reduces as the carbon offset price increases since they must buy extra carbon credits to address the reduced carbon cap. Similar to other carbon policies, the carbon offset policy does not have any impacts on CBSC emissions since the existing corn-based supply chain is not able to find an alternative network design to reduces its' emissions further. When the carbon offset price is at least \$10/M Kg CO_2e, the CSBSC starts to reduce its' emissions and SBSC acts similarly when at least a \$20/M Kg CO_2e is imposed. Unlike CSBSC, the SBSC is profitable when the carbon offset price is \$40/M Kg CO_2e or less and less incentive is required to compensate the profit loss resulting from switching from CBSC to SBSC.

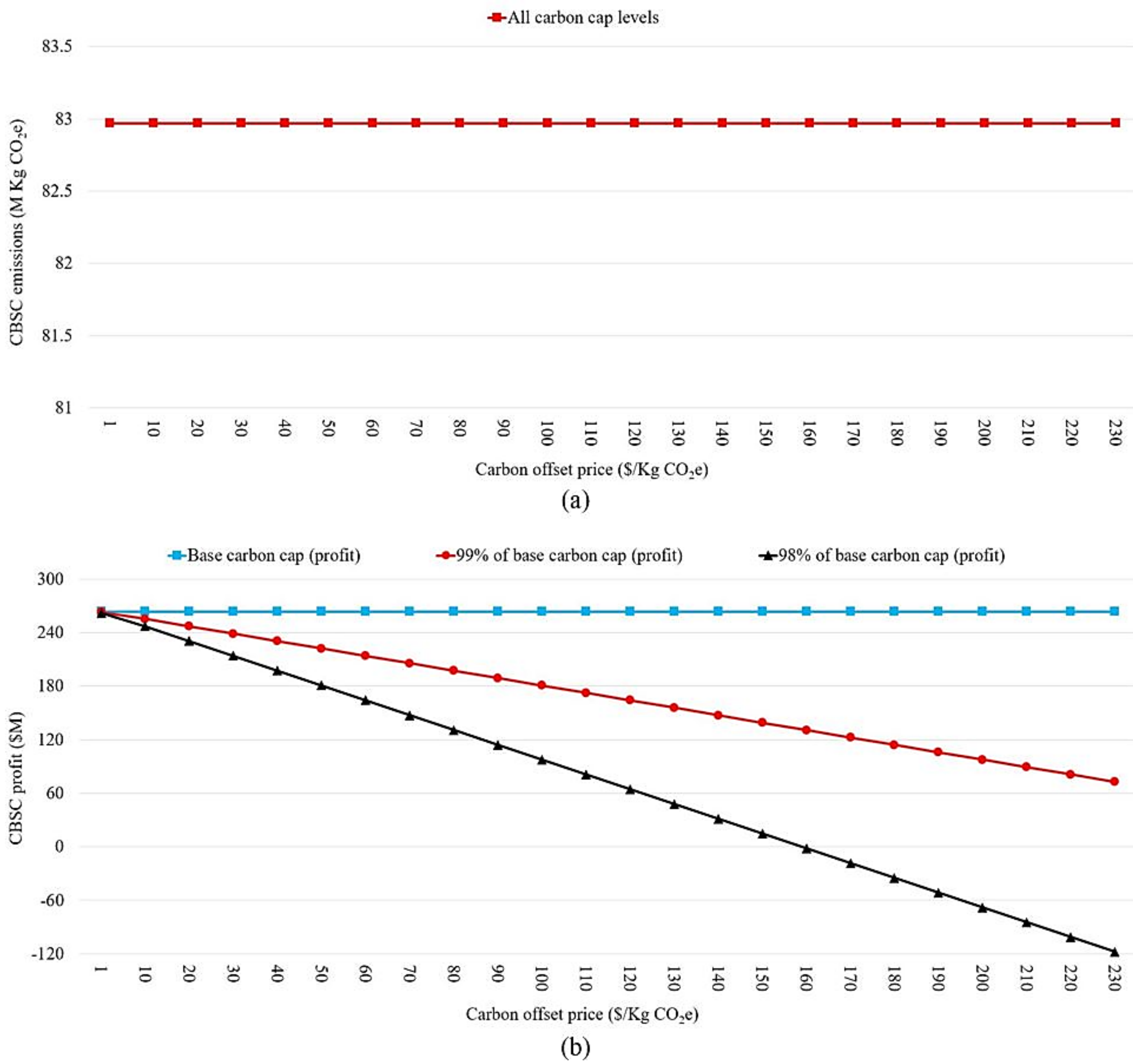


Figure 4.8. Emissions (a) and profit (b) of CBSC under carbon offset policy

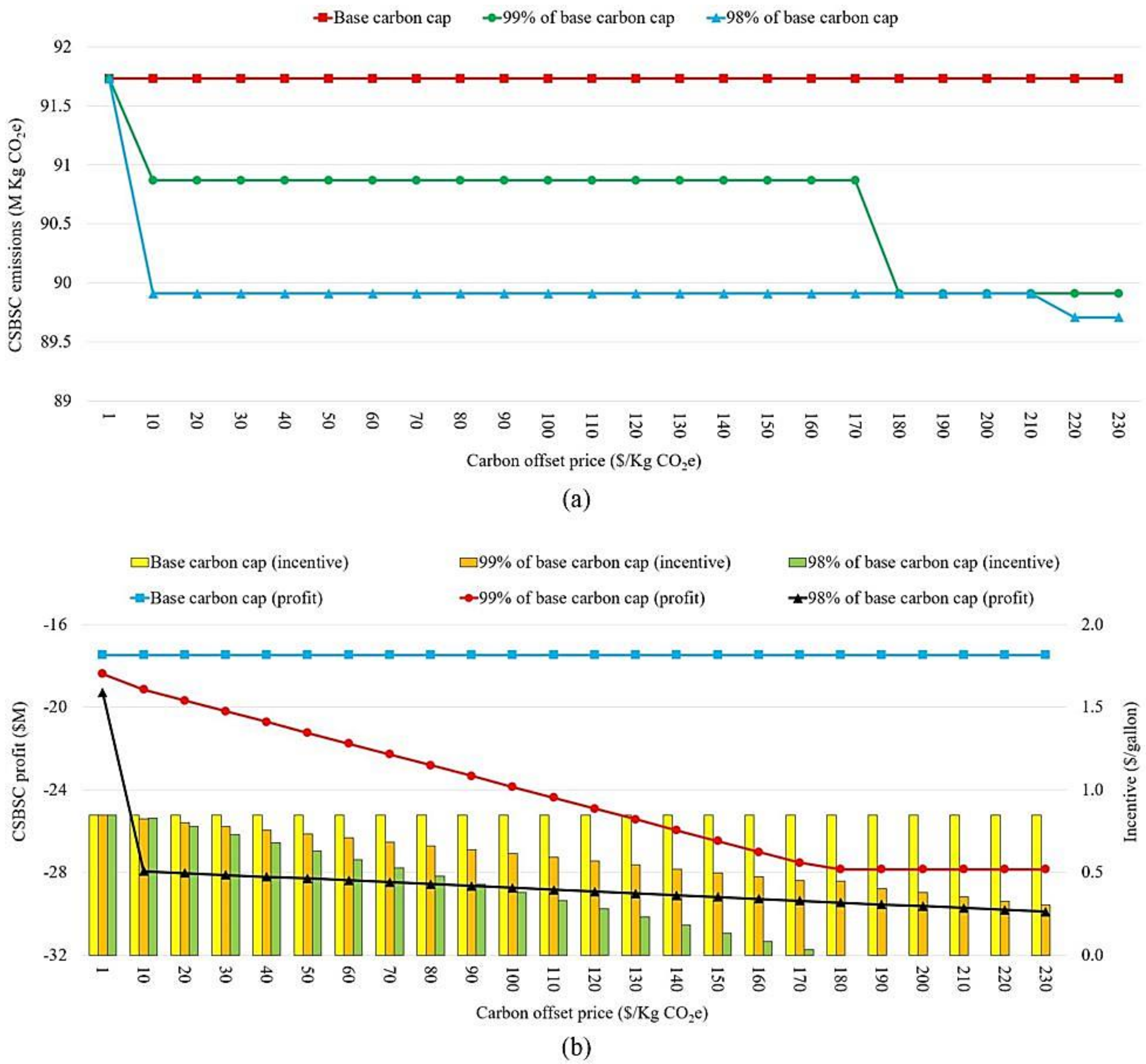
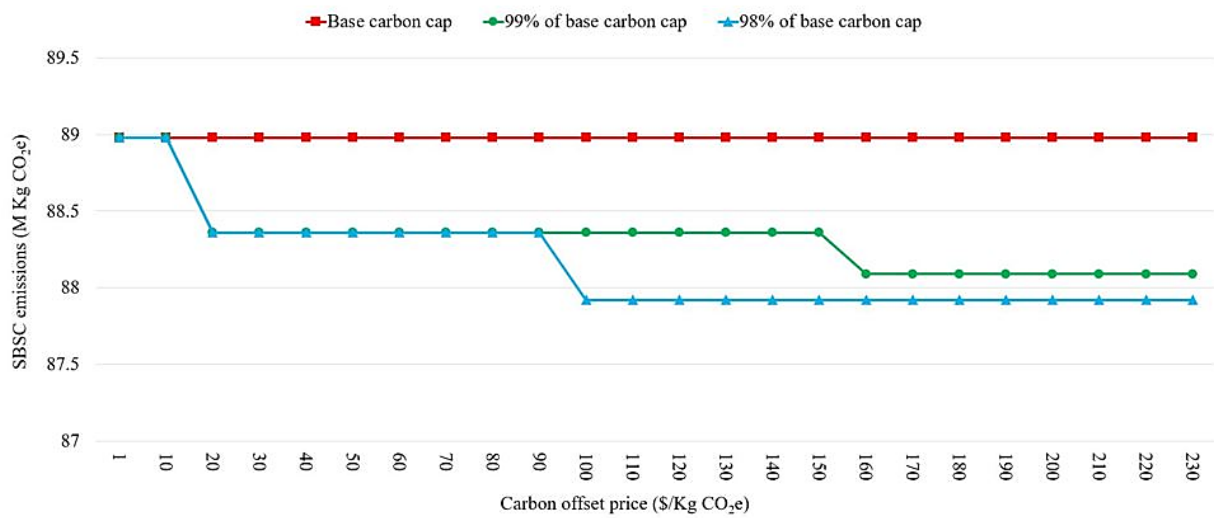
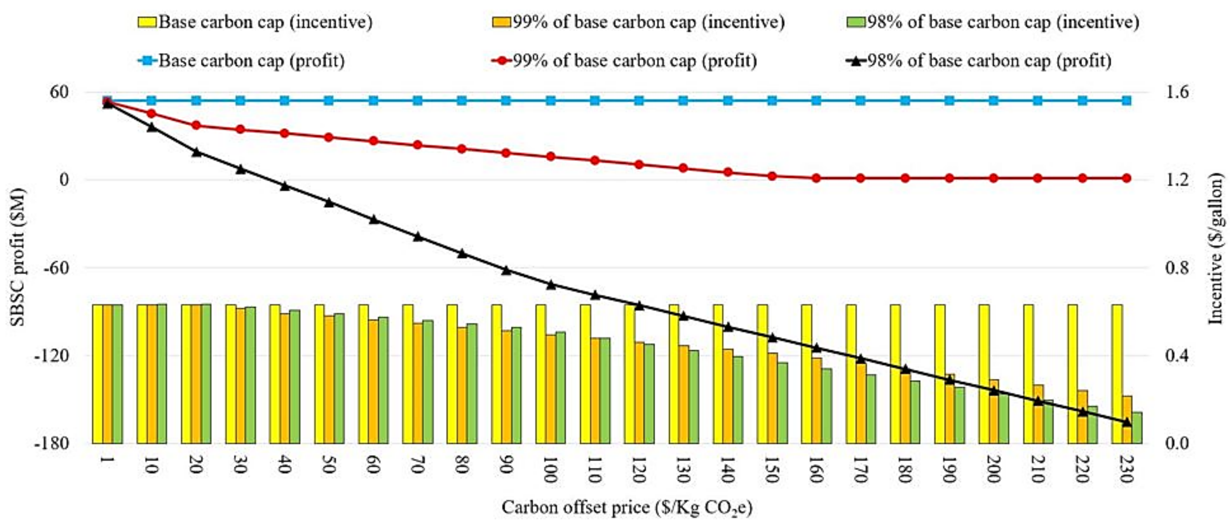


Figure 4.9. Emissions (a), profit, and required incentive (b) of CSBSC under carbon offset policy



(a)



(b)

Figure 4.7. Emissions (a), profit, and required incentive (b) of SBSC under carbon offset policy

4.4.6. Comparison of the four carbon policies

Comparison of CBSC, CSBSC, and SBSC performances under four carbon policies are investigated in Table 4.7. For the sake of comparison, when carbon tax policy is implemented, the reactive carbon tax for each supply chain is considered (see Table 4.5). When carbon cap, carbon cap-and-trade, and carbon offset policies are implemented, the carbon cap is set to 99% of the base carbon cap level of each supply chain. Also, for cap-and-trade, and carbon offset policies, the carbon buying/selling price and carbon offset price are set to \$20/M Kg CO_2e. Table 4.7 indicates that carbon cap-and-trade policy has the lowest profit loss and the highest reduction in emissions compared to other policies (except for SBSC when carbon cap policy is implemented; however, it is not reasonable to lose 66.5% of profit to decrease the emissions by 0.3% when carbon cap policy is compared to carbon cap-and-trade policy). Also, when carbon cap-and-trade policy is imposed on supply chains, less incentive is required to compensate for the profit loss resulting from switching from CBSC to CSBSC or SBSC. Therefore, the best carbon policy option is carbon cap-and-trade both economically and environmentally compared to other policies, followed by carbon offset, carbon cap, and carbon tax policies, respectively.

Table 4.7. Comparison of CBSC, CSBSC, and SBSC performances under four carbon policies

Carbon Policy	CBSC		CSBSC			SBSC		
	Profit change (%) [a]	Emissions change (%) [a]	Profit change (%) [a]	Emissions change (%) [a]	Incentive ($/gallon) [b]	Profit change (%) [a]	Emissions change (%) [a]	Incentive ($/gallon) [b]
Carbon tax	No reaction		-698%	-0.94%	1.2131	-3084%	-0.7%	5.6515
Carbon cap	No feasible solution		-59%	-1.98%	0.8774	-98%	-1%	0.7901
Carbon cap-and-trade	-6.3%	0%	46.1%	-1.98%	0.7728	-31.5%	-0.7%	0.6321
Carbon offset	-6.3%	0%	-7%	-0.94%	0.8029	-31.5%	-0.7%	0.6321

[a] Change in profit and emissions of the supply chains with and without carbon policies are compared for this analysis
[b] Required incentive to compensate the profit loss of switching from CBSC to CSBSC or SBSC when the same carbon policy is implemented for supply chains (except when carbon tax and carbon cap policies are implemented where the profit of CBSC without carbon policies consideration is considered for incentive calculation)

4.5. Conclusions

Increasing demand for energy, the food versus fuel debate, and market pressure for environmental sustainability are pushing bioethanol supply chain decision-makers to use non-edible second-generation biomass feedstocks while emitting fewer carbon emissions. At present, most bioethanol producers utilize edible first-generation biomass feedstocks, therefore motivating them to switch to a second-generation feedstock appears essential in this context from both economic and environmental perspectives. This study proposes quantitative optimization models to compare an existing first-generation (corn) BBSC with two proposed second-generation (corn stover and switchgrass) BBSCs to investigate which type of second-generation biomass is a better alternative to corn. To do so, this study takes the advantages of using incentives as a motivator to facilitate the transition of first-generation bioethanol producers to second-generation bioethanol production. The proposed models are developed further by exploring the impact of four different carbon policies including carbon tax, carbon cap, carbon cap-and-trade, and carbon offset on the supply chain decisions to restrict carbon emissions and address sustainability issues. To derive more realistic results and policies, the presented methodology is analyzed by applying a case study for the state of North Dakota. Our study aims to promote second-generation biomass utilization for bioethanol production while investigating the most effective carbon policy to protect the environment and better addressing sustainability issues. The results show that various policy insights can be derived from the proposed model. A summary of our main observations is given below:

Observation 1: The existing CBSC makes more profits and emits fewer emissions compared to CSBSC and SBSC which makes it a better option both economically and environmentally. However, it brings different social issues which are required to be addressed such as food versus fuel debates and higher food prices. In this case, switching to an SBSC is a better option both economically and environmentally than CSBSC which makes the switchgrass a better alternative for corn rather than corn stover to be utilized for bioethanol production.

Observation 2: At the base demand level (443 MGPY) and without any carbon policy consideration, to switch from CBSC to CSBSC and SBSC, a minimum incentive of $0.7632/gallon and $0.5517/gallon of bioethanol are required respectively to compensate the profit loss resulting from technology transition. Similarly, at the 75% of the base demand level, a minimum incentive of $0.8462/gallon and $0.6308/gallon are needed to switch from CBSC to CSBSC and SBSC. This indicates that SBSC requires fewer incentives compared to SCBSC to be paid by the government to corn-based bioethanol producers.

Observation 3: When the carbon tax policy is implemented, the existing CBSC does not react to carbon taxes even when it stops making profits. This occurs because the network design of the CBSC is optimized and the supply chain is not able to find a better network design. When a minimum carbon tax, which makes the supply chain reduces its' emissions, is imposed on the CSBSC and SBSC, the profit loss of the supply chains are significantly high (698% and 3084%, respectively) compared to emissions reductions (0.94% and 0.70%, respectively) which make the carbon tax policy an unsuitable carbon policy to reduce emissions.

Observation 4: Under carbon cap policy, when a 1% reduction in emissions is desired, the CBSC model is unable to find a solution (network design) to address this target, however, CSBSC and SBSC could reduce their emissions by losing 59% and 98% of their maximum profits. In this case, higher incentives are also required to motivate corn-based bioethanol producers to switch. When a 2% reduction in emissions is imposed, both CBSC and SBSC are incapable of finding a feasible solution for their network, however, the CSBSC is able to find a solution to follow the new carbon cap by losing 299% of its' maximum profit which makes the supply chain not profitable. When a 3% or higher reduction in total emissions are targeted, there are no feasible network designs for all supply chains. This specifies that when the supply chains are at their optimal network design, up to a 2% decrease in emissions is only possible.

Observation 5: By implementing the carbon cap-and-trade policy, although different carbon caps and buying/selling carbon prices are imposed, the volume of emissions emitted in the CBSC is constant. Under all carbon cap levels, the CSBSC emits the same volume of emissions. First, a decrease in supply chain emissions happens by choosing other suppliers and producers compared to the initial network design, then another drop in emissions occurs when the supply chain adds a new biorefinery to the initial network design. When there is no carbon cap or 1% reduction in emissions is imposed, as the buying/selling carbon price increases, the supply chain starts to be a carbon seller and hence the total profit increases. Also, less incentive is required to switch from using corn to corn stover for bioethanol production. When a 2% reduction in emissions is imposed, the supply chain is not profitable and starts to buy carbon credits since it can reduce its' emissions by 2%. For SBSC, when the carbon price increases, the total supply chain's profit increases when there is no carbon cap (base level) and when there is 98% carbon cap level (2% reduction in emissions), the total supply chain's profit decreases and the supply chain is not profitable anymore. When a 1% reduction in emissions (99% of base carbon cap) is desired, the supply chain profit does not change significantly as the carbon buying/selling price increases. This would be a great policy both economically and environmentally since the supply chain remains profitable and a decrease in emissions is achieved.

Observation 6: Under carbon offset policy, in all three supply chains, when a reduction in emissions is targeted, the total profit of the supply chains reduces as the carbon offset price increases since they must buy extra carbon credits to address the reduced carbon cap. Similar to other carbon policies, the carbon offset policy does not have any impacts on CBSC emissions since the existing corn-based supply chain is not able to find an alternative network design to reduces its' emissions further. When the carbon offset price is at least \$10/M Kg CO_2e, the CSBSC starts to reduce its' emissions and SBSC acts similarly when at least a \$20/M Kg CO_2e is imposed. Unlike CSBSC, the SBSC is profitable when the carbon offset price is \$40/M Kg CO_2e or less, and less incentive is required to compensate for the profit loss resulting from switching from CBSC to SBSC.

Observation 7: By comparing the performances of CBSC, CSBSC, and SBSC under four carbon policies, it can be concluded that carbon cap-and-trade policy has the lowest profit loss and the highest reduction in emissions compared to other policies. Also, when carbon cap-and-trade policy is imposed on supply chains, less incentive is required to compensate for the profit loss resulting from switching from CBSC to CSBSC or SBSC. Therefore, the best carbon policy option is carbon cap-and-trade both economically and environmentally compared to other policies, followed by carbon offset, carbon cap, and carbon tax policies, respectively. However, decision-makers may choose other policies depending on which biomass feedstock they want to replace corn with and whether their main objective is profit maximization or emissions minimization.

The proposed model can be valuable to the researchers, investors and decision-makers by choosing the proper second-generation biomass to replace corn with for bioethanol production, offering the right amount of incentives to bioethanol producers, and imposing the best carbon policy on bioethanol supply chains to curb carbon emissions. For future research, more complex biomass-to-bioethanol supply chain networks can be integrated with carbon policies and incentive payments. Also, considering multiple regions and areas would help the model to be more comprehensive. A similar analysis can be implemented for other second-generation biomass feedstocks where more than two species can be investigated as alternatives for corn. Another future research direction could be incorporating the impacts of risks, uncertainties, or societal objectives on the proposed model, which can be addressed through developing stochastic, risk-averse, or multi-objective mathematical modeling to broaden the scope of this study.

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APPENDIX A. SUPPLEMENTAL TABLES

The distances between supply zones, biorefineries, and demand zones ($d_{ik}, d_{ke}, d_{kr}, d_{ik}^{c}, d_{ke}^{c}, d_{kr}^{c}, d_{ik}^{s}, d_{ke}^{s}, d_{kr}^{s}, d_{ik}^{g}, d_{ke}^{g}, d_{kr}^{g}$) are available as an Excel file upon request.

Table A1. Values of input parameters used in Chapter 2

Parameter & Value	Description	Source
π = 2.21	Bioethanol selling price ($/gallon)	(Mohamed Abdul Ghani et al., 2018)
ρ = 0.9	Production cost of bioethanol at biorefinery ($/gallon)	(J. Zhang et al., 2013)
γ^s = 6	Transportation fixed cost of switchgrass via truck ($/ton)	(Sokhansanj et al., 2009)
η^s = 0.08	Transportation variable cost of switchgrass via truck ($/ton-mile)	(Sokhansanj et al., 2009)
γ^t = 0.01159	Transportation fixed cost of bioethanol via truck ($/gallon)	(Searcy, Flynn, Ghafoori, & Kumar, 2007)
η^t = 0.00024	Transportation variable cost of bioethanol via truck ($/gallon-mile)	(Searcy et al., 2007)
γ^r = 0.06183	Transportation fixed cost of bioethanol via rail ($/gallon)	(Kocoloski, Michael Griffin, & Scott Matthews, 2011)
η^r = 0.000069	Transportation variable cost of bioethanol via rail ($/gallon-mile)	(Kocoloski et al., 2011)
θ = 82.63	Bioethanol conversion rate from switchgrass (gallons/ton)	(J. Zhang et al., 2013)
б = 0.0085	Bioethanol co-product conversion rate (ton/gallon)	(Gonela, Zhang, Osmani, et al., 2015)
φ = 134	Bioethanol co-product selling price ($/ton)	Assumption
CAP = 150,000,000	Capacity of biorefineries (gallons)	(Kou & Zhao, 2011)
f^b = $101,145,437	Annualized fixed capital cost for opening a biorefinery ($)	(Osmani & Zhang, 2013) (estimate)
ACE = 0.00015	Emission factor of switchgrass acquisition (kg CO_2e/ton)	(You & Wang, 2011) (estimate)
STE = 0.1103	Emission factor of transporting switchgrass via truck (kg CO_2e/ton-mile)	(You & Wang, 2011) (estimate)
PRE = 0.000008	Emission factor of producing bioethanol from switchgrass (kg CO_2e/gallon)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
BTE = 0.0005624	Emission factor of transporting bioethanol via truck (kg CO_2e/gallon-mile)	(F. Zhang, Johnson, & Wang, 2015) (estimate)
BRE = 0.0001135	Emission factor of transporting bioethanol via rail (kg CO_2e/gallon-mile)	(F. Zhang et al., 2015) (estimate)
λ = 16.32	Mean yield rate of switchgrass (ton/ha)	(J. Zhang et al., 2013) (estimate)
v = 395	Cultivation cost of switchgrass ($/ha)	(J. Zhang et al., 2013)
h = 27.9	Harvesting cost of (square bale) switchgrass ($/ha)	(Larson, Yu, English, Mooney, & Wang, 2010)
ACG = 228.95	Energy consumed during switchgrass acquisition (MJ/ton)	(Gonela, Zhang, & Osmani, 2015) (estimate)
STG = 171.97	Energy consumed during transporting switchgrass via truck (MJ/ton-mile)	(Gonela, Zhang, & Osmani, 2015) (estimate)
PRG = 13.82	Energy consumed during bioethanol production (MJ/gal)	(Gonela, Zhang, & Osmani, 2015) (estimate)
BTG = 1.58	Energy consumed during transporting bioethanol via truck (MJ/gallon-mile)	(Gonela, Zhang, & Osmani, 2015) (estimate)
BRG = 0.00001279	Energy consumed during transporting bioethanol via rail (MJ/gallon-mile)	(F. Zhang et al., 2015) (estimate)
ξ = 0.1231 (Regular)	Carbon tax / Environmental cost factor of emissions ($/kg CO_2e)	(Nguyen & Gheewala, 2008; X-Rates, 2018) (estimate)
ψ = 0.0215 (Regular)	Energy cost factor of fossil fuel consumed ($/MJ)	(E.I.A., 2018; F. Zhang et al., 2017) (estimate)

Table A2. Values of input parameters used in Chapter 3

Parameter & Value	Description	Source
α^c = 2.9	Selling price of corn ($/bushel)	(State Agriculture Overview, 2018)
α^s = 45	Selling price of corn stover ($/ton)	(Maung & Gustafson, 2011)
π = 2.21	Bioethanol selling price ($/gallon)	(Mohamed Abdul Ghani et al., 2018)
φ^c = 134	Corn co-product (DDG) selling price ($/ton)	(Kennedy, 2018)
φ^s = 134	Corn stover co-product (Lignin pallet) selling price ($/ton)	Assumption
ρ^c = 0.43	Production cost of bioethanol at corn biorefinery ($/gallon)	(Awudu & Zhang, 2013)
ρ^s = 0.9	Production cost of bioethanol at corn stover biorefinery ($/gallon)	(J. Zhang et al., 2013)
γ^c = 0.000857	Transportation fixed cost of corn via truck ($/bushel)	(Gonela, Zhang, Osmani, et al., 2015)
η^c = 0.00146	Transportation variable cost of corn via truck ($/bushel-mile)	(Gonela, Zhang, Osmani, et al., 2015)
γ^s = 6	Transportation fixed cost of corn stover via truck ($/ton)	(Sokhansanj et al., 2009)
η^s = 0.08	Transportation variable cost of corn stover via truck ($/ton-mile)	(Sokhansanj et al., 2009)
γ^t = 0.01159	Transportation fixed cost of bioethanol via truck ($/gallon)	(Searcy et al., 2007)
η^t = 0.00024	Transportation variable cost of bioethanol via truck ($/gallon-mile)	(Searcy et al., 2007)
γ^r = 0.06183	Transportation fixed cost of bioethanol via rail ($/gallon)	(Kocoloski et al., 2011)
η^r = 0.000069	Transportation variable cost of bioethanol via rail ($/gallon-mile)	(Kocoloski et al., 2011)
θ^c = 2.8	Bioethanol conversion rate from corn (gallons/bushel)	(ND Studies Energy Curriculum, 2019)
6^c = 0.009	Corn co-product (DDG) conversion rate (ton/gallon)	(ND Studies Energy Curriculum, 2019)
θ^s = 80.6	Bioethanol conversion rate from corn stover (gallons/ton)	(Xie, Huang, & Eksioglu, 2014)
6^s = 0.0085	Corn stover co-product (Lignin pallet) conversion rate (ton/gallon)	(Gonela, Zhang, Osmani, et al., 2015)
e_s^{truck} = 0.1103	Emission factor of transporting corn stover via truck (Kg CO_2e/ton-mile)	(You & Wang, 2011) (estimate)
e_c^{truck} = 0.0028	Emission factor of transporting corn via truck (Kg CO_2e/bushel-mile)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
e_{be}^{truck} = 0.0005624	Emission factor of transporting bioethanol via truck (Kg CO_2e/gallon-mile)	(F. Zhang et al., 2015) (estimate)
e_{be}^{rail} = 0.0001135	Emission factor of transporting bioethanol via rail (Kg CO_2e/gallon-mile)	(F. Zhang et al., 2015) (estimate)
$e_c^{\text{acquisition}}$ = 0.000004	Emission factor of corn acquisition (Kg CO_2e/bushel)	(You & Wang, 2011) (estimate)
$e_s^{\text{acquisition}}$ = 0.00015	Emission factor of corn stover acquisition (Kg CO_2e/ton)	(You & Wang, 2011) (estimate)
$e_c^{production}$ = 0.000023	Emission factor of producing bioethanol from corn (Kg CO_2e/gallon)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
$e_s^{production}$ = 0.000008	Emission factor of producing bioethanol from corn stover (Kg CO_2e/gallon)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
ξ = 0.1231 (Regular)	Carbon tax / Environmental cost factor of emissions ($/Kg CO_2e)	(Nguyen & Gheewala, 2008) (estimate)

Table A3. Values of input parameters used in Chapter 4

Parameter & Value	Description	Source
α^c = 3.3	Selling price of corn ($/bushel)	(NASS Statistics by State, 2019)
α^s = 45	Selling price of corn stover ($/ton)	(Maung & Gustafson, 2011)
π = 1.4	Bioethanol selling price ($/gallon)	(Johanns, 2019)
ρ^c = 0.43	Production cost of bioethanol at corn biorefinery ($/gallon)	(Awudu & Zhang, 2013)
ρ^s = 0.9	Production cost of bioethanol at corn stover biorefinery ($/gallon)	(J. Zhang et al., 2013)
ρ^g = 0.9	Production cost of bioethanol at switchgrass biorefinery ($/gallon)	(J. Zhang et al., 2013)
γ^c = 0.000857	Transportation fixed cost of corn via truck ($/bushel)	(Gonela, Zhang, Osmani, et al., 2015)
η^c = 0.00146	Transportation variable cost of corn via truck ($/bushel-mile)	(Gonela, Zhang, Osmani, et al., 2015)
γ^s = 6	Transportation fixed cost of corn stover via truck ($/ton)	(Sokhansanj et al., 2009)
η^s = 0.08	Transportation variable cost of corn stover via truck ($/ton-mile)	(Sokhansanj et al., 2009)
γ^g = 6	Transportation fixed cost of switchgrass via truck ($/ton)	(Sokhansanj et al., 2009)
η^g = 0.08	Transportation variable cost of switchgrass via truck ($/ton-mile)	(Sokhansanj et al., 2009)
γ^t = 0.01159	Transportation fixed cost of bioethanol via truck ($/gallon)	(Searcy et al., 2007)
η^t = 0.00024	Transportation variable cost of bioethanol via truck ($/gallon-mile)	(Searcy et al., 2007)
γ^r = 0.06183	Transportation fixed cost of bioethanol via rail ($/gallon)	(Kocoloski et al., 2011)
η^r = 0.000069	Transportation variable cost of bioethanol via rail ($/gallon-mile)	(Kocoloski et al., 2011)
θ^c = 2.8	Bioethanol conversion rate from corn (gallons/bushel)	(ND Studies Energy Curriculum, 2019)
6^c = 0.009	Corn-based bioethanol co-product (DDG) conversion rate (ton/gallon)	(ND Studies Energy Curriculum, 2019)
θ^s = 80.6	Bioethanol conversion rate from corn stover (gallons/ton)	(Xie et al., 2014)
6^s = 0.0085	Corn-stover-based bioethanol co-product conversion rate (ton/gallon)	(Gonela, Zhang, Osmani, et al., 2015)
θ^g = 82.63	Bioethanol conversion rate from switchgrass (gallons/ton)	(J. Zhang et al., 2013)
6^g = 0.0085	Switchgrass-based bioethanol co-product conversion rate (ton/gallon)	(Gonela, Zhang, Osmani, et al., 2015)
φ^c = 134	Corn-based bioethanol co-product (DDG) selling price ($/ton)	(Kennedy, 2018)
φ^s = 134	Corn-stover-based bioethanol co-product (lignin pallet) selling price ($/ton)	Assumption
φ^g = 134	Switchgrass-based bioethanol co-product (lignin pallet) selling price ($/ton)	Assumption
e_c^{truck} = 0.0028	Emission factor of transporting corn via truck (kg CO_2e/bushel-mile)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
e_s^{truck} = 0.1103	Emission factor of transporting corn stover via truck (kg CO_2e/ton-mile)	(You & Wang, 2011) (estimate)

Table A3. Values of input parameters used in Chapter 4 (continued)

Parameter & Value	Description	Source
e_{be}^{truck} = 0.0005624	Emission factor of transporting bioethanol via truck (kg CO_2e/gallon-mile)	(F. Zhang et al., 2015) (estimate)
e_{be}^{rail} = 0.0001135	Emission factor of transporting bioethanol via rail (kg CO_2e/gallon-mile)	(F. Zhang et al., 2015) (estimate)
$e_c^{\text{acquisition}}$ = 0.000004	Emission factor of corn acquisition (kg CO_2e/bushel)	(You & Wang, 2011) (estimate)
$e_s^{\text{acquisition}}$ = 0.00015	Emission factor of corn stover acquisition (kg CO_2e/ton)	(You & Wang, 2011) (estimate)
$e_g^{\text{acquisition}}$ = 0.00015	Emission factor of switchgrass acquisition (kg CO_2e/ton)	(You & Wang, 2011) (estimate)
$e_c^{production}$ = 0.000023	Emission factor of producing bioethanol from corn (kg CO_2e/gallon)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
$e_s^{production}$ = 0.000008	Emission factor of producing bioethanol from corn stover (kg CO_2e/gallon)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
$e_g^{production}$ = 0.000008	Emission factor of producing bioethanol from switchgrass (kg CO_2e/gallon)	(Gonela, Zhang, Osmani, et al., 2015) (estimate)
λ_g = 16.32	Mean yield rate of switchgrass (ton/ha)	(J. Zhang et al., 2013) (estimate)
v_g = 395	Cultivation cost of switchgrass ($/ha)	(J. Zhang et al., 2013)
h_g = 27.9	Harvesting cost of (square bale) switchgrass ($/ha)	(Larson et al., 2010)

APPENDIX B. ADDITIONAL INFORMATION

Table B1. Conversion factors

1 mile = 1.609 km
1 ton = 0.907 metric ton
1 gallon = 3.785 liter
1 corn bushel = 0.028 ton of corn