THREE ESSAYS ON SUSTAINABILITY OF TRANSPORTATION AND SUPPLY CHAIN

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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

Climate change has emerged as one of the most problematic issues and key global threats to mankind, and sustainability has become an important issue for any organizations. Therefore, managing supply chains in a more sustainable way has become an increasing concern for many businesses across a wide range of companies around the world. Designing efficient and effective supply chains improves overall environmental performance in business operations and is essential to not only mitigate climate change, but also to benefit human life and environment.

The objective of this dissertation is to address issues in sustainability of transportation and supply chains with three essays focusing on three aspects - measure, manage, and mitigate - that contribute to the practice and literature of sustainable transportation and supply chain.

Chapter Two of this dissertation utilizes slack-based date envelopment analysis to form an environmental efficiency index comprising various sustainability indicators in transportation sector. This index may function as a decision-making tool for transportation planners and practitioners to compare sustainability performance of U.S. states, to benchmark sustainability performance, and also to develop carbon emission reduction strategies.

Chapter Three of this dissertation adopts multimodal transportation to formulate the cost-effective strategies for managing a switchgrass-based biofuel supply chain. This study captures the benefit of a modal shift in designing the biofuel supply chain network; thus, practitioners who want to plan for multimodal transportation of biofuel can learn its practical relevance.

Chapter Four of this dissertation address greening the biomass supply chain for animal manure by formulating mathematical model for design and management of biomass to a biogas supply chain, including anaerobic digestion as a source of renewable energy production. This

study handled waste management issues by incorporating carbon policy into the biomass supply chain, with due consideration accorded to both monetary and environmental factors.

Overall, the research outcome will provide practitioners and researchers with scientific information and tools that will enable them to become better stewards by virtue of healthy and sustainable development and practices in transportation and supply chain.

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The experience in UGPTI has expanded my knowledge of various “Sustainability” - and “Transportation and Logistics” - related topics through project and has given me a platform to perform high-quality research and analysis. Dr. Denver Tolliver must be mentioned for his development of UGPTI and the unending financial and non-financial support I received from him while I was involved with the UGPTI.

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DEDICATION

This work is dedicated to my father, mother, and wife for all of the sacrifices they made for me to accomplish my dream.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

SSCM ..... Sustainable Supply Chain Management

DEA..... Data Envelopment Analysis

DMU ..... Decision Making Unit

EE..... Environmental Efficiency

MILP ..... Mixed Integer Linear Programming

GIS ..... Geographic Information System

ADS..... Anaerobic Digester System

EPA ..... Environmental Protection Agency

USDA..... United States Department of Agriculture

EIA ..... Energy Information Administration

CHAPTER 1. INTRODUCTION

1.1. Background and Motivation

With globalization, there has been tremendous growth in networks of suppliers, distributors, and transportation providers, where sustainable supply chain management (SSCM) must be considered for not only maximizing the financial performance but also for minimizing adverse impacts on business activities. It is inevitable that sustainability issues in business will arise because of various interactions of supply chain activities (Lee & Wu, 2014). Because climate change has emerged as one of the biggest problematic issues and key drivers of global threats for mankind, sustainability has become an important issue for any organizations. Thus, successful sustainable development practices will significantly reduce energy consumption or other waste, resulting in a positive impact on the bottom line as well.

In this regard, the term 'sustainable development' has multi-faceted meaning including the implications for social responsibility, the environment, the economy, and business ethics. It is defined as "the development meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987). Recently, sustainable development movement focused on the environmental aspects of sustainability because of issues of global warming resulting from carbon dioxide (CO_2) and other greenhouse gases (GHGs) (e.g. methane (CH_4), nitrous oxide (N_2O), and hydrofluorocarbons (HFCs)), and there is still ongoing development worldwide with much attention on sustainability.

Therefore, managing supply chains in a more sustainable way has become an increasing concern for many businesses across a wide range of companies around the world. Designing efficient and effective SCM of material and information, and capital flow associated with raw material extraction, production, processes, and distribution of products or services to meet

stakeholder's requirements are key goals to achieve a sustainable supply chain (SSC) (Ahi & Searcy, 2013). Especially, the distribution stage is among the most important components across supply chain activities as it handles raw material, intermediate product, and finished goods from origin to destination. Without transportation, input cannot arrive to the production stage, nor can finished product reach the final stage (Nagurney, Liu, & Woolley, 2007). Therefore, without a well-developed distribution/transportation system, a supply chain cannot perform successfully.

Supply chain systems are usually complex in nature due to a variety of suppliers, demands, transport modes, technologies, and fuels (Connolly, Mathiesen, & Ridjan, 2014), and they highly correlate with contextual socio-economic and environmental factors (Javid, Nejat, & Hayhoe, 2014). Thus, SSC planning that improves overall environmental performance in business operations is essential to not only mitigate climate change, but also to benefit human life and environment.

The identification of the most influential enabler for SSC is the transportation sector. Transportation is a fundamental part of the U.S. economy and society, which also has a great role in supply chains at the local and global levels. Thus, it requires critical emphasis on innovative and progressive infrastructure planning of transportation to meet the sustainable development goal. In the United States, the transportation sector accounts for 26% of GHG emissions, making it the second largest GHG emissions contributor (U.S. EPA, 2014). Freight, especially trucking (road transportation) among different transport modes has experienced fastest growth in the U.S, which itself account for over 60% of total GHG emissions due to increasing supply chain activities in the industry (Merkert & Hensher, 2011). Also, the transportation sector uses a tremendous amount of fossil fuels (e.g. petroleum, natural gas), which are dominant source of transportation fuel in the U.S. About 92% of the total energy consumption in this sector was

from gasoline and diesel in 2015 and only 5% was from biofuels such as ethanol and biodiesel (U.S. EIA, 2014). This has a negative impact on the environment because of increasing GHG emissions and high dependence on fossil fuel energy may fluctuate oil prices as well as supply and demand for energy. This highlights the significant impact on policy formulation across the entire supply chain to reduce CO_2 emissions (Javid et al., 2014).

Therefore, green transportation practices associated with product delivery are a key part in any business, which is directly related with SSCM. With the globalization of supply chains, there has been a substantial increase in transportation distances in supply chain networks, which resulted in more carbon emissions and energy consumption. Therefore, many practitioners are increasingly aware of the importance of improving performance in terms of environmental accountability. This includes selection of sustainable modes, consolidation practices, location decisions, distribution, production, and even for the end of life of the product (Carter & Easton, 2011). Therefore, effective and efficient design of sustainable supply chains is far more important to improving economic and environmental conditions, and the bottom line (Elhedhli & Merrick, 2012).

One mitigation strategy for better SSCM of transportation is switching to renewable energy based sources that can be used as transportation fuel. The Energy Policy Act (EPA) of the U.S government encourages use of alternative fuel sources including biofuels, hydrogen, and electricity that are extracted from renewable energy sources which are less CO_2 intensity. This has resulted in a large increase in the use of renewable fuel in the U.S (C2ES, 2012). Other opportunities and several different strategies to reduce GHG emissions associated with transportation have been considered such as using advanced vehicle technologies and material toward fuel-efficient vehicles (Vanek & Morlok, 2000). In recent years, many transportation

sectors utilize bioethanol, which is one type of biofuel (Zhang, Osmani, Awudu, & Gonela, 2013). Also, biogas is already proven as transportation fuel. Due to state and federal regulations and policies, the production and consumption of biofuels has dramatically increased since 2005 (C2ES, 2012).

Biofuel or biogas can be produced from biomass such as corn, wheat, sugarcane, and soy bean, which are known as first-generation biomass and are dominant sources for biofuel in the U.S. However, many companies in the U.S are developing advanced second-generation renewable energy using non-food feedstock such as corn stover, woody residue, switchgrass, and municipal and animal waste. because of their advantages over first-generation based biofuel, including food security, and carbon emission. Utilizing renewable energy that is produced from second - generation biomass, provides economic, environmental, and societal benefits to the SSCs.

Another consideration for sustainability is modal shifting to more sustainable transport modes such as rail or ship. A modal shift occurs when there is a competitive advantage of one mode over another over the same route or market (Rodrigue, Comtois, & Slack, 2016). The competitive advantages behind a modal shift may include costs, capacity, time, reliability, and environmental concern. For example, in a biofuel supply chain, time is a very important factor to meet the demand requirement and a modal shift will take place if the other transport mode provides a time improvement. Choosing optimal transportation modes to deliver products to ensure economic and environmental performance is difficult for decision makers because of geographic dispersion of supply and demand. The choice of transportation mode, and consequently transportation distances, greatly impacts the economic and environmental competitiveness (Wakeley, Hendrickson, Griffin, & Matthews, 2009).

1.2. Research Objectives

It is important to understand an overview of the sustainability of the transportation and supply chain system. By analyzing and measuring, we can find what causes environmental impact and how we can possibly reduce emissions and energy use, which is a byproduct from all kinds of economic activity. In the current business environment, global warming and climate change critical issues that all the stakeholders must support for mid and long run impact on corporate sustainability. Therefore, it is worthwhile for researchers and practitioners to consider the environmental impact on planning and managing sustainability in transportation and supply chains. Thus, a sustainable transportation and supply chain system that ensures strong costs and environmental and societal benefit is very important to facilitate sustainable development for the next generation.

Therefore, it is crucial to develop robust assessment tools to compile a sustainability performance metric in a scientific way so that decision makers can compare the results and capture benchmarks to improve their environmental performance. Also, establishing strategic and tactical supply chain planning to minimize adverse effects and maximize beneficial effects are also critical in the decision-making process toward a SSC. However, it is a challenging and difficult job to measure sustainability in business because of the complex involvement of practitioners, differences in knowledge and understanding of the problem, lack of applicable tools and limitations in transportation and supply chain planning, and the many decision-making processes involved.

1.3. Research Contributions and Structure

To address sustainability in transportation and supply chains, I made three major research contributions. These three studies will provide my original contribution to the development of sustainability for the U.S. transportation system followed by designing a multimodal biofuel supply chain and, more importantly, the general research domain of green supply chain network design under carbon policies. The three essays in my dissertation are as follows:

- *Environmental efficiency assessment of U.S. transport sector: a slack-based data envelopment analysis approach* will measure environmental sustainability performance of the U.S. transportation sector. To be specific, a metric called environmental efficiency is developed with consideration of economic, environmental, and social factors using Slack-based Measurement Data Envelopment Analysis (SBM-DEA). From this study, we can answer the following research questions:

  1. Is the U.S transportation system environmentally sustainable?
  2. What are the potential savings of carbon emissions? If so, what would be the most influential factors to improve sustainability of the U.S transportation system?
  3. What are the best practices to enhance sustainability in the U.S?

  - Research significance:

  i. This research is the first study in measuring environmental efficiency of the U.S. transportation system with consideration of economic, environmental and social factors.

  ii. This study provides what policy interventions such as benchmarking and potential carbon reduction that is needed to move toward a sustainable transportation system, which is of great interest to transportation planners and practitioners.

The details of this study are shown in Chapter 2. The final product was published in Transportation Research Part D: Transport and Environment.

- *Integrated Multimodal Transportation Model for a Switchgrass-Based Bioethanol Supply Chain: Case Study in North Dakota* will formulate a modal shift policy that finds the cost effective strategy using an optimization approach. There is an important aspect to designing sustainable transportation and supply chain systems due to the complex environment. For example, the biofuel industry has been challenged by many factors such as location setup, feedstock procurement, storage, transport and biofuel production. Ensuring cost efficient supply chains is challenging because of the physical characteristics of the biomass used to produce biofuel. Biomass is bulky and difficult to transport with seasonal variation and uncertainty. The optimization model integrates both road and rail transportation modes into the biofuel supply chain network. As a case study, switchgrass, a second-generation lignocellulosic biomass based biofuel, is addressed for North Dakota. Three research questions are as follows:

  1. Where should an intermodal facility be located to support the biomass supply chain?
  2. Is a multimodal solution better than a single mode transportation (Truck) solution?
  3. What are the key factors affecting supply chain design and biofuel related cost?

  - Research significance:

  i. This research is the first study that incorporates multimodal transportation into the switchgrass- based biofuel supply chain in USA.

  ii. This study captures the benefit of a modal shift in designing the biofuel supply chain network. Therefore, practitioners who want to plan multimodal transportation of biofuel can learn the practical relevance.

The details of this study are shown in Chapter 3. The final product was published in Transportation Research Record.

- *Determination of Potential Infrastructure and Production of Biogas from Animal Manure: Impact of Carbon Policy on Supply Chain Design* will address the importance of economic and environmental measures in the biogas supply chain. Biogas is known as one of the promising sources for electricity and transportation fuel. Bioenergy sectors are facing numerous challenges in deciding the location of infrastructure and production of energy. There is scarce research on biogas supply chain design. Therefore, this study aims to develop a biogas supply chain optimization model considering environmental and financial aspects with consideration of carbon policy. Research questions that I will address with this study include:

  1. Where should biogas production occur and what capacity of biogas plant should be installed?
  2. What is the impacts of a carbon policy on the biogas supply chain?
  3. Can a carbon policy reduce environmental impact?

  - Research significance:

  i. This research is the first study that models the biogas supply chain for the U.S.
  ii. Potential biogas production from animal waste will be identified as a pilot study.
  iii. This study finds the potential benefit that the North Dakota farmers and ranchers, and bioenergy industry can obtain from a carbon credit that would be used as a valuable new source in generating revenue.

  The details of this study are shown in Chapter 4.

CHAPTER 2. ENVIRONMENTAL EFFICIENCY ASSESSMENT OF U.S. TRANSPORT SECTOR: A SLACK-BASED DATA ENVELOPMENT ANALYSIS APPROACH [1]

2.1. Abstract

Sustainable transportation in the U.S. is essential for long-term economic growth and mobility, and environmental preservation. Using a non-radial slack-based measurement data envelopment analysis (SBM-DEA) model and state-level data, this study assesses the environmental efficiency of the transportation sector in the U.S. from years 2004 to 2012. In addition to environmental efficiency, carbon efficiency and potential carbon reduction were estimated for the 50 U.S. states. The findings of this study reveal that U.S. transportation sector was environmentally inefficient; U.S. states had an average transportation environmental efficiency score below 0.64. Therefore, the states could substantially reduce carbon emissions to improve the environmental efficiency of their transportation sectors.

2.2. Introduction

Transportation has great influence on the economy of the United States (U.S.). However, one of the most serious issues arising from transportation and economic growth is the environmental impacts across the country, especially increased transportation carbon emissions (Chang, 2013). In recent years, there has been increasing global interest in environmental sustainability issues because of its main concerns about the global warming and climate change. Sustainable development is defined as a "development that meets the needs of the present

[1] The material in this chapter was co-authored by Yong Shin Park, Siew Hoon Lim, Gokhan Egilmez, and Joseph Szmerekovsky. Yong Shin Park had primary responsibility for collecting samples in the field and analyzing the test system. Yong Shin Park was the primary developer of the conclusions that are advanced here. Yong Shin Park also drafted and revised all versions of this chapter. This chapter appears in Transportation Research Part D: Transport and Environment (Park et al., 2015).

without compromising the ability of future generations to meet their own needs" (WCED, 1987, Chapter 2, Section IV). Transportation consumes a high amount of energy (Zhou, Chung, & Zhang, 2014), and sustainable transportation hinges on the ability to maximize transportation environmental performance and to minimize the associated adverse impacts (Hendrickson, Cicas, & Matthews, 2006).

The transportation sector accounted for approximately 10% of the U.S. Gross Domestic Product (GDP) in 2014 (RITA, 2014). The same sector was found to be the second largest source of greenhouse gas (GHG) emissions accounting for 27% of total U.S. GHG emissions, following the power generation industry (US EPA, 2014). Additional critical environmental concern is that energy consumption by the transportation sector is expected to increase dramatically in the next quarter century (Frey & Kuo, 2007). In this context, President Barack Obama initiated a climate action plan that seeks to reduce 17% of total carbon dioxide (CO_2) by 2020 (Leggett, 2014).

Increasing concerns over the recent environmental issues related to transportation activities have led to sustainable development initiatives becoming a central element of public policy (Egilmez & Park, 2014) and transporting goods and services in a more sustainable way has become an essential topic of discussion. These discussions and projects are expected to contribute to the overall objective of sustainable development (Benjaafar & Savelsbergh, 2014; Choi, Park, & Park, 2015). Therefore, it is essential to study the environmental performance of transportation activities from a holistic viewpoint to facilitate sustainable development in the transportation sector of a country or a region (Goldman & Gorham, 2006). Recognizing the importance of reducing GHG emissions and energy consumption, a number of studies have evaluated the environmental efficiency of U.S. industries, but they have focused on the environmental efficiency of the industrial sector (Gokhan Egilmez, Kucukvar, & Tatari, 2013),

freight transportation from a manufacturing perspective (Egilmez & Park, 2014; Park, Egilmez, & Kucukvar, 2015), cross-country comparison (Zhou, Ang, & Poh, 2006), and the electricity sector (Barba-Gutiérrez, 2009). No study in the literature has been conducted on the overall environmental performance of the U.S.'s transportation sector.

Given this context, the main objective of this study is to analyze U.S. transportation environmental efficiency over a 9-year period (2004–2012) using a slack-based non-radial data envelopment analysis (SBM-DEA), and to estimate the potential reduction of transportation CO_2 emission. This study first measure the environmental efficiency of the transportation sectors in all 50 U.S. states through the SBM-DEA model by incorporating CO_2 as an undesirable output (Chang, Zhang, Danao, & Zhang, 2013). More specifically, this study estimate carbon efficiency (CE), potential carbon reduction (PCR), excess of inputs and shortfall of output of the U.S. transportation sector. The paper is organized as follows: Section 2.3 reviews the literature; Section 2.4 provides the methodology of this study and data description; Section 2.5 presents the results of the analysis and discussion. Finally, Section 2.6 provides the conclusion, a discussion on policy implications, and suggests the direction for future research.

2.3. Literature Review

Various approaches for measuring environmental efficiency have been proposed in the literature. First of all, one can consider the presence of undesirable outputs using an index number approach. For example, Pittman (1983) extended the study by Caves, Christensen, & Diewert (1982) incorporating undesirable outputs into a multilateral productivity index. The drawback of this method is the difficulty of measuring the shadow price of undesirable outputs for the productivity index (Chang, 2013; Zhou, Poh, & Ang, 2007). Another widely used approach is Data Envelopment Analysis (DEA). DEA has become one of the most used

approaches in measuring environmental efficiency due to its robustness in finding optimal efficiency scores for different problems and datasets (Chang, 2013).

As the primary approach, Charnes, Cooper, & Rhodes (1978) proposed the constant returns to scale DEA (CCR-DEA). DEA is a non-parametric approach for estimating the relative efficiency of decision making units (DMUs) by comparing multiple inputs with outputs in the framework of frontier analysis (Cooper, Seiford, & Tone, 2007). Banker, Charnes, & Cooper, (1984) extended the basic CCR-DEA model to variable returns to scale DEA (BCC-DEA). Since then, DEA has been a popular benchmarking approach commonly used to identify best management practice within a set of DMUs.

In an output-oriented DEA model, an inefficient DMU could expand all its outputs simultaneously and equal-proportionally without increasing its input use. While in an input-oriented model, an inefficient DMU could reduce all its inputs simultaneously and equal-proportionally without sacrificing or reducing its outputs. Hence, the conventional DEA models provide a radial efficiency measure that is either output- or input-oriented (Charnes, Haag, Jaska, & Semple, 1992; Charnes, Roussea, & Semple, 1996; Cook & Seiford, 2009). However, when an environmental pollutant is present in the model, the efficiency assessment becomes a challenging task (Chang, 2013), especially since an environmental pollutant need not increase or decrease equal-proportionally with outputs or inputs (Cooper, Seiford, & Tone, 2007).

Various methods for modeling undesirable outputs in DEA have been proposed in the literature. One treatment is to consider the pollutant as a free disposable input variable (Hailu & Veeman, 2001), but this concept was challenged by Färe & Grosskopf (2003) who viewed undesirable byproducts as weakly disposable outputs. The concepts of weak disposability and strong disposability of undesirable outputs were proposed by Faere, Grosskopf, Lovell, &

Pasurka (1989). Under the weak disposability property, a reduction in undesirable outputs will result in a reduction of desirable outputs, while strong disposability also means free disposability, and it assumes that it is possible to reduce the desirable output without reducing the undesirable outputs (Färe et al., 1989). Another approach involves the use of translated input and output data in the traditional BCC-DEA model, and the resulting efficiency classifications remain invariant to data transformation (Rousseau & Semple, 1995; Seiford & Zhu, 2002). In addition to the abovementioned radial approaches, a non-radial DEA model can be used to handle undesirable outputs (Peng Zhou, Poh, & Ang, 2007), and a slack-based measurement model proposed by Tone (2001) has also been used to account for the presence of undesirable outputs (Chang, 2013; Hu & Wang, 2006; Lozano & Gutiérrez, 2011; Hong Li, Fang, Yang, Wang, & Hong, 2013).

The slack-based measure (SBM) of efficiency was first proposed by Tone (2001). One main advantage of SBM over the aforementioned radial DEA models is that SBM captures input excesses and output shortfalls of the DMUs while conventional CCR-DEA and BCC-DEA models deal with a proportional reduction or expansion of inputs and outputs (Chang, 2013).

Based on the principle of a non-radial model, the primary purpose of the SBM is to locate the DMUs on the efficient frontier, and the objective function of the SBM is to be minimized by finding the maximum slacks (Tone, 2001). Non-radial efficiency SBM-DEA is found to be more appropriate compared to traditional DEA models when it comes to modeling undesirable byproducts (Hernández-Sancho, Molinos-Senante, & Sala-Garrido, 2011; Zhou et al., 2006), since the traditional models and radial approaches neglect the presence of slacks (Cooper et al.,

2007). [2]Zhou et al. (2006) found that SBM-DEA has a higher discriminatory power when compared to the conventional radial efficiency measures, since the radial approach tends to yield a large number of efficient firms with an efficiency score of 1. Another advantage of non-radial SBM-DEA is that the efficiency indicator for each variable can be identified to increase the efficiency level of the DMU being studied (Zhang & Kim, 2014).

The non-radial efficiency SBM-DEA model was applied by Zhang, Bi, Fan, Yuan, & Ge (2008) to the industrial systems in China. The authors measured industrial eco-efficiency by considering the pollutants chemicals' oxygen demand, nitrogen, soot, dust and solid waste as inputs and value added of industries as a desirable output. Besides the pollutants, material and energy consumption were incorporated as inputs in the model as well.

Chang et al. (2013) applied a non-radial efficiency SBM-DEA model to measure the environmental efficiency of the transportation sector in China. They used CO_2 emission as an undesirable output. This approach provided more comprehensive efficiency measures by estimating the economic and environmental performances through capturing the slack values of input and undesirable output as well as the shortfalls of desirable output. Another recent study by Zhou et al. (2014) performed an energy efficiency assessment of the regional transport sectors in China from 2003 to 2009. Some other studies associated with transportation such as a passenger airlines (Merkert & Hensher, 2011), airports (Lin & Hong, 2006), global airlines (Scheraga,

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[2] A slacks-based directional distance function is a viable alternative to SBM since the directional distance function has an additive structure like the SBM, and it has been shown by Fukuyama and Weber (2009) and Färe and Grosskopf (2010) that the two measures are very much related. Fukuyama and Weber's slacks-based directional distance function (2009) generalized Tone's SBM by normalizing the slacks in inputs and outputs in percentage terms. Färe and Grosskopf (2010) showed that SBM is a special case of their slacks-based directional distance function (DDM), and that "the two efficiency measures have the same indication of efficiency (page 321)." They showed that a DMU is SBM efficient if and only if it is DDM efficient.

2004), and ports (Chang, 2013; Liu & Hoon Lim, 2017) are found in the literature. The only study using the DEA model to assess eco-efficiency of U.S. transportation was conducted by Egilmez & Park (2014). The authors only considered the environmental and economic impacts of transportation from a manufacturing perspective, and environmental impact was incorporated as an input while economic outputs were considered as desirable outputs for assessing eco-efficiency.

The literature shows that environmental impacts are considered as inputs or outputs depending on the type of models used. Based on the literature review, no paper has adopted SBM-DEA approach on measuring the environmental performance of the U.S. transportation sector. There is only a handful of works available in the literature that use SBM-DEA for assessing environmental efficiency, these include an environmental efficiency assessment of OECD countries (Zhou et al., 2006) and a paper on environmental efficiency of transportation activities in China and Korean ports (Chang, 2013). This study applies the SBM-DEA model with a non-radial approach to analyze the environmental efficiency of the transportation sector in U.S. states.

2.4. Methodology

2.4.1. Slack-Based Measure Model Description

The aim of this study is to develop a framework to measure the environmental efficiency and potential CO_2 reduction of the transportation sector in the U.S. Following Chang (2013) and Zhou et al. (2006), this paper presents a DEA framework based on the slack-based measure (SBM) by incorporating the undesirable output into the objective function and the constraint function (Tone, 2001). We assume that reducing input resources relative to producing more outputs is a criterion for efficiency measurement.

When considering an undesirable output in the model, it should be noted that efficiency can be formed with more desirable output relative to less undesirable output and less input resources (Chang, 2013; Zhang, Su, & Ge, 2011). Suppose that there are j = {1, …, n} DMUs and that each j uses m inputs to produce p_1 desirable outputs and generate p_2 undesirable outputs (CO_2 emissions). The vectors of inputs, desirable outputs and undesirable outputs for DMU_i, are given by $x_j \in R^m$, $y_j \in R^{p1}$ and $c_j \in R^{p2}$, respectively.

Thus, for n DMU's, we define the input, desirable output and undesirable output matrices as $X = [x_1,\ldots,x_n] \in R^{m*n}$, Y as $Y = [y_1,\ldots,y_n] \in R^{p1*n}$, C as $C = [c_1,\ldots,c_n] \in R^{p2*n}$. All data on X, Y and C are positive. The production possibility set (PPS) can be described as follows:

$$P(x) = \{(x, y, c) \mid x \text{ can produce } (y, c),\ x \geq X\lambda,\ y \leq Y\lambda,\ c \geq C\lambda,\ \lambda \geq 0\}, \quad (2.1)$$

where λ denotes the non-negative intensity vector, and the production technology in (2.1) exhibits constant returns to scale (CRS). From the concept of slacks, the efficiency of DMUs must be measured with consideration of how much input waste can be reduced to a given level of output, and how much output can be increased for a given level of input (Tone, 2001). But this original approach developed by Tone (2001) did not consider the presence of any undesirable output in the model. Therefore, this study uses a SBM specification that incorporates an undesirable output into both the objective function and an additional constraint on the undesirable output. The SBM-DEA model can thus be expressed in Model 1 below:

$$e_0^* = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1+\frac{1}{p_1+p_2}\left(\sum_{r_1=1}^{p_1}\frac{s_{r_1 0}^{y}}{y_{r_1 0}}+\sum_{r_2=1}^{p_2}\frac{s_{r_2 0}^{y}}{c_{r_2 0}}\right)} \quad (2.2)$$

s.t.

$$x_0 = X\lambda + s^- \quad (2.3)$$

$$y_0 = Y\lambda - s^y \tag{2.4}$$

$$C_0 = C\lambda + s^c \tag{2.5}$$

$$s^- \geq 0, s^y \geq 0, s^c \geq 0, \lambda \geq 0, \tag{2.6}$$

where,

i = Index of inputs (1,2…,m);

m= Number of inputs;

Subscript '0' = The DMU, whose efficiency is being estimated in the current model;

r_1= Index of good outputs

r_2= Index of bad outputs

p_1 = Number of good outputs;

p_2 = Number of bad outputs;

s^-= Slack of inputs;

s^y= Slack of good outputs;

s^c= Slack of bad outputs;

The DMU is efficient if e_0^* is equal to 1, which implies all the slack values, s^-, s^y and s^c are equal to 0. If e_0^* is less than 1, then the DMU is inefficient, and it can become efficient by eliminating the slacks in inputs and bad outputs and augmenting the shortfalls in good outputs.. But equation (2.2) is not a linear function. Therefore, Model 2, a transformed model which is an equivalent linear programming (LP) model is used (Tone, 2001).

$$r_0^* = \min t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}} \tag{2.7}$$

s.t.

$$1 = t + \frac{1}{p_1+p_2}\left(\sum_{r_1=1}^{p_1}\frac{s_{r_1}^y}{y_{r_1 0}} + \sum_{r_2=1}^{p_2}\frac{s_{r_2}^c}{c_{r_2 0}}\right) \tag{2.8}$$

$$x_0 t = X ß + S^{-} \tag{2.9}$$

$$y_0 t = Y ß - S^{y} \tag{2.10}$$

$$c_0 t = C ß + S^{c} \tag{2.11}$$

$$S^{-} \geq 0,\ S^{y} \geq 0,\ S^{c} \geq 0,\ ß \geq 0,\ t > 0, \tag{2.12}$$

The optimal solution of the LP model (2.7) – (2.12) can be solved, and let the optimal solution be (r^*, t^*, $ß^*$, S^{-*}, S^{y*}, S^{c*}) where $e_0^* = r_0^*$, $\lambda^* = \frac{ß^*}{t^*}$, $s^{-*} = \frac{S^{-*}}{t^*}$, $s^{y*} = \frac{S^{y*}}{t^*}$, $s^{c*} = \frac{S^{c*}}{t^*}$ from Model (2). The solution of t^*, $ß^*$, S^{-*}, S^c and S^y can be generated through Model 2 with $t^* > 0$.

In this paper, carbon efficiency (CE) of each DMU is estimated based on the method proposed by Hu & Wang (2006) where the index of total factor energy efficiency was introduced using DEA-generated optimal energy input level, and by Zhou & Ang (2008) of evaluating energy efficiency with undesirable output. The carbon efficiency (CE) can be estimated as follows (Chang, 2013):

$$\text{CE} = \text{Target carbon emission/ Real carbon emission} = \frac{C_0^t - S_0^c}{C_0^t} \tag{2.13}$$

where C_0^t is the observed carbon emission, and S_0^c is the slack of carbon emission, therefore $C_0^t - S_0^c$ is the target carbon emission level. Additionally, the potential carbon reduction (PCR) of each state is estimated by the slack variable S_0^c as it is the excess carbon emission. Finally, the performance improvement of each input and output indicator is evaluated in percentage terms.

2.4.2. Data Description

In many empirical studies, capital, energy and labor are considered three major inputs in production, and gross domestic product (GDP) is a measure of the overall economic output of a sector or an economy. In order to analyze the environmental efficiency of the U.S transportation sector, this study uses a panel data set of all 50 U.S. states from 2004 to 2012. The data include

capital expense, energy consumption and labor in the transportation sector as input variables. The labor and capital input data were collected from the U.S Bureau of Labor Statistics and the U.S Census Bureau. The data on the volume of energy consumed by the transportation sector were collected from the U.S. Energy Information Administration. Each state's transportation value added (GDP) was considered a desirable output (Chang et al., 2013; Zhou et al., 2014), and the data were collected from the Bureau of Economic Analysis. Additionally, an undesirable output, CO_2, is also taken into account as a byproduct of producing transportation services (Simsek, 2014). The data on CO_2 emissions were available from the U.S Energy Information Administration (U.S. EIA). The data descriptions are provided in Table 1.

Table 1. Input and Output Variables and Data Sources, 2004-2012.

	Variables	Unit	Sources
Input	Capital expenses	In millions	U.S Census Bureau
	Energy use	In trillion Btu	U.S. Energy Information Administration
	Labor	In thousands (person)	U.S Bureau of Labor Statistics
Output	Desirable output: Value added (GDP)	In millions of U.S. dollars	Bureau of Economic Analysis
	Undesirable output: CO_2 emission	In millions of metric tons	U.S. Energy Information Administration

2.5. Results and Discussion

2.5.1. Input and Output Indicators

Table 2 shows the descriptive statistics of the state-level data from 2004 to 2012. The capital expenditure of U.S states' transportation sectors averaged 4.76 million dollars for 2004 - 2012. The average state transportation sector consumed 599.5 trillion Btu of energy, employed 168 thousand people, produced 8,090 million dollars in transportation GDP (value-added) and

emitted 37.9 million metric tons of CO_2. Variations in the input and output variables across the states can be seen from the standard deviations in Table 2. The correlation matrix of inputs and outputs in Table 3 is analyzed to see if there is a significant relationship between the input and output variables. From the results in Table 3, we can see that a significantly high correlation exists between the input and the output variables in that the correlation coefficients are all above 0.60.

Table 2. Descriptive Statistics of Input and Output, 2004- 2012.

Variable	Unit	Min	Max	Mean	Std. Dev
Capital	10^6 dollar	3.8	30,312.6	4,762.6	5,301.7
Energy	10^{12} btu	19.6	3,387.3	599.5	697.8
Labor	10^3 persons	7	951	167.7	178.6
GDP (value- added)	10^6 dollar	298	53,443.0	8,090.0	8,982.6
CO_2	10^6 ton	1.1	238.1	37.9	41.6

Table 3. Correlation Matrix of Inputs and Outputs.

	Capital	Energy	Labor	CO2	GDP
Capital	1.00				
Energy	0.67	1.00			
Labor	0.84	0.80	1.00		
CO2	0.81	0.83	0.96	1.00	
GDP	0.83	0.81	0.97	0.96	1.00

2.5.2. U.S. Transportation Environmental Efficiency Performance

As mentioned in Section 2.3, the environmental efficiency (EE) score in the transportation sector is evaluated by e_0^* in equation (2.2), because it includes the slack values of all input and output variables. The carbon efficiency (CE) score is estimated by equation (2.13), and finally potential carbon reduction (PCR) is calculated by the slack variable s_0^c. Tables 4 and 5 show the results of EE and CE indicators for each U.S. state from 2004 to 2012.

The overall average EE performance from 2004 to 2012 of the transportation sector in the U.S. indicates that only four of the fifty states (Alaska, Illinois, Nebraska and Vermont) were

found to be relatively environmentally efficient as scores of EE in the four states are ranked as the best in the country (EE = 1). The EE scores of the inefficient states ranged from 0.341 to 0.965 (average = 0.640), with Texas ranking first and Alabama ranking last among the inefficient states. The EE scores suggest considerable room for transportation environmental efficiency improvements in most states.

In terms of CE, five states (the four previously mentioned states and Texas) were found to be (relatively) carbon efficient states. CE scores for the inefficient states ranged from 0.307 to 0.975 (average = 0.638) with Rhode Island ranking first and South Carolina ranking last among the inefficient states. In figures 1 and 2, we use graduated colors with equal interval labels to present the annual average EE and CE scores of the states during the study period. It can be easily observed that there is a consistent spatial distribution pattern of EE and CE, in that states that are low on EE are also low on CE.

Taking all 50 states' performance as a whole, Figure 3 displays the sector's mean EE and CE scores by year. The EE and CE performance fluctuated every year. The average EE scores hovered between 0.62 and 0.66.. There was a decreasing trend in EE from 2004 to 2008, and the average percentage change was found to be -0.58%. However, after 2008, the transportation sector exhibited an upward trend in EE. The sector's CE performance slid to 0.6 in 2008, but rose to nearly 0.69 in the next 2 years. The sector's EE performance also was lowest in 2008 but rose above 0.65 in 2010. The EE trend reflects the rate of CO_2 emissions by the U.S. transportation sector during the same period (US EPA, 2014).

Table 4. Environmental Efficiency based on SBM, 2004-2012.

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	Mean
Alaska	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Illinois	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Nebraska	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Vermont	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Texas	1.000	1.000	1.000	0.686	1.000	1.000	1.000	1.000	1.000	0.965
Wyoming	0.838	0.984	1.000	0.818	1.000	1.000	1.000	1.000	1.000	0.960
California	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.825	0.776	0.956
Hawaii	1.000	1.000	1.000	0.758	0.748	0.820	0.911	0.842	1.000	0.898
Rhode Island	0.797	0.841	0.851	0.868	0.844	1.000	0.873	1.000	1.000	0.897
New Jersey	0.832	0.861	0.779	1.000	1.000	1.000	0.832	0.771	0.790	0.874
Tennessee	1.000	1.000	1.000	0.302	1.000	0.896	0.720	0.854	1.000	0.864
Delaware	0.747	0.734	0.789	1.000	0.719	0.764	1.000	0.879	0.834	0.830
Georgia	0.869	0.774	0.677	0.708	0.846	0.890	0.676	1.000	1.000	0.827
North Dakota	0.737	0.813	1.000	0.713	0.812	0.917	0.811	0.849	0.745	0.822
New York	0.739	0.791	0.726	0.666	0.820	0.831	1.000	0.813	0.799	0.798
Montana	0.683	0.728	0.709	0.644	0.672	0.740	0.747	0.742	0.712	0.709
South Dakota	0.700	0.711	0.746	0.659	0.672	0.684	0.700	0.662	0.626	0.684
Ohio	0.650	0.713	0.652	0.527	0.742	0.742	0.781	0.661	0.662	0.681
Pennsylvania	0.760	0.703	0.627	0.548	0.699	0.695	0.683	0.656	0.650	0.669
Florida	0.620	0.653	0.600	0.554	0.708	0.747	0.613	0.706	0.669	0.652
New Hampshire	0.645	0.715	0.680	0.580	0.588	0.618	0.595	0.674	0.695	0.643
Idaho	0.574	0.596	0.596	0.593	0.547	0.577	0.691	0.579	0.602	0.595
Maine	0.529	0.538	0.567	0.519	0.577	0.605	0.743	0.598	0.595	0.586
Virginia	0.520	0.504	0.535	1.000	0.500	0.585	0.514	0.526	0.534	0.580
Indiana	0.582	0.609	0.595	0.623	0.553	0.561	0.513	0.550	0.569	0.573
Nevada	0.565	0.568	0.531	0.501	0.554	0.597	0.553	0.642	0.631	0.571
Connecticut	0.506	0.535	0.530	0.619	0.571	0.580	0.588	0.592	0.579	0.567
Arkansas	0.538	0.572	0.580	0.624	0.519	0.525	0.569	0.535	0.561	0.558
Washington	0.575	0.591	0.547	0.465	0.516	0.557	0.569	0.578	0.587	0.554
Kentucky	0.583	0.672	0.544	0.677	0.436	0.509	0.504	0.500	0.516	0.549
New Mexico	0.475	0.453	0.444	0.410	0.467	0.482	1.000	0.569	0.547	0.539
Kansas	0.502	0.526	0.517	0.601	0.505	0.520	0.558	0.548	0.569	0.538
Missouri	0.568	0.589	0.555	0.459	0.558	0.550	0.545	0.468	0.505	0.533
Utah	0.565	0.602	0.549	0.528	0.492	0.513	0.497	0.499	0.492	0.526
Louisiana	0.454	0.432	0.469	0.603	0.553	0.569	0.507	0.470	0.541	0.511
Michigan	0.568	0.549	0.496	0.432	0.486	0.463	0.453	0.526	0.553	0.503
Minnesota	0.582	0.567	0.467	0.591	0.438	0.438	0.424	0.461	0.461	0.492
West Virginia	0.458	0.462	0.480	0.431	0.478	0.486	0.558	0.517	0.495	0.485
Arizona	0.459	0.516	0.466	0.581	0.367	0.410	0.469	0.483	0.503	0.473
Iowa	0.487	0.464	0.459	0.542	0.441	0.451	0.471	0.452	0.453	0.469
Massachusetts	0.405	0.404	0.388	1.000	0.367	0.403	0.405	0.412	0.429	0.468
Wisconsin	0.540	0.540	0.493	0.449	0.395	0.436	0.422	0.415	0.427	0.457
North Carolina	0.479	0.487	0.454	0.391	0.429	0.483	0.383	0.430	0.466	0.445
Oregon	0.491	0.472	0.449	0.417	0.423	0.421	0.357	0.445	0.474	0.439
Oklahoma	0.454	0.452	0.436	0.353	0.353	0.368	0.596	0.408	0.410	0.426
Maryland	0.427	0.416	0.386	0.484	0.356	0.375	0.408	0.396	0.365	0.402
Mississippi	0.359	0.399	0.349	0.339	0.334	0.387	0.405	0.373	0.367	0.368
Colorado	0.347	0.396	0.368	0.418	0.340	0.351	0.337	0.342	0.389	0.365
South Carolina	0.317	0.337	0.343	0.434	0.342	0.375	0.364	0.337	0.347	0.355
Alabama	0.340	0.338	0.336	0.357	0.329	0.329	0.354	0.337	0.344	0.341
Mean	0.637	0.652	0.635	0.629	0.622	0.645	0.654	0.638	0.645	0.640

Table 5. Carbon Efficiency based on SBM, 2004-2012.

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	Mean
Alaska	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Nebraska	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Illinois	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Vermont	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Texas	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Rhode Island	0.942	0.955	0.950	1.000	0.932	1.000	1.000	1.000	1.000	0.975
California	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.913	0.856	0.974
Wyoming	0.767	0.980	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.972
Tennessee	1.000	1.000	1.000	0.735	1.000	0.871	0.777	0.870	1.000	0.917
New York	0.852	0.967	0.838	0.929	0.895	0.924	1.000	0.931	0.872	0.912
Delaware	0.860	0.822	0.832	1.000	0.787	0.831	1.000	0.915	0.903	0.883
Hawaii	1.000	1.000	1.000	0.916	0.665	0.705	0.929	0.724	1.000	0.882
New Jersey	0.714	0.783	0.619	1.000	1.000	1.000	0.835	0.806	0.833	0.843
North Dakota	0.731	0.781	1.000	0.926	0.754	0.893	0.908	0.765	0.758	0.835
Georgia	0.774	0.772	0.587	0.792	0.716	0.902	0.736	1.000	1.000	0.809
Pennsylvania	0.713	0.769	0.650	0.692	0.703	0.720	0.794	0.704	0.701	0.716
South Dakota	0.734	0.737	0.737	0.842	0.682	0.673	0.741	0.629	0.599	0.708
Montana	0.665	0.638	0.634	0.691	0.623	0.666	0.857	0.671	0.736	0.687
Ohio	0.600	0.774	0.615	0.645	0.643	0.641	0.716	0.582	0.600	0.646
Nevada	0.561	0.550	0.516	0.537	0.544	0.636	0.794	0.791	0.835	0.640
New Hampshire	0.599	0.657	0.668	0.754	0.567	0.584	0.668	0.586	0.611	0.633
Idaho	0.601	0.609	0.580	0.822	0.572	0.588	0.684	0.564	0.587	0.623
Florida	0.562	0.637	0.564	0.614	0.643	0.674	0.687	0.586	0.570	0.615
Indiana	0.512	0.637	0.507	0.726	0.495	0.502	0.543	0.573	0.582	0.564
Maine	0.547	0.510	0.524	0.638	0.550	0.541	0.655	0.533	0.565	0.563
Washington	0.535	0.570	0.510	0.495	0.498	0.536	0.629	0.573	0.565	0.546
Connecticut	0.441	0.463	0.485	0.538	0.530	0.544	0.608	0.607	0.668	0.543
Kansas	0.512	0.537	0.506	0.514	0.497	0.485	0.593	0.567	0.637	0.539
Arkansas	0.493	0.492	0.487	0.821	0.445	0.439	0.547	0.502	0.561	0.532
Utah	0.523	0.527	0.479	0.519	0.482	0.510	0.593	0.528	0.596	0.529
Wisconsin	0.588	0.615	0.543	0.522	0.437	0.471	0.525	0.515	0.498	0.524
West Virginia	0.471	0.467	0.472	0.536	0.512	0.508	0.646	0.530	0.531	0.519
Missouri	0.525	0.610	0.493	0.490	0.478	0.486	0.501	0.455	0.511	0.506
Michigan	0.511	0.621	0.441	0.464	0.426	0.411	0.486	0.560	0.556	0.497
Kentucky	0.488	0.590	0.472	0.453	0.427	0.440	0.510	0.510	0.506	0.488
Minnesota	0.552	0.539	0.442	0.466	0.434	0.446	0.503	0.508	0.482	0.486
Iowa	0.488	0.472	0.465	0.470	0.440	0.465	0.527	0.486	0.554	0.485
Colorado	0.449	0.482	0.400	0.781	0.395	0.416	0.482	0.470	0.479	0.484
New Mexico	0.382	0.393	0.384	0.442	0.409	0.409	1.000	0.443	0.461	0.480
Virginia	0.431	0.482	0.430	0.425	0.422	0.471	0.592	0.491	0.557	0.478
Arizona	0.405	0.442	0.406	0.706	0.372	0.408	0.515	0.496	0.498	0.472
Oregon	0.446	0.440	0.425	0.423	0.403	0.399	0.476	0.467	0.524	0.445
North Carolina	0.454	0.535	0.417	0.404	0.373	0.412	0.510	0.425	0.453	0.442
Massachusetts	0.405	0.382	0.366	0.370	0.340	0.380	0.444	0.432	0.449	0.396
Maryland	0.388	0.371	0.365	0.370	0.351	0.357	0.450	0.437	0.465	0.395
Louisiana	0.280	0.312	0.297	0.367	0.409	0.485	0.490	0.420	0.469	0.392
Oklahoma	0.342	0.320	0.312	0.530	0.293	0.304	0.421	0.382	0.416	0.369
Alabama	0.283	0.285	0.283	0.524	0.282	0.289	0.347	0.316	0.344	0.328
Mississippi	0.303	0.305	0.286	0.310	0.282	0.297	0.383	0.327	0.338	0.315
South Carolina	0.270	0.289	0.275	0.501	0.260	0.256	0.325	0.283	0.307	0.307
Mean	0.614	0.642	0.605	0.674	0.599	0.620	0.689	0.638	0.661	0.638

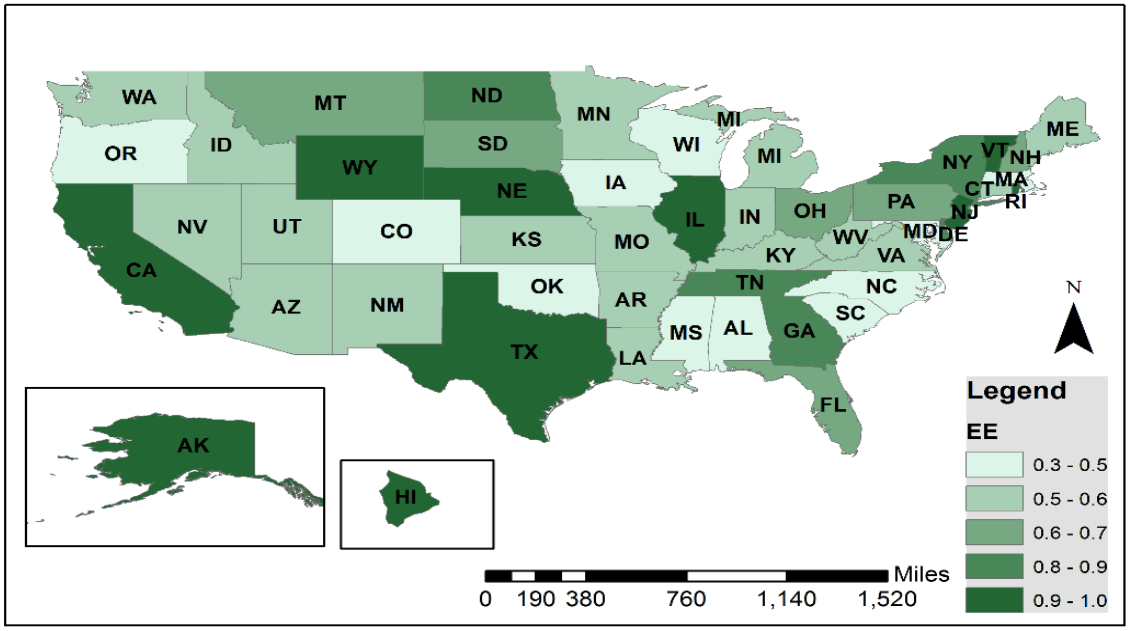

Figure 1. Spatial Distribution of Average Environmental Efficiency Values for the Transportation Sector in 50 U.S States between 2004 and 2012.

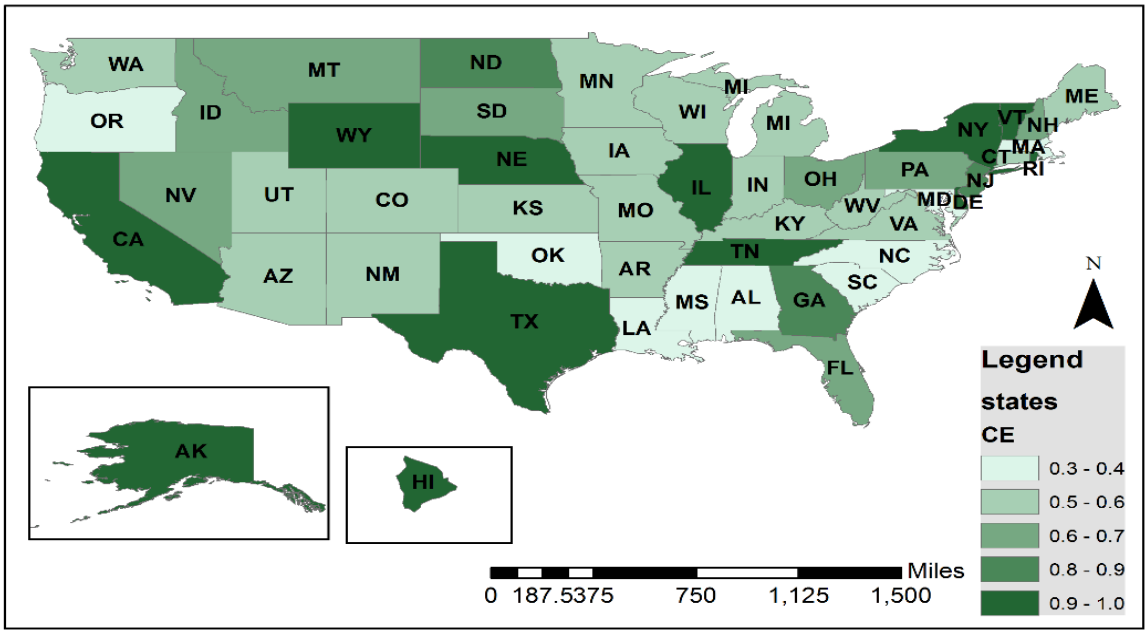

Figure 2. Spatial Distribution of Average Carbon Efficiency Values for the Transportation Sector in 50 U.S States between 2004 and 2012.

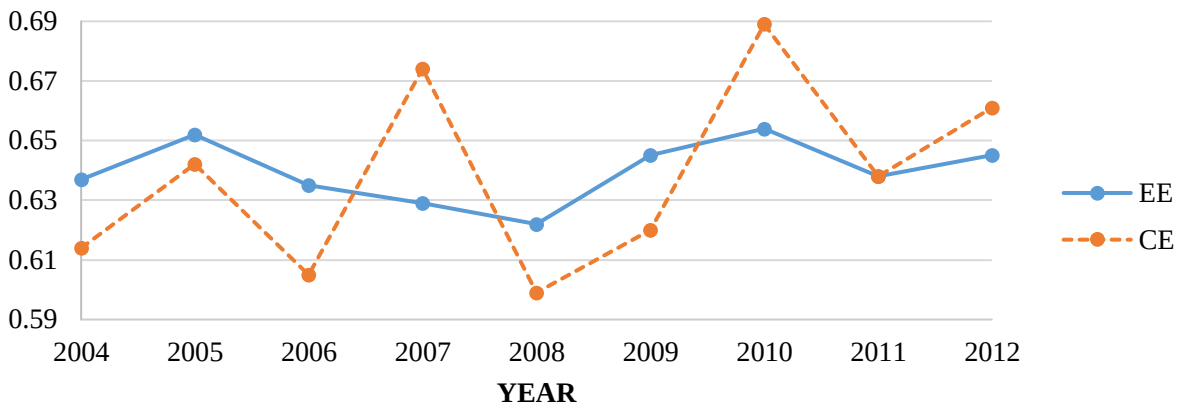

Figure 3. Average Environmental Efficiency and Carbon Efficiency Scores of U.S. Transportation Sector, 2004-2012.

2.5.3. Potential Carbon Emission Reduction of Transportation Sector

As the results of EE and CE indicate, most of the states are not performing efficiently in the transportation sector, leading to the conclusion that there is great potential to reduce transportation CO_2 emissions in each state. We can see in Table 6 that the U.S. transportation sector could reduce a great deal of CO_2 ranging from at least 0.03 million metric tons to 23.40 million metric tons. The average PCR was found to be 7.10 million metric tons. As shown in the last column of Table 6, on average, 46 U.S. states' transportation sectors showed excessive CO_2 emissions that need to be reduced. Among the states, Florida shows the highest potential for carbon reduction with 23.40 million metric tons, followed by Louisiana with 23.18 million metric tons and North Carolina with 20.33 million metric tons. Compared to Louisiana and North Carolina, Florida had a relatively higher EE score but also a large PCR. This suggests that the inefficiency in Florida's transportation sector can be explained in large part by the presence of environmental slack. On the other hand, North Dakota, Tennessee, Delaware and Rhode Island were found to have only a small amount of excess CO_2 emissions, showing 0.62, 0.61, 0.29 and 0.03 million metric tons of PCR, respectively.

Table 6. Potential Carbon Reductions, 2004-2012.

State	2004	2005	2006	2007	2008	2009	2010	2011	2012	Mean
Florida	21.53	18.48	48.46	44.11	7.39	4.53	29.60	13.86	22.64	23.40
Louisiana	27.01	24.56	26.27	19.02	23.62	23.13	14.46	27.64	22.90	23.18
North Carolina	17.22	18.94	18.58	14.79	28.59	24.14	17.49	22.72	20.49	20.33
Michigan	16.40	17.32	18.75	12.93	23.26	24.55	15.19	18.67	19.06	18.46
Virginia	19.82	22.21	20.05	15.67	23.99	19.93	7.22	17.12	19.91	18.43
Alabama	16.19	15.99	16.31	8.50	24.11	23.11	11.99	23.01	21.34	17.84
South Carolina	15.98	14.16	15.73	4.79	22.69	23.11	13.78	22.17	19.44	16.87
Oklahoma	10.13	12.13	12.83	7.54	22.86	21.50	5.04	19.74	18.87	14.52
Mississippi	11.52	11.38	13.11	5.83	18.42	17.44	12.39	16.61	14.77	13.50
Massachusetts	8.32	9.33	9.05	0.00	22.07	19.06	8.21	17.58	16.99	12.29
Indiana	10.73	10.58	10.51	4.58	15.78	15.51	8.88	16.14	15.51	12.02
Arizona	10.00	10.26	10.32	5.40	21.58	18.98	0.00	14.79	14.46	11.76
Ohio	12.73	8.52	18.73	16.59	5.89	5.62	16.82	8.66	11.43	11.67
Missouri	8.06	9.17	9.00	3.47	16.53	16.32	5.34	18.53	17.66	11.56
Maryland	7.56	8.78	8.95	1.72	19.90	20.39	0.52	16.48	16.00	11.14
Minnesota	4.73	6.35	7.77	4.42	17.90	16.75	3.22	14.18	15.60	10.10
Washington	8.77	9.07	9.56	7.71	15.65	13.44	0.03	10.20	11.58	9.56
Colorado	4.46	4.40	6.24	1.16	18.25	17.12	0.00	15.32	14.98	9.10
Kentucky	6.11	4.57	5.25	0.74	17.53	17.18	0.02	15.49	14.04	8.99
Oregon	3.39	3.71	4.43	0.56	13.60	13.64	6.04	11.24	9.36	7.33
Wisconsin	1.16	0.92	1.66	0.00	16.46	14.77	2.85	13.51	14.11	7.27
Iowa	1.43	2.14	2.33	0.12	12.07	11.21	2.51	11.15	8.88	5.76
New Mexico	5.90	5.71	6.22	3.51	8.43	8.03	0.00	7.74	6.08	5.73
Arkansas	1.22	1.26	1.37	0.31	11.39	11.30	0.21	10.03	7.76	4.98
Georgia	3.93	9.58	17.90	9.92	0.14	2.02	0.28	0.00	0.00	4.86
Pennsylvania	0.00	1.46	17.15	13.96	0.00	0.00	7.97	0.00	2.87	4.82
California	0.00	0.00	0.00	0.00	0.00	0.00	0.00	17.81	25.29	4.79
New Jersey	5.20	8.08	16.64	0.00	0.00	0.00	0.00	5.95	5.81	4.63
Kansas	0.54	0.00	0.75	0.00	9.59	10.08	0.00	8.22	6.41	3.95
Utah	0.40	0.35	2.04	0.00	8.83	7.90	0.36	8.17	5.68	3.75
Connecticut	3.47	2.70	1.90	0.00	7.89	7.34	0.00	6.15	4.20	3.74
West Virginia	3.02	3.35	3.34	0.19	5.39	5.33	0.51	5.16	4.13	3.38
Maine	2.29	3.06	2.80	0.36	3.69	3.64	2.54	3.75	3.14	2.81
Nevada	0.00	0.00	0.52	0.00	7.46	5.27	0.00	2.74	2.04	2.00
Idaho	1.02	1.01	1.49	0.23	3.76	3.30	0.37	3.83	2.91	1.99
New Hampshire	1.64	0.90	0.84	0.08	3.15	2.69	1.55	2.76	2.52	1.79
New York	0.00	0.00	8.80	3.73	0.00	0.00	0.00	0.00	0.00	1.39
South Dakota	0.59	0.55	0.59	0.52	1.93	1.82	1.54	2.26	2.68	1.39
Montana	0.21	0.60	0.64	0.72	3.14	2.62	1.05	2.27	1.07	1.37
Hawaii	0.00	0.00	0.00	0.32	3.25	2.72	0.23	2.82	0.00	1.04
North Dakota	0.30	0.17	0.00	0.53	1.49	0.06	0.64	1.55	0.87	0.62
Tennessee	0.00	0.00	0.00	3.40	0.00	1.41	0.00	0.65	0.00	0.61
Delaware	0.01	0.28	0.19	0.00	1.07	0.54	0.00	0.17	0.35	0.29
Rhode Island	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.00	0.00	0.03
Texas	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wyoming	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nebraska	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Vermont	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Alaska	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	5.46	5.64	7.54	4.35	9.78	9.15	8.98	9.14	8.88	7.10

2.5.4. Analysis of Slack Variables

There are only four environmentally efficient states, and most EE scores are quite low. Therefore, it is imperative for us to examine the slack values of the inputs and outputs in the model. The purpose of measuring relative efficiency is to determine the amount of excess inputs and the shortfall of output so that inefficient DMUs can identify the best management practices in developing and maintaining a sustainable transportation system. The estimated slack values and the associated percentages of improvements (reported in parentheses) are presented in Table 7. The negative values in the parentheses in Table 7 indicates the percentage of potential input reduction, and the positive values in the parentheses implies the potential increase in percentage terms.

By comparing the results in Tables 4, 5, 6 and 7, we can see that low-ranked environmentally inefficient states have extremely high input slacks in both level and percentage terms. This pattern suggests that in order to increase efficiency the input levels need to be lowered by the estimated input slacks in Table 7. Meanwhile, carbon emissions excess needs to be cut, and good output shortfall should also be eliminated. For example, among the environmentally inefficient states, Alabama has excesses in capital, labor and CO_2, while producing insufficient transportation output. The state could increase its transportation output by 33% per year, while reducing its carbon emissions by as much as 52% per year, and slashing its capital and labor inputs by 21% and 14%, respectively. Other inefficient states, such as Maryland, Mississippi, Colorado and South Carolina also show much waste in input variables and high shortfalls in transportation GDP. In addition, the third-best state among the inefficient states, California, has extremely high excess values in capital, energy and labor, as well as a shortfall in transportation GDP. Florida and Louisiana show the greatest excess in undesirable

output (CO_2). On average, capital investment has the highest percentage of slack at -31.3%, CO_2 has the second highest in slack at -21.9%, and labor has the third highest in slack at -14%, while energy input has relatively less slack at -2.4%.

Figure 4 represents the dynamic changes of slacks in inputs, desirable output, and undesirable output from 2004 to 2012. A positive percentage change indicates the shortfall of desirable output, and a negative percentage change indicates the excesses in inputs and undesirable output that need to be reduced. The average shortfall in transportation GDP peaked at 16% in 2007 and dropped to a minimum in 2008, after which it continually increased until 2012. Additionally, the percentages of average excesses in capital and labor fluctuated every year. The large capital excess in 2007 coupled with the output shortfall in the same year suggest that the industry may have overinvested during a time when the overall U.S. economic growth was slowing down. As the U.S. economy showed signs of recovery, and as a result of a direct fiscal stimulus in 2009 (Federal Reserve Bank of St. Louis, udated; Transportation Resarch Board, 2014), excess capital spiked in 2010. At the same time, the CO_2 slack largely mirrored the movement of transportation GDP and reached a minimum in 2008. Other than 2008, the sector's CO_2 slack was prevalent over the study period. This result indicates that U.S. policy on transportation carbon emissions has yet to improve. The slack in energy is negligible, which shows little dynamic change over the study period.

Table 7. Summary of Average Excess in Inputs and Shortfall in Outputs, 2004-2012.

State	Inputs (Excess)						Undesirable Output (Excess)		Desirable Output (Shortfall)	
	Capital ($)	Slack (%)	Energy (Btu)	Slack (%)	labor (Person)	Slack (%)	CO_2 (Ton)	Slack (%)	GDP ($)	Slack (%)
Alabama	960010.8	(-21.3)	1.6	(0.0)	30.5	(-14.4)	17.8	(-52.0)	2107.9	(32.9)
Alaska	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)
Arizona	2002066.5	(-43.2)	9.5	(-1.7)	24.3	(-14.3)	11.8	(-33.8)	209.6	(1.2)
Arkansas	664862.4	(-24.5)	0.3	(-0.1)	22.7	(-19.5)	5.0	(-24.4)	51.9	(0.8)
California	9333921.1	(0.0)	25.3	(0.0)	144.0	(0.0)	4.8	(-2.2)	2134.7	(0.0)
Colorado	1894182.3	(-46.8)	2740.2	(-86.5)	16.4	(-13.3)	9.1	(-30.5)	62.3	(0.5)
Connecticut	995853.6	(-38.7)	6.7	(-3.3)	16.3	(-25.3)	3.7	(-21.9)	63.8	(0.5)
Delaware	668498.0	(-20.9)	0.7	(-0.4)	6.9	(-9.5)	0.3	(-6.0)	86.3	(3.0)
Florida	8996813.9	(-29.2)	6.1	(-0.3)	119.9	(-4.1)	23.4	(-21.6)	1438.4	(3.9)
Georgia	1679037.6	(-11.1)	1.1	(0.0)	73.6	(-3.3)	4.9	(-7.4)	77.3	(0.0)
Hawaii	103764.6	(0.0)	0.0	(0.0)	0.0	(0.0)	1.0	(-9.2)	0.0	(0.0)
Idaho	656505.5	(-34.7)	0.6	(-0.8)	14.2	(-32.1)	2.0	(-22.0)	301.9	(27.7)
Illinois	4432319.3	(0.0)	6.0	(0.0)	110.8	(0.0)	0.0	(0.0)	0.0	(0.0)
Indiana	1393073.0	(-28.4)	4.0	(-0.3)	67.9	(-26.2)	12.0	(-27.5)	315.7	(4.0)
Iowa	1714996.1	(-48.7)	2.0	(-0.7)	45.4	(-40.1)	5.8	(-26.9)	162.9	(6.0)
Kansas	1602683.8	(-50.0)	3.2	(-1.8)	12.5	(-18.6)	4.0	(-20.7)	0.0	(0.4)
Kentucky	1636427.3	(-36.2)	2.2	(-0.3)	30.6	(-15.8)	9.0	(-27.1)	95.4	(2.7)
Louisiana	554242.0	(0.0)	0.2	(0.0)	2.3	(0.0)	23.2	(-46.2)	791.9	(0.0)
Maine	648567.3	(-28.0)	0.5	(-0.5)	11.3	(-22.3)	2.8	(-32.3)	406.1	(50.3)
Maryland	3132041.5	(-56.9)	8.7	(-2.1)	19.9	(-16.4)	11.1	(-36.0)	255.8	(2.3)
Massachusetts	2618724.1	(-52.4)	8.9	(-1.9)	28.5	(-16.9)	12.3	(-38.1)	246.3	(3.2)
Michigan	2491423.2	(-38.4)	15.8	(-1.9)	75.8	(-24.8)	18.5	(-35.2)	534.6	(4.7)
Minnesota	3663932.0	(-59.2)	9.5	(-2.0)	24.6	(-12.3)	10.1	(-29.3)	69.0	(0.4)
Mississippi	1002122.2	(-31.7)	2.2	(-0.5)	10.7	(-13.2)	13.5	(-52.7)	1337.2	(37.5)
Missouri	1949786.2	(-37.2)	2.5	(-0.2)	44.5	(-21.6)	11.6	(-28.4)	456.3	(7.4)
Montana	1145352.6	(-43.4)	0.9	(-0.7)	1.5	(-4.9)	1.4	(-16.5)	79.5	(16.7)
Nebraska	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)
Nevada	4848524.0	(-60.1)	1.3	(-0.8)	14.7	(-23.3)	2.0	(-12.7)	0.0	(0.3)
New Hampshire	920129.6	(-32.3)	0.9	(-0.8)	7.7	(-16.3)	1.8	(-24.6)	188.8	(39.2)
New Jersey	1286622.8	(-8.5)	3.4	(0.0)	33.6	(-0.5)	4.6	(-7.0)	8.7	(0.0)
New Mexico	630779.4	(-25.9)	2.2	(-0.9)	6.3	(-16.5)	5.7	(-38.8)	755.6	(39.2)
New York	10321008.7	(-45.6)	20.4	(-0.5)	175.5	(-20.6)	1.4	(-1.9)	0.0	(0.0)
North Carolina	4344011.3	(-44.0)	5.6	(-0.6)	82.3	(-21.0)	20.3	(-39.8)	1038.6	(9.9)
North Dakota	1249116.5	(-31.2)	3.2	(-2.0)	1.0	(-1.4)	0.6	(-8.9)	95.8	(8.8)
Ohio	2854580.2	(-31.9)	8.1	(-0.5)	138.8	(-26.5)	11.7	(-17.0)	62.4	(2.1)
Oklahoma	761736.8	(-22.9)	3.5	(-0.8)	5.4	(-8.7)	14.5	(-46.1)	559.4	(6.8)
Oregon	2970890.4	(-50.9)	2.1	(-0.6)	24.5	(-23.3)	7.3	(-32.2)	141.9	(2.4)
Pennsylvania	6901247.5	(-54.7)	9.8	(-0.4)	159.6	(-27.2)	4.8	(-7.0)	0.0	(1.0)
Rhode Island	765612.9	(-17.3)	1.9	(-0.3)	11.5	(-20.2)	0.0	(-0.7)	68.1	(0.0)
South Carolina	813063.1	(-19.7)	1.1	(-0.1)	23.2	(-6.9)	16.9	(-53.9)	1602.3	(42.8)
South Dakota	1128334.9	(-47.3)	1.4	(-1.4)	2.5	(-5.0)	1.4	(-21.9)	179.0	(34.0)
Tennessee	943627.2	(-19.0)	1.1	(-0.2)	18.3	(-1.5)	0.6	(-1.4)	0.0	(0.0)
Texas	5494902.7	(0.0)	8.8	(0.0)	74.1	(0.0)	0.0	(0.0)	882.7	(0.0)
Utah	1542717.3	(-48.8)	0.9	(-0.6)	18.8	(-24.7)	3.7	(-21.8)	106.7	(3.2)
Vermont	878603.2	(0.0)	0.4	(0.0)	4.4	(0.0)	0.0	(0.0)	149.8	(0.0)
Virginia	2891505.3	(-43.3)	6.8	(-0.7)	24.4	(-9.1)	18.4	(-34.7)	758.3	(3.3)
Washington	4156807.1	(-55.9)	1.7	(-0.1)	43.4	(-11.0)	9.6	(-22.1)	168.1	(3.3)
West Virginia	1274187.0	(-52.8)	4.9	(-3.3)	15.4	(-32.8)	3.4	(-28.4)	251.7	(29.2)
Wisconsin	3656673.2	(-62.2)	3.0	(-1.1)	78.0	(-37.0)	7.3	(-24.1)	0.0	(0.0)
Wyoming	329295.6	(-11.3)	2.1	(-0.2)	1.1	(0.0)	0.0	(0.0)	0.0	(0.0)
Mean	2338103.7	(-31.3)	59.1	(-2.4)	38.4	(-14.0)	7.1	(-21.9)	366.1	(8.6)

Note: Slack (%) = (Target-Actual) / Actual × 100

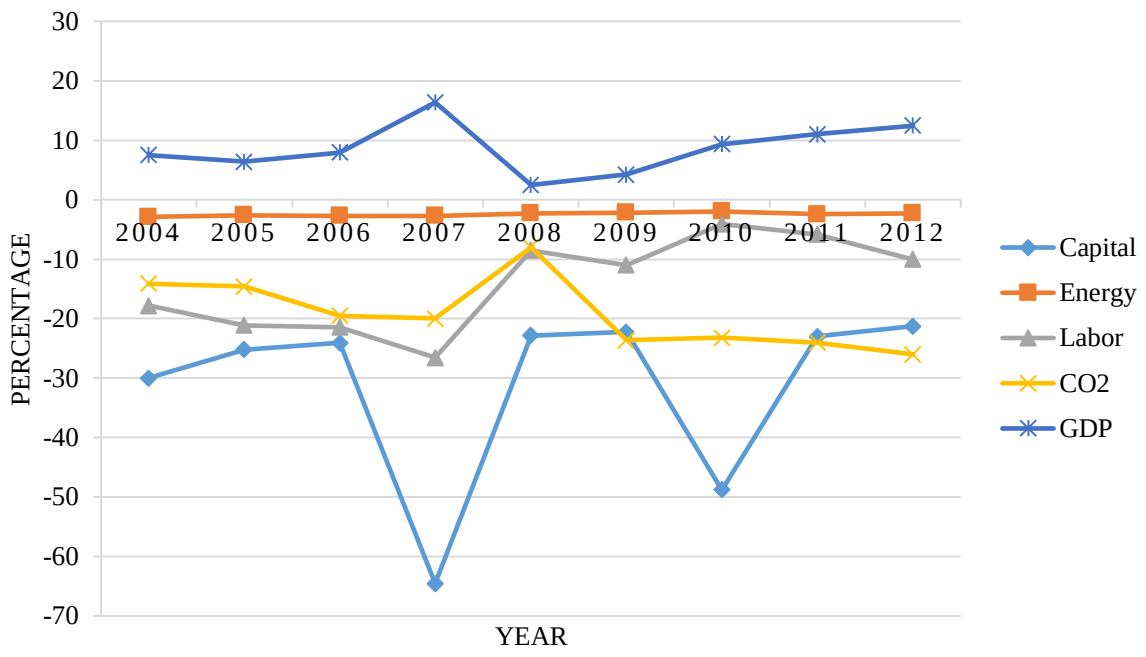

Figure 4. The Percentage Change of Input Excesses, and Output Shortfall.

2.6. Summary and Conclusion

Sustainable development in U.S. transportation is not only essential for economic growth and mobility, but also for the environment. However, no previous studies has been conducted on the environmental efficiency of the U.S's. transportation sector. This study uses a non-radial SBM-DEA model with an undesirable output (CO_2) to measure the environmental efficiency of the U.S transportation sector from 2004 to 2012. Using the SBM-DEA model, environmental efficiency (EE), carbon efficiency (CE) and potential carbon reduction (PCR) are estimated for each state, and we measure the size of slack input resources and excess CO_2 emissions as well as the shortfall of desirable output (transportation GDP).

According to the results we draw the following conclusions: 1) most states had an average EE below 0.64 during 2004-2012, meaning that these states had considerable room for improvements in transportation environmental efficiency; 2) among the 50 U.S. states, four

states were found to be environmentally efficient (Alaska, Illinois, Nebraska and Vermont), the remaining 46 were inefficient with Alabama, South Carolina, Colorado and Mississippi being the most inefficient with average EE and CE scores below 0.4; 3) there was a large PCR for most of U.S. states, and the average PCR was 7.10 million metric tons; 4) the U.S.'s transportation sector still had great amount of excess in transportation capital and labor, and a potential for more CO_2 emissions reduction .

Striking a balance between adequate transportation provisions and reducing transportation carbon footprint has been a challenging task. The findings of this study provide policy insights as well as an overview of the transportation sector's environmental performance in the U.S. First of all, the slack analysis shows the potential improvement of state-level environmental efficiency performances in the transportation sector through better resource utilization and reduced carbon emissions. Second, the policy should adopt the goal and strategy of encouraging energy conservation to reduce CO_2 emissions in the transportation sector. The DEA benchmarking results of this study show that state policymakers could learn and adopt the best practices in eco-efficient states to enhance transportation environmental efficiency. Finally, the U.S. could improve technological innovation and the current fuel economy standards to produce a more environmentally friendly transportation system.

Although this study provides an overall understanding of the environmental performance of the U.S.'s transportation sector, limitations exist. First of all, individual states' performances were compared with other states in the country, and the results may be sensitive to the number of inputs and outputs as well as the levels of aggregation in the data. Also, this study uses state-level transportation sector's GDP as the only good output, but state-level transportation output may vary by the geographical location or the composition of the transportation sector within the

state. For example, coastal water transportation is not part of the sector in landlocked states in the U.S. continent. Therefore, future research could consider using more disaggregated market data rather than the sector's GDP to try to capture the relative efficiencies of the states. In this paper, we did not consider the technological change of the transportation sector. It is recommended that future studies further examine the dynamic changes of environmental efficiency as well as the technological changes of the sector. Lastly, the environmental efficiency of the sector may also be analyzed using stochastic frontier analysis. A slacks-based directional distance function (Färe & Grosskopf, 2003; Fukuyama & Weber, 2009) may also be used as an alternative to the SBM efficiency.

CHAPTER 3. INTEGRATED MULTIMODAL TRANSPORTATION MODEL FOR A SWITCHGRASS-BASED BIOETHANOL SUPPLY CHAIN: CASE STUDY IN NORTH DAKOTA [3]

3.1. Abstract

In this study, a mixed integer linear programming model that integrates multimodal transport—truck and rail—into the switchgrass-based bioethanol supply chain was formulated. The objective of this study was to minimize the total cost for cultivation and harvesting, infrastructure, the storage process, bioethanol production, and transportation. Strategic decisions, including the number and location of intermodal facilities and biorefineries, and tactical decisions, such as the amount of biomass shipped, processed, and converted into bioethanol, were validated by using North Dakota as a case study. It was found that the multimodal transport scenario was more cost effective than a single mode of transport (truck) and resulted in a lower cost for bioethanol. A sensitivity analysis was conducted to demonstrate the impact of key factors in the decision to use multimodal transport in a switchgrass-based bioethanol supply chain and on the cost of bioethanol.

3.2. Introduction

Because of worldwide global warming, energy security, societal issues, and the growing demand for oil, there has been increased interest in the development of cellulosic biofuel from

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[3] The material in this chapter was co-authored by Yong Shin Park, Joseph Szmerekovsky, Atif Osmani, N Muhammad Aslaam. Yong Shin Park had primary responsibility for collecting samples in the field and analyzing the test system. Yong Shin Park was the primary developer of the conclusions that are advanced here. Yong Shin Park also drafted and revised all versions of this chapter. This chapter appears in Transportation Research Record: Journal of the Transportation Research Board (Park et al., 2017). I acknowledge that the material from Park et al. (2017) is reproduced with permission of the Transportation Research Board.

renewable biomass feedstock from wood, forest residue, and agricultural residue, which are the best alternatives for transportation fuel. According to the U.S. Energy Information Administration, in 2015, the United States consumed about 7.08 billion barrels of petroleum products (i.e., an average of about 20 million barrels per day), which accounts for 21% of worldwide consumption (U.S. EIA, 2015).

The transportation industry is the dominant sector in the nation's petroleum consumption, accounting for 56% of total U.S. fuel use (U.S. EIA, 2016). Bioethanol is one type of cellulosic biofuel, and corn is the major current source of bioethanol as a first generation renewable resource in the United States. However, there is much debate about first-generation biofuel associated with global food security because this biofuel is produced directly from food crops (Zhang et al., 2013). As an alternative to corn, lignocellulosic biomass feedstock is a promising source of bioethanol. Switchgrass is a type of lignocellulosic biomass that is regarded as one of the best second-generation renewable energy resources (Sokhansanj et al., 2009).

3.3. Literature Review

Many researchers have worked on designing a lignocellulosic biomass–based bioethanol supply chain with a primary focus on minimizing the total system cost by prescribing a supply chain plan that is strategic (i.e., location of the biomass storage and size of the new refinery) and tactical (i.e., amount of biomass shipped and processed) (Akgul, Zamboni, Bezzo, Shah, & Papageorgiou, 2011; Marvin, Schmidt, Benjaafar, Tiffany, & Daoutidis, 2012; Cundiff, Dias, & Sherali, 1997; Huang, Chen, & Fan, 2010; Mansoornejad, Chambost, & Stuart, 2010).

Other studies have presented a model that maximizes profit (Walther, Schatka, & Spengler, 2012) or minimizes risk associated with investment in a biomass supply chain (or both) (Dal Mas, Giarola, Zamboni, & Bezzo, 2010). Several studies have extended previous

models by considering a multiperiod model to deal with the spatial and temporal dimensions for a long-term strategic plan for a biomass supply chain (You, Graziano, & Snyder, 2012). Multiple types of biomass feedstock have been addressed, including forests (Kanzian, Kühmaier, Zazgornik, & Stampfer, 2013; Zhang, Johnson, & Wang, 2016), urban waste (Parker et al., 2010), and other types of agricultural biomass (Sarder, Adnan, & Miller, 2013). Recent studies have contributed to sustainability issues by investigating environmental impacts and regulations (Osmani & Zhang, 2013; Zhong et al., 2016).

A typical plan for a biofuel supply chain should simultaneously consider determination of the location of feedstock areas, the harvesting method, storage, biorefineries, the transport of biomass and biofuel, and biofuel production (Zhang et al., 2016). Making decisions that are financially optimal is a key strategy in a biomass supply chain. Locating storage close to biorefineries reduces unit transportation costs but might increase the transportation costs if the storage is far away from the harvesting or collecting area.

Biomass can be shipped directly to a preprocessing plant or sent to an intermodal hub or storage facility from the harvesting or collecting area. Storage serves as a warehouse for both storing biomass and managing inventories. Intermodal hubs also play an important role in consolidating freight loads of multiple modes of transportation (i.e., truck, rail, and ship) in supply chain networks (Sarder et al., 2013). Each transportation mode also affects supply chain costs (Zhang et al., 2013). The truck is known to be the most economical mode for short-haul shipments, and the rail car is the cheapest mode for long-haul shipments. The rail car can handle more tons of cargo at a lower cost than the truck and is also the more energy efficient transportation mode of the two (Rodrigue, Comtois, & Slack, 2013). Multimodal transport,

which is a combination of at least two modes of transport, offers more flexibility, is cheaper, and is a more efficient transportation mode than single-mode transport.

It enhances commercial viability and should be integrated into the cellulosic biofuel supply chain design (Xie, Huang, & Eksioglu, 2014). However, the assumption in the existing literature related to the cellulosic bioethanol supply chain design is that the truck is the only transport mode, although the multimodal transportation option is very attractive for the geographic dispersion of the demand and the supply chain of biofuel (U.S. DOE, 2016).

To the best of the authors' knowledge, few studies in the literature have addressed the application of multimodal transport in the design of a bioethanol supply chain (Ekşioğlu, Li, Zhang, Sokhansanj, & Petrolia, 2010; Mahmudi & Flynn, 2006; Roni, Eksioglu, Cafferty, & Jacobson, 2017; Xie et al., 2014; Zhang et al., 2016). This research was motivated by a study Ekşioğlu et al. (2010) which addressed the impact of intermodal facilities on the decision support system for the design of corn-based biofuel supply chains. Their study also determined the minimum cost of biofuel delivery with different levels of production capacity and transportation costs.

However, they did not investigate the impact on the biofuel supply of the location of the biomass storage when it is integrated with an intermodal facility chain. Additionally, there has been limited work integrating multimodal transport into switchgrass-based bioethanol supply chains (MTSBSC). Morrow, Griffin, & Matthews (2006) examined the cost comparison between truck and rail transport modes for downstream switchgrass based bioethanol supply chains throughout the United States. Other works, including Zhu & Yao (2011), You et al. (2012), An, Wilhelm, & Searcy (2011), and Zhang et al. (2013), only considered the truck transport mode in a switchgrass-based bioethanol supply chain as a whole.

This study drew on the aspects of supply chains commonly identified in the reviewed literature in the development of mixed integer linear programming for investigating a cost-effective MTSBSC. The goal of this study was to minimize the total system cost, including marginal rental cost, cultivation cost, harvesting cost, infrastructure capital cost, and transportation costs across the entire supply chain over a 1-year planning horizon.

The proposed supply chain structure of the MTSBSC model is shown in Figure 5. The switchgrass biomass is harvested and transported by trucks directly either to storage located at an intermodal facility or to a refinery. The switchgrass biomass stored at the truck yard is shipped to biorefineries by truck; biomass stored at rail yards is transported by rail. Then, bioethanol produced from biorefineries is delivered to demand zones via truck.

Key features of this study include (a) use of two transport modes— truck and rail—in demonstrating the applicability of the model for the case of North Dakota throughout the switchgrass-based bioethanol supply chain from feedstock to end user and (b) investigation of the use of a tarp storage system built near rail spurs or along state highways near the intermodal facility for storing switchgrass biomass as either round or square bales. Apart from a study by Zhang et al. (2016). Zhang et al. (2016) investigated putting forest wood storage near rail spurs and Class A highways to alleviate the impact of the spring breakup period on truck flow, a situation applicable to this case study as well.

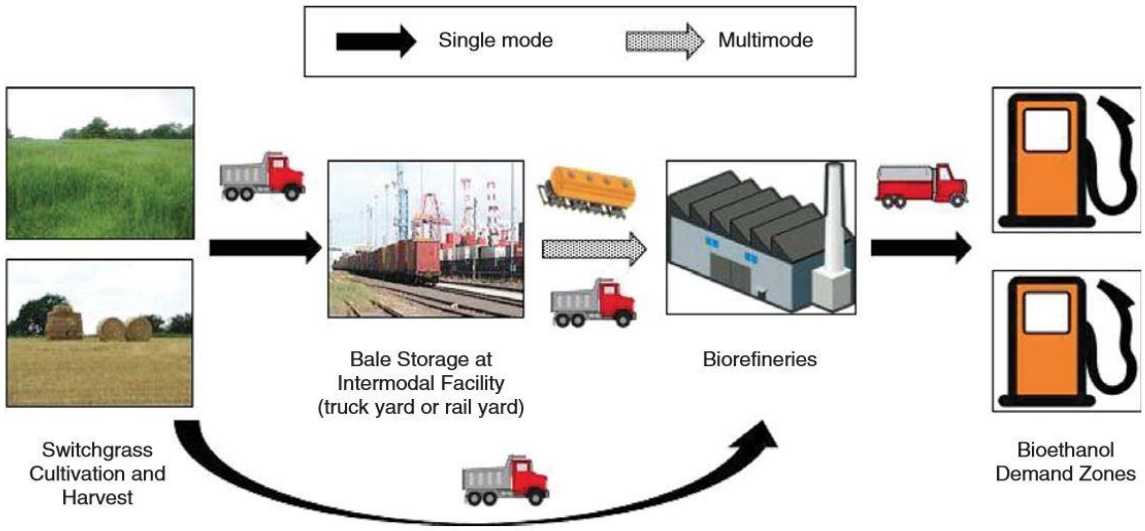

Figure 5. Switchgrass -based Multimodal Bioethanol Supply Chain Structure.

3.4. Problem Statement and Model Formulation

The main objective of this study was to build an MTSBSC model that aids in the design and operational management of the bio ethanol supply chain network. The MTSBSC design problem consists of locating a set of intermodal hubs, selecting suitable biorefineries from the existing locations, and determining the route of biomass and bioethanol flows.

Two sets of decision, strategic and tactical, must be made simultaneously. The strategic decisions were mainly concerned with the location of the intermodal storage, the quantity of intermodal storage, the biorefinery location, assignment of a harvesting area to a particular intermodal storage or to biorefineries, and storage assigned to a particular biorefinery. Tactical decisions included the amount of biomass harvested and shipped through the multimodal supply chain network, the amount of biomass stored, and the amount of bioethanol produced.

The objective of this study was to seek a minimum cost strategy for the total switchgrass-based bioethanol supply chain that integrates both truck and rail by determining various decision

variables for the supply chain logistics. Notations of subscript indices, input parameters, and decision variables used in formulating the model are presented in Table 8.

The objective function (Equation 3.1) minimizes the annual total supply chain cost, including the switchgrass marginal rental cost C^{rent} (Equation 3.2), cultivation cost C^{cult}(Equation 3.3), harvesting cost C^{harv} (Equation 3.4), storage cost at an intermodal facility C^{stor} (Equation 3.5), bioethanol production cost C^{prod} (Equation 3.6), intermodal facility capital investment cost C^{intcap} (Equation 3.7), biorefinery capital investment cost C^{brcap} (Equation 8), and switchgrass and bioethanol transportation cost C^{trans} (Equation 3.9).

Transportation cost C^{trans} in Equations 3.9–3.13 comprises four terms: costs for transportation from (a) the switchgrass harvesting area to the biorefinery $c^{trans,sb}$, (b) the switchgrass harvesting area to the intermodal storage $c^{trans,si}$, (c) the intermodal storage to the biorefinery $c^{trans,ib}$, and (d) the biorefinery to the demand zone $c^{trans,bd}$. In particular, Equation 3.12 shows both the truck and rail transportation modes used in formulating the model. All variables except binary variables are nonnegative continuous.

$$\text{Minimize } C^{rent} + C^{cult} + C^{harv} + C^{stor} + C^{trans} + C^{prod} + C^{intcap} + C^{brcap} \tag{3.1}$$

$$C^{rent} = \sum_{t\epsilon T} \sum_{i\epsilon I} c_i \times Q_{it} \tag{3.2}$$

$$C^{cult} = \sum_{t\epsilon T} \sum_{i\epsilon I} v_i \times Q_{it} \tag{3.3}$$

$$C^{harv} = \sum_{t\epsilon T} \sum_{i\epsilon I} h_i \times Q_{it} \tag{3.4}$$

$$C^{stor} = \sum_{t\epsilon T} \sum_{i\epsilon I} c^{istor} \times S_{jt} \tag{3.5}$$

$$C^{prod} = \sum_{t\epsilon T} \sum_{i\epsilon I} c^{bp} \times Q_{kt} \tag{3.6}$$

$$C^{intcap} = \sum_{t\epsilon T} \sum_{j\epsilon J} f_{ic} \times X_j \tag{3.7}$$

$$C^{brcap} = \sum_{t\epsilon T} \sum_{j\epsilon J} f_{bc} \times Y_{kp} \tag{3.8}$$

$$C^{trans} = c^{trans,sb} + c^{trans,si} + c^{trans,ib} + c^{trans,bd} \tag{3.9}$$

$$c^{trans,sb} = \sum_{t\epsilon T} \sum_{i\epsilon I} \sum_{k\epsilon K} (c^{truck,mc} \times d^{sb} + c^{truck,lu}) \times Q_{sbt} \tag{3.10}$$

$$c^{trans,si} = \sum_{t\epsilon T} \sum_{i\epsilon I} \sum_{j\epsilon J} (c^{truck,mc} \times d^{si} + c^{truck,lu}) \times Q_{sit} \tag{3.11}$$

$$c^{trans,ib} = \sum_{t\epsilon T} \sum_{j\epsilon J} \sum_{k\epsilon K} \sum_{m\epsilon M} \{(c^{truck,mc} \times d^{ib} + c^{truck,lu}) \times Q_{ibmt}\} + \{(c^{rail,mc} \times d^{ib} + c^{rail,fc}) \times Q_{ibmt}\} \tag{3.12}$$

$$c^{trans,bd} = \sum_{t\epsilon T} \sum_{k\epsilon k} \sum_{e\epsilon E} (c^{truck,mc} \times d^{si} + c^{truck,lu,b}) \times Q_{bdt} \tag{3.13}$$

The model constraints are presented in Equations 3.14 through 3.21. The constraint in Equation 3.14 ensures that the amount of switchgrass harvested at area i does not exceed the marginal land availability. The constraint in Equation 3.15 is the feedstock flow conservation constraint that ensures that the amount of biomass transported from the harvesting area to the intermodal storage and refinery represents what is actually available in the feedstock area during time period t.

The constraint in Equation 3.16 imposes a flow conservation on intermodal storage. The constraint in Equation 3.17 is a logical constraint, stating that there is no flow through intermodal storages unless at least one facility is open. The constraint in Equation 3.18 is a flow conservation constraint for refineries. The constraint in Equation 3.19 ensures that a maximum of one biorefinery can be chosen at each location. The constraint in Equation 3.20 is another logical constraint indicating that there is no biofuel production unless at least one refinery is open. The

constraint in Equation 3.21 ensures that during any time period t, the volume of bioethanol transported from biorefineries to each demand zone must be greater or equal to the biofuel requirement for each demand zone.

$$Q_{it} \leq a_{it} \qquad \forall i \in I, \ \forall t \in T \tag{3.14}$$

$$Q_{it} = \sum_{i\epsilon I} Q_{sit} + \sum_{j\epsilon J} Q_{sbt} \tag{3.15}$$

$$\sum_{i\epsilon I} Q_{sit} + (1-\delta) \times S_{j,t-1} = S_{jt} + \sum_{k\epsilon K}\sum_{m\epsilon M} Q_{ibmt} \quad \forall j \in J, \forall k \in K, \forall t \in T \tag{3.16}$$

$$S_{jt} \leq \sum_{j\epsilon J} p_j \times X_j \quad \forall j \in J, \forall t \in T \tag{3.17}$$

$$\sum_{k\epsilon K}\sum_{j\epsilon J}\sum_{m\epsilon M} (Q_{sbt} + Q_{ibmt}) \times \theta = \sum_{k\epsilon K}\sum_{e\epsilon E} Q_{bdt} \quad \forall j \in J, \forall k \in K, \forall m \in M, \forall t \in T \tag{3.18}$$

$$\sum_{p\epsilon P} Y_{kp} \leq 1 \tag{3.19}$$

$$S_{kt} \leq \sum_{k\epsilon K} b_k \times Y_k \quad \forall k \in K, \forall t \in T \tag{3.20}$$

$$\sum_{k\epsilon K} Q_{kt} \geq d_t \quad \forall e \in E, \forall t \in T \tag{3.21}$$

Table 8. Notations Used in Model Development.

Variable	Description
Index//sets	
i	Switchgrass supply points
j	Intermodal facility locations
k	Biorefinery locations
q	Capacity level of biorefineries
e	Bioethanol demand points
m	Transport mode
t	Modeling horizon of 1 year with time periods
Input parameters used in model development	
C^{rent}	Marginal land rental cost ($)
C^{cult}	Biomass cultivation cost ($)
C^{harv}	Biomass harvesting cost ($)
C^{trans}	Biomass transport cost ($)
C^{intcap}	Intermodal facility capital cost ($)
C^{brcap}	Biorefinery capital cost ($)
C^{stor}	Biomass storage cost ($)
C^{prod}	Biofuel production cost ($)
a_i	Maximum marginal biomass availability (ton)
$c^{trans,sb}$	Transport cost of biomass from supply area to biorefineries ($/ton-mi)
$c^{trans,si}$	Transport cost of biomass from supply area to intermodal facility ($/ton-mi)
$c^{trans,ib}$	Transport cost of biomass from intermodal facilities to biorefineries ($/ton-mi)
$c^{trans,bd}$	Transport cost of biofuel from biorefineries to demand points ($/ton-mi)
p_j	Storage capacity (ton)
f_{ic}	Annualized intermodal facility fixed capital cost ($)
b_k	Biorefinery capacity (gal)
f_{bc}	Annualized biorefinery fixed capital cost ($)
c_i	Annual rental cost of marginal land in i ($/ha)
v_i	Cultivation cost of switchgrass ($/ha)

Variable	Description
h_i	Harvesting cost of switchgrass ($/ha)
c^{istor}	Unit storage cost at storage yard at intermodal facilities ($/ton)
c^{brstor}	Unit storage cost at biorefineries ($/ton)
c^{bp}	Bioethanol production cost at refineries ($/gal)
$c^{truck,lu}$	Truck loading and unloading cost ($/ton)
$c^{truck,mc}$	Truck variable mileage cost ($/ton-mi)
$c^{rail,fc}$	Rail fixed cost ($)
$c^{rail,mc}$	Rail variable mileage cost ($/ton-mi)
$c^{truck,lu}$	Truck loading and unloading cost ($/ton)
d^{si}	Transport distance from supply area to intermodal facilities (mi)
d^{sb}	Transport distance from supply area to biorefineries (mi)
d^{ib}	Transport distance from intermodal facilities to biorefineries (mi)
d^{bd}	Transport distance from biorefineries to demand points (mi)
δ	Biomass deterioration rate (%)
θ	Bioethanol conversion rate (gal/ton)
d_t	Biofuel demand in period t (gal)
Decision variable used in model development	
X_j	= 1 if an intermodal facility is opened at location j; 0 otherwise (binary)
Y_{kp}	= 1 if a biorefinery is opened at location k with capacity level p; 0 otherwise (binary)
Q_{it}	Quantity of biomass harvested at supply area i (ton)
S_{jt}	Quantity of biomass stored at intermodal facility (ton)
S_{kt}	Quantity of biomass stored at biorefinery (ton)
Q_{sit}	Quantity of biomass transported from supply area to intermodal facility (ton)
Q_{sbt}	Quantity of biomass transported from supply area to biorefinery (ton)
Q_{ibmt}	Quantity of biomass transported from intermodal facility to biorefinery by transport mode during time (ton)
Q_{bdt}	Quantity of biofuel transported from biorefinery to demand point (gal)
Q_{kt}	Quantity of biofuel produced at biorefinery (gal)

3.5. Case Study

For validation and in response to state policy that promotes the use of multimodal transportation in delivering switchgrass-based alternative transportation fuel, the proposed model was applied to a case study of a switchgrass-based bioethanol supply chain in North Dakota. North Dakota is an ideally suited region for commercial cultivation of switchgrass with great potential for using switchgrass-based bioethanol in the future (Zhang et al., 2013).

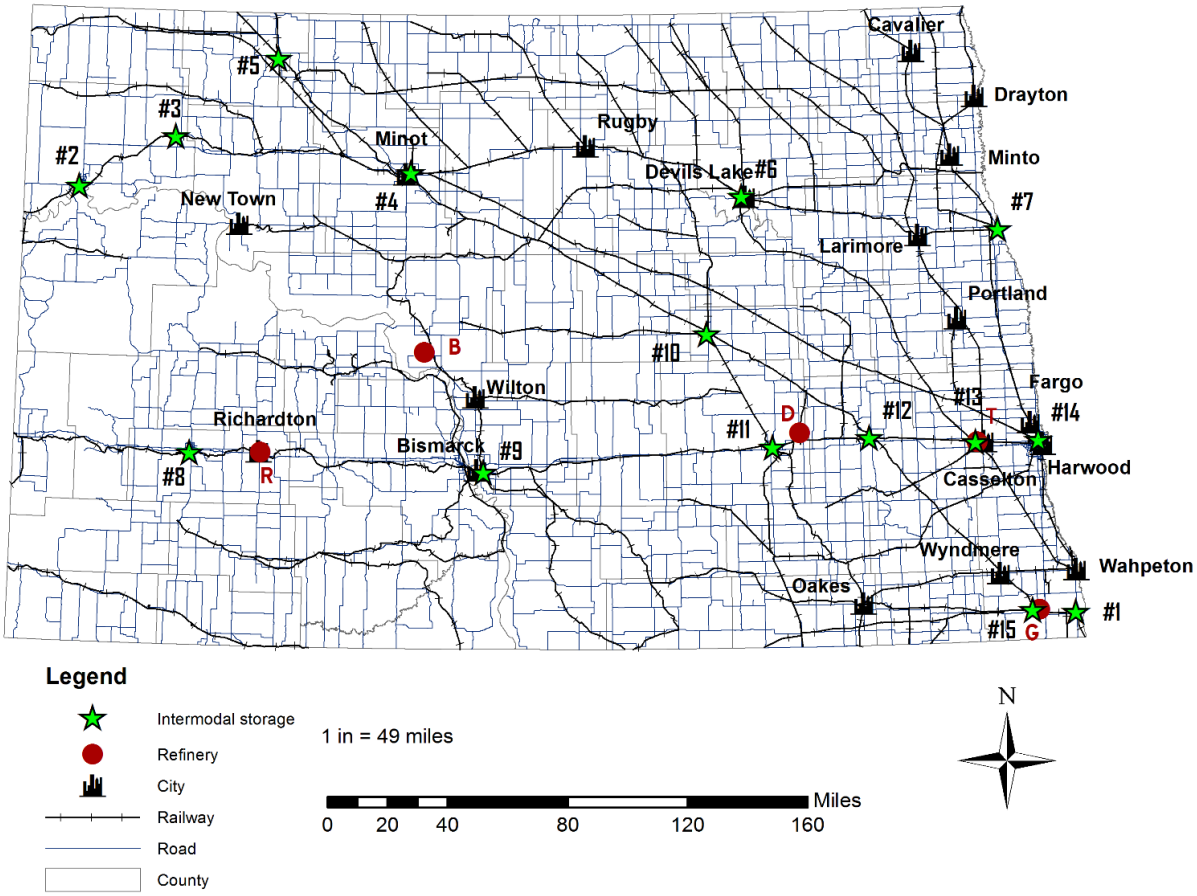

Figure 6. Intermodal Facility and Biorefinery Candidates in North Dakota.
Intermodal facilities are as follows: 1 = Fairmount, 2 = Williston, 3 = Tioga, 4 = Minot, 5 = Bowbells, 6 = Devils Lake, 7 = Grand Forks, 8 = Dickinson, 9 = Bismarck, 10 = Carrington, 11 = Jamestown, 12 = Valley City, 13 = Casselton, 14 = Fargo, and 15 = Hankinson.

3.5.1. Harvesting Area

For the purposes of this study, all 53 counties in North Dakota were considered as potential feedstock areas that could produce switchgrass. The switchgrass yield rate was assumed to be a linear function of the annual rainfall in North Dakota, which can be used to estimate the amount of switchgrass a supply zone can produce (Zhang et al., 2013). Two types of bale, square and round, were considered. Harvesting areas of switchgrass were defined by using county boundaries on the ArcGIS mapping platform. Feedstock data were integrated with transportation network data by assuming that the centroid of each county's polygon was a feedstock supply area, which was auto-generated and identified on the ArcGIS map. The associated feedstock parameters, including marginal rental cost (which varies by county) (USDA, 2012), cultivation cost ($85.0/ton) (Wilkes, 2007), harvesting cost (round bale =$48.2/ha, square bale =$27.9/ha) (Larson, Yu, English, Mooney, & Wang, 2010), marginal land availability for each county (USDA, 2012) were collected.

3.5.2. Intermodal Storage

There is only one intermodal facility used for freight transportation in North Dakota. With increasing agricultural demand and oil delivery, more intermodal options could enhance traffic and customer service for the agricultural and energy industries. Fifteen intermodal facility candidates (numbered 1 through 15, including the existing intermodal facility at Minot) were selected by using the North Dakota strategic freight analysis report from the Upper Great Plains Transportation Institute (Berwick, Bitzan, Chi, & Lofgren, 2002). By using ArcGIS, tarp systems for bale storage were located at yards where both railway and highway were available.

The capacity of storage was set at 125,000 tons regardless of locations (Zhang et al., 2016). The storage cost was set at $21.7/ton, which included any expense incurred to maintain

inventory and storage (Larson et al., 2010). Dry matter loss for both types of bale is assumed to be 2% (Shinners & Binversie, 2007). The fixed intermodal facility capital investment cost was set at $470,597 (Berwick et al., 2002).

3.5.3. Biorefinery

There are five corn-based biorefineries in North Dakota, including Blue Flint Ethanol (B, 65 million gallons per year), Dakota Spirit (D, 70 million gallons per year), Guardian Hankinson (G, 132 million gallons per year), Red Trail Energy (R, 50 million gallons per year), and Tharaldson Ethanol (T, 153 million gallons per year), shown in Figure 6. It was assumed that with advanced biofuel conversion technology, multiple types of feedstock could be converted to bioethanol at refineries. Therefore, these five biorefineries were used as switchgrass-based bioethanol production candidates in this study. A conversion factor of 85 gal of bioethanol per ton of biomass was used (National Academy of Sciences, 2009).

The capital cost of a biorefinery includes fixed and variable capital costs (Huang et al., 2010). Each biorefinery has a different fixed cost, and variable cost was proportional to the size of the refinery (Parker et al., 2010). The fixed capital cost for each biorefinery was determined by multiplying a cost scaling factor of 1.6 by the size of the biorefinery (Wallace, R., Ibsen, K., McAloon, A. and Yee, 2005). Therefore, a medium level of annualized fixed capital cost was interpolated. The fixed capital cost was $27 million for a biorefinery that produces 65 million gallons per year, $28 million for a biorefinery that produces 70 million gallons per year, $42.8 million for a biorefinery that produces 132 million gallons per year, $22 million for a biorefinery that produces 50 million gallons per year, and $46.8 million for a biorefinery that produces 153 million gallons per year. The variable cost was 0.64/gal regardless of the variation in fixed capital costs (Haque & Epplin, 2012).

3.5.4. Transportation Data

The multimodal transportation network is presented in Figure 6. In this study, transportation networks, including local, rural, urban roads and highways, and railways, were considered. It was assumed that the centroid of each harvesting area was the origin of the biomass supply chain. The longitudes and latitudes of the intermodal facilities and biorefineries were identified in ArcGIS. The shortest path from origin to destination, determined by using Dijkstra's algorithm, was calculated with the origin–destination cost matrix application in the ArcGIS network analysis. The following costs were associated with transport by truck and rail: loading and unloading costs for trucks, $5/ton (Xie et al., 2014); variable mileage cost for trucks, $0.1/ton-mi for round bales, and $0.12/ton-mi for square bales (Larson et al., 2010); variable mileage cost for rail, $0.02/ton-mi (Morrow et al., 2006); and fixed cost for rail, $6.54/ton (Zhang et al., 2016).

3.5.5. Bioethanol Demand

Cities that provide E85 ethanol are considered to be demand centers, and 18 of these cities were chosen for this study. Figure 6 shows their geographic distribution. The total annual demand for bioethanol was set at 30 million gallons per year, according to the official portal for the North Dakota state government (ND.gov, 2016).

3.6. Results and Discussion

3.6.1. The Optimal System Results and Comparison with Single Mode

The minimum cost strategy for integrating a multimodal transportation model into a switchgrass-based supply chain suggests that four intermodal facilities (Numbers 3, 4, 6, and 14) are required and two biorefineries (D and R) should be selected. The optimized total cost for the supply chain is $237 million. The total system cost breakdown is presented in Figure 7. It was

found that cultivation costs represented the largest part of the total cost, accounting for 36.64%, followed by production costs, which accounted for 19.46%. The optimal assignment and its flow pattern of biomass to intermodal storages and biorefineries were analyzed, as shown below:

- Counties assigned to intermodal storage:

– Burke, Divide, Mountrail, and Williams counties assigned to Tioga (Facility 3);

– Bottineau, McHenry, Pierce, Renville, Rolette, Sheridan, and Ward counties assigned to Minot (Facility 4);

– Cavalier, Pembina, Ramsey, Towner, Walsh, and Rolette counties assigned to Devils Lake (Facility 6); and

– Richland and Sargent counties assigned to Hankinson (Facility 14);

- Counties assigned to biorefineries:

– Barnes, Cass, Dickey, Eddy, Foster, Grand Forks, Griggs, Kidder, LaMoure, Logan, McIntosh, Nelson, Ransom, Steele, Stutsman, Traill, and Wells counties assigned to Biorefinery D; and

– Adams, Billings, Bowman, Burleigh, Dunn, Emmons, Golden Valley, Grant, Hettinger, McKenzie, McLean, Mercer, Morton, Oliver, Sioux, Slope, and Stark County's assigned to Biorefinery R; and

- Intermodal storage assigned to biorefineries (rail is the only mode that ships biomass from intermodal storage to a biorefinery)

– Hankinson (Facility 14) assigned to Biorefinery D and

– Tioga (Facility 3), Minot (Facility 4), Devils Lake (Facility 6), and Hankinson (Facility 14) assigned to Biorefinery R.

Only rail transport mode was used from the intermodal storage to the biorefinery because rail haulage costs are lower than rail for long distance shipment. Trucks were used for transport from the harvesting area to the intermodal facility and from the biorefineries to the demand center, because it was the only possible mode for some segments that originated at a harvesting area or ended at market (Xie et al., 2014).

For comparison of the multimodal and single-mode solutions to be possible, the model was run again without the rail transport mode. The cost comparison of the single- and multimodal solutions shown in Table 9 indicates that the single-mode solution would cost about $76 million more than the multimodal solution. The optimal delivered cost when the multimodal solution was used was $1.904/gal, which is cheaper than that of the single-mode solution ($2.663/gal).

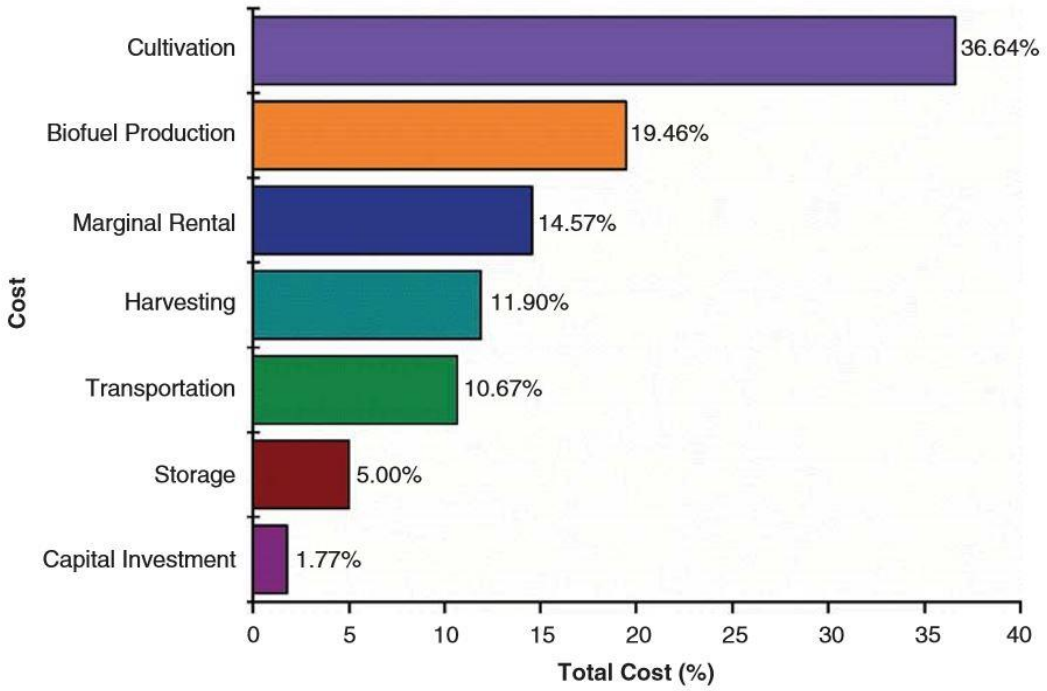

Figure 7. Total Cost Breakdown for Switchgrass-based Multimodal Bioethanol Supply Chain.

Table 9. Cost Comparison for Single Mode and Multimode.

Cost breakdown		Single mode		Multimode
Transportation	$	107,592,261.18	$	82,601,443.23
Bioethanol delivered	$	2.663	$	1.904
Total supply chain	$	313,716,741.38	$	237,253,908.70

3.6.2. Sensitivity Analysis

This section provides a discussion of the results from several sensitivity analyses and an analysis of significant factors in the switchgrass-based multimodal bioethanol supply chain. Key inputs in the sensitivity analysis included the conversion rate of switchgrass feedstock to bioethanol, biomass feedstock availability, levels of bioethanol demand, and all the unit cost factors—marginal rental cost, cultivation cost, harvesting cost, transportation cost, storage cost, bioethanol production cost, and capital investment cost.

3.6.2.1. Influence of biomass availability and conversion rate on bioethanol cost and location

The baseline figures used were a conversion rate of 85 gal/ton and 13 million tons of available biomass in 53 counties in North Dakota (Zhang et al., 2013). It was assumed that the conversion rate would decrease from 85 to 55 gal/ton in increments of 5 gal/ton, and that the availability of switchgrass would increase by a total of 5% from the starting available volume.

Table 10 presents the changes in bioethanol delivered costs and decisions about the locations of intermodal facilities and biorefineries by biomass availability and conversion rate. The highest bioethanol cost was $2.977/gal with a 3% increase in biomass availability and a conversion rate of 55 gal/ton, and the lowest bioethanol cost was $1.850/gal with a 5% increase in biomass availability and a conversion rate of 80 gal/ton. It was found that the cost of bioethanol increased dramatically at the lowest biomass availability and at the lowest conversion

rate; which is because long-haul shipments occur at low biomass availability (Zhang et al., 2016). Locations of intermodal storage and biorefineries changed with changes in biomass availability and conversion rates. The results show that Intermodal Storage Locations 3 and 6 would be optimal candidate locations in most scenarios, as is Storage Location 4, which is currently operating in North Dakota. The greater the biomass availability and conversion rate, the more intermodal facilities are needed. In terms of biorefinery locations, most of the scenarios showed that when capacity increased, Biorefineries D and R would be candidate sites for converting multiple types of feedstock into bioethanol and minimizing total cost.

Table 10. Bioethanol Cost and Location Decision by Biomass Availability and Conversion Rate.

Biomass availability (%)	**Conversion rate (gallon/ton)**						
	Bioethanol delivered cost ($/gallon)						
	Baseline	80	75	70	65	60	55
Baseline	1.904	2.016	2.352	2.346	2.520	2.524	2.951
1%	1.885	2.001	2.373	2.355	2.540	2.712	2.931
2%	1.863	1.987	2.384	2.339	2.489	2.729	2.912
3%	1.862	1.972	2.100	2.359	2.505	2.674	2.977
4%	1.863	1.958	2.040	2.353	2.465	2.664	2.873
5%	1.856	1.850	1.970	2.388	2.448	2.637	2.855
Biomass availability (%)	*Intermodal facility location*						
	Baseline	80	75	70	65	60	55
Baseline	3,4,6,14	3,4,6	3,4,6	3,4,6	3,4,6	3,6,8	3,6,8
1%	3,4,6,14	3,4,6	3,4,6	3,4,6	3,4,8	3,4,6,8	3,6,8
2%	3,4,6,10,15	3,4,6	3,4,6	3,4,6	3,4,6	3,4,6	3,4,6
3%	3,4,6,14	4,6,7	3,4,6	3,4,6	3,4,6	3,4,6,8	3,4,6
4%	3,4,6,10,11,14	3,4,6,14	3,4,6,14	3,4,6	3,4,6	3,4,6	3,6
5%	3,4,6,14	3,4,6,14	3,4,6	3,4,6	3,4,6	3,4,6	3,6,8
Biomass availability (%)	*Refinery location*						
	Baseline	80	75	70	65	60	55
Baseline	D,R	D,R	D,R	D,R	D,R	B,T	B,T
1%	D,R	D,R	D,R	D,R	D,R	B,T	B,T
2%	D,R	D,R	D,R	D,R	D,R	D,R	B,T
3%	D,R	D,R	D,R	D,R	D,R	B,T	D,R
4%	D,R	D,R	D,R	D,R	D,R	D,R	B,T
5%	D,R	D,R	D,R	D,R	D,R	D,R	B,T

3.6.2.2. Change in bioethanol delivered costs resulting from change in bioethanol demand and conversion rates

In addition to the change in the bioethanol delivered cost in different scenarios of biomass availability and conversion rates, changes in the bioethanol delivered cost with different annual levels of bioethanol demand (millions of gallons per year) versus the conversion rate (gallons per ton) were investigated. It was assumed that bioethanol demand would increase from the current annual level of demand of 30 million gallons per year to 45 million gallons per year (a 50% increase in total). Figure 8 presents the resulting changes in the bioethanol delivered cost by bioethanol demand and conversion rate. When the bioethanol demand was fixed, the delivered cost of bioethanol increased with the increase in conversion rate (Figure 8a). When the conversion rate remained the same, the delivered cost of bioethanol also increased, meaning that the delivered cost of bioethanol is higher when there is an increasing demand for bioethanol and a decreasing conversion rate (Figure 8b).

The experimental results from Tables 10 and Figure 8 indicate that the relationship between biomass availability and conversion rate and between bioethanol demand and conversion rate is a major factor affecting the bioethanol delivered cost. Greater biomass availability means that harvesting areas would supply nearby intermodal storage and biorefineries; the result would be a lower shipment cost and, therefore, a lower unit cost for bioethanol (Zhang et al., 2016). A lower conversion rate with a higher demand implies a higher bioethanol production cost, which would increase the cost of transportation and the unit cost of bioethanol.

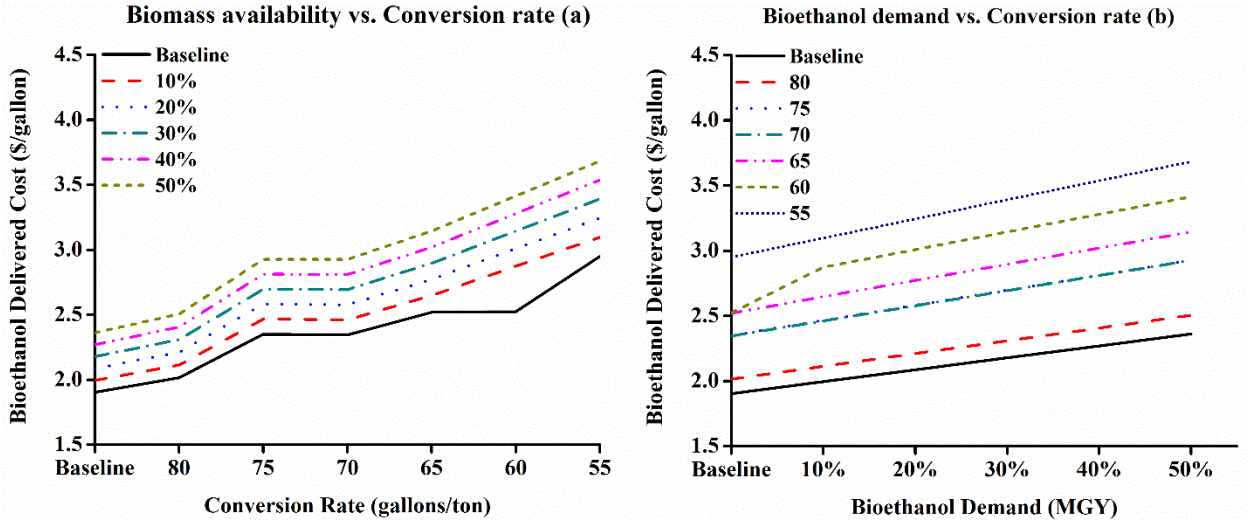

Figure 8. Bioethanol Delivered Cost by Bioethanol Demand Change and Conversion Rate.

3.6.2.3. Influence of unit cost factors on the cost of bioethanol

The unit cost factors that most influence the delivered cost of bioethanol were identified by increasing or decreasing each unit cost by 10% for a sensitivity analysis so that the overall switchgrass-based bioethanol multimodal supply chain system could be investigated, as presented in Table 11. The results show that the cost of bioethanol is not dependent on rental, cultivation, or harvesting costs. The most influential unit cost factor is the cost of truck transportation for biomass, which accounts for a 1.42% increase and a 5.62% decrease of the optimal value of the cost of bioethanol ($1.904/gal). The second most influential factor is the cost of rail transportation, which accounts for a 0.95% increase and a 3.52% decrease. Capital investment costs and bioethanol production costs are the third and fourth most influential factors.

Table 11. Sensitivity Analysis for Delivered Bioethanol Cost.

Unit cost factor	Bioethanol cost ($/gal)	Percentage change (%)
Rental		
10% increase	0	0
10% decrease	0	0
Cultivation		
10% increase	0	0
10% decrease	0	0
Harvesting		
10% increase	0	0
10% decrease	0	0
Truck Transportation		
10% increase	1.931	1.42%
10% decrease	1.797	-5.62%
Rail Transportation		
10% increase	1.922	0.95%
10% decrease	1.837	-3.52%
Storage		
10% increase	1.899	-0.26%
10% decrease	1.894	-0.53%
Production		
10% increase	1.917	0.68%
10% decrease	1.906	0.11%
Capital		
10% increase	1.920	0.84%
10% decrease	1.841	-3.31%

3.7. Summary and Conclusion

This study formulated a mixed integer linear programming model for integrating multimodal transport (truck and rail) into an MTSBSC design. The model was applied to a case study in North Dakota. This research demonstrated how the proposed model could be adopted to make strategic and tactical decisions for the bioethanol supply chain. Experimental results indicate that the multimodal solution would be more cost effective than the single-mode solution in terms of total system costs and bioethanol delivered costs. Additionally, there was an interaction between the bioethanol conversion rate and biomass availability as well as between the conversion rate and the bioethanol demand, which affects decisions on locations of biorefineries and intermodal storage. Greater biomass availability resulted in a lower unit cost for

bioethanol. On the other hand, higher demand for bioethanol increased the cost of bioethanol. The results of the sensitivity analysis indicated that transportation costs are the most influential factor in the bioethanol delivered cost, followed by capital investment and the production cost. The storage cost showed no impact on bioethanol cost. This impact should be identified in future research by considering changes in biomass inventory over time. This study optimized MTSBSC by using a single objective of economic performance. The current study can be extended by considering multiple objectives that incorporate the environmental impact of MTSBSC.

CHAPTER 4. DETERMINATION OF POTENTIAL INFRASTRUCTURE AND PRODUCTION OF BIOGAS FROM ANIMAL MANURE: IMPACT OF CARBON POLICY ON SUPPLY CHAIN DESIGN

4.1. Abstract

Faced with increasing concerns over the negative environmental impact due to human and industrial activities, biomass industry practitioners and policy makers have great interest in green supply chains to reduce carbon emissions from supply chain activities. There are many studies which model the biomass supply chain and its environmental impact. However, animal waste sourced biogas supply chain has not received much attention in the literature. Biogas from animal manure not only provides energy efficiency, but also minimizes carbon emissions compared to existing biomass products. Therefore, this study proposes a mixed integer linear program that minimizes total supply costs and carbon emissions from an animal waste sourced biogas supply chain while also incorporates carbon price in the model to see the impact of a carbon policy on tactical and strategic supply chain decisions. To validate the model proposed, a case study of North Dakota is adopted where there is a high potential for a biogas plant to be developed. The results of our optimization experiment indicate that supply chain performance in terms of both costs and emissions is very sensitive to a carbon pricing mechanism.

4.2. Introduction

The burning of fossil fuels primarily oil, coal and natural gas is the dominant source of greenhouse gas (GHG) emissions, which results in contemporary issues of global climate change. Global cconsumption of energy is expected to increase by 48% between 2012 and 2040 (U.S. EIA, 2017). Because of growing demand and environmental concerns over global warming, there has been great interest in the development of renewable energy sources. Many

practitioners, policy makers, and researchers have raised concerns regarding climate change and making an effort to reduce levels of GHGs. In recent years, it has been observed that the production of bio-diesel, biogas, and ethanol are the most attractive components among the energy produced from biomass and bio wastes and one of the pathways to replace fossil fuel resources. Biomass is derived from plant material (agricultural/ forest residues), animal waste (manure, animal fat, etc.) and food crops (corn, sugar, and wheat), it can be used for transportation fuels and to generate electricity.

Biomass is the fastest-growing energy source in the U.S with expected growth over the next 25 years at an average annual rate of 2 percent. In transportation sector, there is an expected growth of bioenergy consumption from 9 billion gallons per year (BGY) in 2008 to 16 BGY in 2022 (U.S. EPA, 2016). Thus, the nation will be less dependent on fossil fuels, thereby having a positive impact on human health, socio-economic conditions and the environment. In fact, the U.S. Congress has decided to forgo comprehensive climate change legislation in recent sessions. Initially, the Renewable Fuel Standard program (RFS2) was authorized under the Energy Policy Act of 2005 and expanded under the Energy Independence and Security Act of 2007. Its goal was to reduce GHG emissions and to expand the nation's renewable energy dependency. Regulating GHG emissions from large stationary sources such as refineries and power plants is ongoing. California's statewide cap-and-trade program was launched in 2013, and the Regional Greenhouse Gas Initiative (RGGI) for power plants in the northeastern United States has had emissions capped for several years. But, this effort to reduce GHG emissions could not succeed.

In such an environment, biogas, a low-GHG, fuel has significant advantages over higher-GHG fossil counterparts. Biomethane is formed in nature by the biological degradation of biodegradable organic material such as bio-waste, sludge, manure, and agro-residues under

anaerobic conditions. The main components of biogas are methane and carbon dioxide which can be captured and used to generate energy in the form of heat and electricity. They can also be used as vehicle fuel in either a compressed or liquefied form and as power for fuel cell vehicles (Höhn, Lehtonen, Rasi, & Rintala, 2014).

An anaerobic digester systems (ADSs) is well-known process that converts organic feedstock into biogas (Balaman et al., 2014). Methane generated from biodegradable organic material in the United States is estimated at about 7.9 million tons per year, which is equivalent to about 420 billion cubic feet. According to U.S. Energy Information Administration (EIA), biogas could displace about 5 % and 56% of natural gas consumption in the electric power and transportation sectors, respectively. There were 242 operating ADSs on livestock farms in the U.S. in 2016, producing about 981 million kilowatt-hours (kWh) of energy (U.S. EPA, 2016). There is growing interest in installing ADSs converting daily manure of beef cattle, cows, hogs and poultry, and, other animals to biogas due to both its economic and environmental benefit. Biogas produced from ADSs is considered methane neutral process because it has potential to capture methane that escapes into the atmosphere. It was found that the impact of methane on climate change is more than 20 times that of carbon dioxide over a 100-year period.

Required by the RFS2, developing a financially feasible and environmentally sustainable bioenergy supply chain across diverse feedstock harvesting, collection, storage, production, and transportation is challenging (Zhang, Osmani, Awudu, & Gonela, 2013). Strategic, tactical, and operational level decisions related to location, capacity, logistic issues, transportation networks, feed stock acquisition, and distribution of biomass or biofuel must be made for efficient and effective optimal network configuration (Balaman et al., 2014; Rezaee, Dehghanian, Fahimnia, & Beamon, 2015). Traditional supply chain network design has focused on cost efficiency, but

recent regulatory mandates require federal, states, and local authorities to expand their objectives beyond just economic metrics. Now, environmental performance consideration, such as carbon reduction and waste minimization need to be part of the project (Palak, Ekşioğlu, & Geunes, 2014). Thus, modeling sustainable supply chains has been recognized as an important step toward the sustainable development in the business and governmental organizations. Many of these modeling efforts focus on traditional supply chain network design, while challenges for planning bioenergy supply chains are explored less (Ren et al., 2016).

Motivated by the evolving regulatory climate change pressures in the United States, this paper develops and applies two carbon policy models, including carbon pricing and carbon trading mechanisms, which are two popular environmental regulatory policy schemes that have been widely implemented in different nations (Abdallah, Farhat, Diabat, & Kennedy, 2012; Zakeri, Dehghanian, Fahimnia, & Sarkis, 2015). A new approach in the biogas supply chain system is also required to face ever-changing energy markets. Uncertainties in climate change calculation continue to pose some of the most challenging aspects in designing sustainable bioenergy supply chains. To deal with this multi-faceted situation, biogas investment decisions should be supported by quantitative design tools. These are necessary to evaluate both financial and environmental performance of biogas production from a holistic point of view for the entire biogas supply chain - over the short and long term.

In this paper, we formulate an optimization model and consider the strategic decisions of the number and location of biogas plants, as well as the tactical optimization of its capacity and the biogas production in order to explore how the bioenergy industry can manage its supply chain under the two carbon regulatory schemes. The primary objective of this work focuses on green supply chain management to minimize supply chain costs such as acquisition, production,

and transportation, as well as carbon emissions through a carbon cap and trade mechanism. In this regard, Mixed Integer Linear Programming (MILP) is an effective optimization tool, which captures the impact of different scenarios of emission price and caps on the biogas supply chain and provides optimal strategies in designing and planning for practitioners and policy makers.

The remainder of the paper is organized as follows: Section 4.3 reviews the literature on carbon regulatory schemes and green supply chains related to biomass and bioenergy; Section 4.4 presents the problem statement and optimization model that is proposed in this research; Section 4.5 describes a case study; Section 4.6 presents the results and the discussion of research findings and potential implications for policy makers. The paper concludes by providing a summary with future research directions in section 4.7.

4.3. Carbon Regulation in the U.S. and Green Supply Chain

In light of climate change concerns, the United States is under mounting pressure to transition to a low carbon economy. Mitigation of climate change resulting from carbon emissions is considered part of a policy to reduce emissions. In an effort to help mitigate climate change and strive to achieve the goals of a low carbon economy, U.S. states initiated climate change policies under the Clean Air Act (CAA). In addition, the U.S. Environmental Protection Agency (EPA)'s laws and regulations called the Energy Policy Act (EPA) addresses the importance of development of biofuel production and use innovative technology to avoid the by-production of GHG, which became an important step toward reducing carbon pollution, especially from the energy industry. (U.S. EPA, 2005)

It is recognized that renewable energy is already playing a great role in reducing emissions in the energy sector in the U.S and many other countries. Fossil fuel-fired power plants are the largest source of emissions accounting for 31 percent of U.S. greenhouse gas

emissions. Interest in imposing a carbon tax on carbon emissions seems to be on the rise in the U.S., among decision makers (Lawrence & Schein, 2013), in order to increase the cost of energy produced from fossil fuels (Zhang et al., 2013). Although President Donald Trump pulled the USA out of the Paris international climate agreement and repealed Clean Power Plan (CPP), California has still decided to extend its cap and trade system through 2030 and nine northeastern and mid-Atlantic states have also agreed on a California's proposal to reduce their cap on carbon emissions from electricity generation by 3% a year (Kuramochi, 2017). A national carbon tax of $40 per metric ton is expected to be raised at a rate of 5.6 percent per year and about $2.5 trillion in revenue would be yield over a 10-year period. It would also cut U.S. emissions by 8 percent by 2021, as well as hike gasoline and electricity prices (Tang, Chiara, & Taylor, 2012). There are significant efforts to design carbon tax and carbon cap-and-trade programs to mitigate climate change in other countries. For example: national cap-and-trade systems in Australia and New Zealand; a carbon tax in the Canadian province of British Columbia (Lawrence & Schein, 2013); and a carbon tax policy program in some European countries along with an Emission Trading System (ETS).

The carbon trading scheme, also known as a cap-and-trade mechanism, is one of the significant policies for carbon emission mitigation (Abdallah et al., 2012). It sets a fixed maximum level of carbon emissions, a cap, to achieve a reduction in emissions. Firms generating more emissions than the allocated allowance either pay a fine or purchase emissions allowance off the market from those firms which generated less than their allocated allowance (Zakeri et al., 2015). This carbon trading scheme is designed to relieve pressure and create incentives to encourage companies to minimize carbon emissions throughout their operations. In the energy sector, environmentally conscious consumers encourage market, stimulate competition among

businesses to produce and provide renewable energy products and thus increase their market share (Abdallah et al., 2012). Therefore, companies should better manage their energy supply chain in order to reduce carbon emissions and adopt greener practices that foster sustainable development. Green or sustainable supply chain management has become increasingly popular due to growing awareness about environmental issues (Brandenburg, Govindan, Sarkis, & Seuring, 2014; Tognetti, Grosse-Ruyken, & Wagner, 2015). Government regulations, community norms, and consumer expectations have all caused organizations to expand their focus beyond the economic aspect of supply chains (Fahimnia, Sarkis, Boland, Reisi, & Goh, 2015). We mainly review supply chain models with carbon regulatorys schemes and sustainable supply chain issues that deal with bioenergy.

Ramudhin, Chaabane, & Paquet (2013) formulated a multi-objective MILP that systematically integrated logistic and carbon emission costs under an emission trading system. Some other studies presented sustainable supply chain designs that integrated life cycle analysis (LCA) into a traditional supply chain network design. Chaabane, Ramudhin, & Paquet (2012) also designed a sustainable supply chain network by integrating LCA into the entire supply chain process. Environmental costs have been considered within supply chain design under an emission trading scheme. Abdallah, Diabat, & Simchi-Levi (2010) developed a carbon-sensitive supply chain that minimizes environmental impact by considering green procurement. LCA for the case of the personal computer supply chain was studied with different carbon emission cost scenarios. Also, more recent modeling efforts in designing supply chains tried to capture several carbon policies, including carbon price, carbon cap-and-trade, and carbon offsets to examine supply chain performance (Fahimnia et al., 2015; Jin, Granda-Marulanda, & Down, 2014; Palak et al., 2014; Marufuzzaman, Ekşioğlu, & Hernandez, 2014); and two carbon regulatory policy

comparisons between carbon pricing and emission trading were made at the tactical/operational planning level (Zakeri et al., 2015).

Production of energy, especially fuel, using renewable sources such as biomass is growing in the U.S. (Palak et al., 2014). Many efforts have been made to quantitatively consider biomass supply chain network design and management practices (Chen & Fan, 2012; Huang, Chen, & Fan, 2010; Roni, Eksioglu, Searcy, & Jha, 2014; Marufuzzaman, Eksioglu, Li, & Wang, 2014; Marufuzzaman & Ekşioğlu, 2017). The objective considered takes into account economic and environmental aspects. The economic aspect identifies the cost-effective manner that minimizes the total supply chain costs regarding the number, capacity and location of bio-refinery facilities and flow of biomass (Zhang, Johnson, & Wang, 2016) or maximizes the net profit (Cambero & Sowlati, 2014).

On the other hand, improved life cycle performance is required to achieve sustainable biofuel supply chains that integrate environmental aspects. One of the challenges would be how to minimize the carbon footprint to maintain a low environmental impact. Recently, a number of authors have presented research on supply chain optimization of biomass that considers financial objectives as well as the environmental impact (Osmani & Zhang, 2014; Lim & Lam, 2016; Ren et al., 2016). Different aspects such as potential GHG savings and impact of carbon tax and carbon trading on economic and environmental performance were also analyzed (Akgul, Shah, & Papageorgiou, 2012). It was found that implementing a carbon emissions scheme was cost-effective that minimizing GHG emissions by promoting competitive advantage in biofuel technologies (Giarola, Shah, & Bezzo, 2012). However, most of these studies focused on the biomass to biofuel supply chain.

From a modeling perspective, mixed integer programming (MIP) and MILP are used extensively in the existing body of literature for strategic or tactical planning of biofuel supply chains (Roni et al., 2014; Huang et al., 2010; Park et al., 2017). However, spatial distribution of supply and demand has a great influence on the design of a biomass supply network (Lautala, Pouryousef, Handler, & Chartier, 2012) and optimal facility location highly affects the transportation cost. Therefore, another commonly used approach to the biofuel supply chain problem is application of geographic information system (GIS) based models, which can help to determine the most appropriate facility location in a specific area. Determining the optimal bio-refinery plant location is a challenging task. Various studies relate to biogas plant location problems and consider the different aspects of the problem, including location, size, and number of biogas plants (Höhn et al., 2014). Other studies consider the sustainability of biogas (Silva, Alcada-Almeida, & Dias, 2017), as well as strategic and tactical optimization of a bio-power supply chain (Kumar et al., 2016; Balaman et al., 2014).

To our knowledge, animal waste based supply chains, including biogas facilities (i.e. anaerobic digestion), have not been addressed in previous research, even though anaerobic digestion is one of the most efficient and environmentally friendly energy production systems. Most of the previous studies formulated effective green supply chain design, while modeling efforts related to green supply chain design, which consider animal waste under a carbon policy strategy are not well established in the literature. Considering these facts and research gaps, this study develops a MILP model to obtain optimal configuration of animal waste based biomass to energy supply chains, particularly to design upstream supply chain at the strategic and tactical planning levels. Also, we utilize the model to investigate how a carbon pricing mechanism influences both the economic and environmental aspects of a biogas energy supply chain.

4.4. Problem Statement and Mathematical Model

A mathematical model for biogas supply chain design under carbon policy is developed using a MILP. Biomass in the form of animal manure is considered as feedstock in the model. A count of animals can be taken from available farms, and the amount of animal manure in tons then were calculated by considering the type of cattle manure (e.g. wet versus dry basis).

This biomass will then be shipped to energy conversion plants for anaerobic digestions (ADs), where the biomass is converted into biogas. Geography and distance can be important factors because biomass to energy schemes are highly geographically dependent due to the fact that manure supply and biogas demand are often widely dispersed. Thus, finding suitable locations for biogas plants, which minimize transportation distances and total supply chain costs, as well as associated carbon emissions is a key issue for sustainable biogas production. One way to serve multiple farms or ranches is to develop centralized or regional ADs, in which case it is important to decide optimal capacity of ADs and locations. The proposed model also considers the carbon pricing and trading scheme. Therefore, the biogas project either incurs costs if the carbon cap that is assigned is lower than the carbon emissions or gains revenues by selling excess carbon credits. The objective of the proposed model is to determine the optimal configuration of the biogas supply chain along with the associated operational decisions that minimizes its economic and environmental performance under carbon policies. Animal manure has been identified as one of the pathways to replace fossil fuel resources for transportation fuels and electricity and mitigate environmental impacts of fossil fuels. However, there is still lack of technical, economic, and environmental information on this technology via ADs which create uncertainty about the feasibility of this approach to biogas. The following supply chain inputs, decisions, and assumptions are made for the model.

Inputs:

- The annual amount of cattle manure and annual natural gas demand. Only natural gas consumption by the electric power sector in North Dakota in 2016 is loaded into the model, because natural gas consumption by vehicle fuel is unknown (U.S. EIA, 2018). Upstream leg of the supply chain is considered and downstream actors are not considered as the output from the plant is injected directly into the natural gas pipeline (Kumar et al., 2016).
- The distance between each node in the supply chain is determined by GIS.
- Costs for acquiring animal manure, transporting it, and for producing biogas.
- Carbon price and cap.
- GHG emissions associated with acquiring manure, transporting manure and biogas and producing biogas.

Decisions:

- Locations of biogas plants.
- Capacity levels for the biogas plants.
- Amount of biomass to be transported from the feedstock region to the biogas plant.
- Biogas production volume of each plant.
- Amount of carbon emissions for the entire supply chain including acquisition, transportation, and production.

Assumptions:

- A refinery will not be shut down once it opens.
- Truck is the only mode for transporting manure and biogas.

Table 12. Notations Used in Model Development.

	Sets
I	set of ranch, indexed by (i= 1,2,…,m)
J	set of potential biogas plant location, indexed by (j= 1,2,…n)
K	set of biogas plant capacity level, indexed by (k=1,2,…,l)
	Parameters
a_i	maximum available animal manure
c_j^{aq}	average acquisition cost of cattle manure
c_j^{pr}	unit cost of biogas production at plant j ($/m^3)
c_{ij}^{t}	transport cost per ton-mile from cattle farm i to plant j
c^{tl}	tons per truck load
c^{hc}	truck hauling cost per loaded mile
β	average wet or dry content of manure (%)
c^{lu}	truck loading and unloading cost of ($/tons) manure
c_j^{k}	investment cost of the plant at location j with plant capacity level k
c_j^{om}	annual operational and maintenance cost of the plant at location j with plant capacity level k
v	lifetime of biogas plant (years)
λ	penalty cost for unmet demand
d_{ij}	road distance (miles) between ranch i and plant j
CO_2^{cap}	maximum amount (tons) of carbon dioxide that can be emitted
p^k	annual production capacity for biogas plant size k
e_i^{aq}	CO_2 factor (CO_2-eq. ton/dry ton) for animal manure acquisition
e^{tr}	CO_2 factor (CO_2-eq. ton-mile/truckload) for transportation
e_j^{pr}	CO_2 factor (CO_2-eq. m^3/dry ton) for biogas production
e_j^{k}	amount (tons) of CO_2 at location j with plant capacity level k
e_j^{moff}	amount of offset methane at location j
α	average expected cost of carbon price in $/ton CO_2
θ	conversion efficiency to produce biogas from cattle manure (m^3/dry ton)
m_{jd}	annual natural gas demand
	Decision Variables
X_{ij}	amount of cattle manure transported to plant j from cattle farm i
Q_j^{k}	amount of biogas converted in plant j at size k
Z_j^{k}	1 if biogas plant with size k is built, 0 otherwise
S_j^{k}	size of a biogas plant, if any, to be built at site k
CO_2^{ce}	amount of CO_2 that is emitted in supply chain

All notation used in the model formulation is summarized in Table 12 and a complete model formulation is presented in (4.1) - (4.15). The function Z_1 represents the total supply chain cost that includes the acquisition costs, investment costs including lifetime operation and maintenance costs, production costs, transportation costs of manure, penalty cost for shortage of biogas, and carbon credit generated from methane offset.

$$Min\ Z_1 = \sum_{i\epsilon I}\sum_{j\epsilon J} c_i^{aq}\ X_{ij} + \sum_{j\epsilon J}(c_j^k + \mathrm{v}c_j^{om})\ Z_j^k + \sum_{j\epsilon J} Q_j^k\ c_j^{pr} + \sum_{i\epsilon I}\sum_{j\epsilon J}\left(c_{ij}^t * d_{ij} * 2\right) + c^{lu}\ )X_{ij} + \sum_{j\epsilon J}\lambda\left(Q_j^k - m_{jd}\right) - \sum_{j\epsilon J}\left(e_j^{moff}\alpha\right) \quad (4.1)$$

Where, the transportation costs of manure is quantity, travel distance, and truck capacity dependent, therefore, equation (4.2) indicates the transport cost per ton-mile.

$$c_{ij}^t = \frac{C^{tl}}{C^{hc}} \quad (4.2)$$

The objective function Z_2 represents the overall supply chain carbon emissions from acquisition, production, and transportation.

$$Min\ Z_2 = \sum_{i\epsilon I}\sum_{j\epsilon J} e_i^{aq}\ X_{ij} + \sum_{j\epsilon J}\sum_{k\epsilon K} e_j^{pr} p^k\ Z_j^k + \sum_{i\epsilon I}\sum_{j\epsilon J} e^{tr}\left(\ d_{ij}\ X_{ij}\ \right) \quad (4.3)$$

Given Z_1 and Z_2, the minimization of the overall supply chain cost when operating under a carbon pricing scheme or carbon trading scheme can be formulated in Equation (4.4) and (4.5) respectively (Zakeri et al., 2015):

Carbon pricing scheme: Minimize $Z_1 + \alpha\ Z_2$ (4.4)

Carbon trading scheme: Minimize $Z_1 + \alpha\ (Z_2 - CO_2^{cap})$ (4.5)

Equation (4.4) charges a carbon price of α corresponding to the amount of emissions generated in a carbon pricing situation. By adding a carbon cap in Equation (4.5), in a carbon trading environment, a plant which generates more emissions than its allocated allowance ($Z_2 >$

CO_2^{cap}) can purchase additional allowance or permits off the market at a price of α. Plants generating fewer emissions than the allowed emission allowance ($Z_2 < CO_2^{cap}$) can sell their surplus to those who may be exceeding their allocated limits. In the latter case, ($Z_2 < CO_2^{cap}$) would be a negative number turning carbon trading into a source of income that might help reduce the overall supply chain costs.

s.t.

$$\sum_{j\epsilon J} X_{ij} \leq a_i\beta \ , \quad \forall \mathrm{i} \tag{4.6}$$

$$\sum_{j\epsilon J} \theta X_{ij} = Q_j^k \quad \forall \mathrm{i,j} \tag{4.7}$$

$$\sum_{j\epsilon J} X_{ij} \leq \sum_{j\epsilon J} p^k Z_j^k, \quad \forall \mathrm{i,j} \tag{4.8}$$

$$\sum_{j\epsilon J} Z_j^k \leq 1, \quad \forall \mathrm{j} \tag{4.9}$$

$$Q_j^k \leq \sum_{j\epsilon J} p^k S_j^k \quad \forall \mathrm{j} \tag{4.10}$$

$$\sum_{j\epsilon J} Q_j^k = m_{jd}, \quad \forall \mathrm{j} \tag{4.11}$$

$$\sum_{i\epsilon I}\sum_{j\epsilon J} e_i^{aq} X_{ij} + \sum_{j\epsilon J}\sum_{k\epsilon K} e_j^{pr} p^k Z_j^k + \sum_{i\epsilon I}\sum_{j\epsilon J} e^{tr}\left(d_{ij} X_{ij}\right) = CO_2^{ce} \tag{4.12}$$

$$X_{ij} \geq 0, \quad \forall \mathrm{i,j} \tag{4.13}$$

$$Q_j^k \geq 0, \quad \forall \mathrm{j} \tag{4.14}$$

$$Z_j^k = \{0, 1\}, \quad \forall j \tag{4.15}$$

The objective functions in Equation (4.4) and (4.5) are subject to the constraints (4.6) to (4.15). Constraints (4.6) limit the amount of animal manure procured to the amount that is available annually in each manure producing location. Constraints (4.7) are flow conservation constraints at the biogas plants, which state that the amount of converted animal manure equals the biogas produced by relating it to conversion rates at plants. Constraints (4.8) are logical constraints, stating that there is no flow through biogas plants unless one is open. Constraints (4.9) ensure that a maximum of one size can be chosen for each plant. Constraints (4.10) ensure that the amount of biomass that can be processed at a biogas plant is limited by the plant capacity. Constraints (4.11) allows biogas produced at each plant is equal to the biogas demand. Constraints (4.12) calculate the carbon dioxide emissions across the whole supply chain. Constraints (4.13) - (4.15) enforce non-negativity and binary restrictions on the decision variables.

4.5. A Case Study: Potential Biogas Production in North Dakota

Methane from decomposing animal manure has about twenty-one times greater global warming effect as carbon emissions. However, burning methane using an anaerobic digestion system offsets its harmful effect and creates useful energy with many ancillary benefits that include creating high-quality fertilizer, and other by-products, while minimizing environmental impacts such as odors and emissions. However, North Dakota (ND) has few anaerobic digestion facilities, although it is a significant livestock producer (ND is ranked 16th in the United States in cattle). Currently ND has only four operational biogas systems, and they involve water resource recovery and landfill. However, it is expected that there will be more than 39 new biogas plants based on ND's available resources. Upon the biogas installment, there could be enough

electricity to generate 52.7 million kWh of power from biogas based natural gas enough to fuel 7,651 vehicles (American Biogas Council, 2015). Also, the carbon credits generated from the offset emissions of methane from producing biogas will result in valuable new revenue source for North Dakota farmers and ranchers.

4.5.1. Cattle Manure Resource

A diverse set of animal waste feedstock resources are available in North Dakota for biogas production. Cattle waste is considered in this study due to its high potential for cattle manure production. Cattle are not uniformly distributed in the state, therefore cattle manure production amounts vary among regions. All cattle feedlots and inventories are collected through the ND State Feedlot Database from the Dickinson Research Extension Center (Kizil, 2017). Annual cattle manure is estimated by converting 1 head of cattle = 0.025 tons of manure/day (Füsun, Boysan, Cigdem Özer, Kagan Bakkaloglu, 2015) and multiplying by 365 and percentage of average wet or dry content of manure. This study considers the moisture content of manure and its effect on the biogas supply chain decisions. According to an expert in agricultural engineering at North Dakota State University, the moisture content of manure comprises a large portion of biomass (e.g. 30-85% on a wet basis, moisture content of cattle manure is 85%) and is a significant factor, especially for planning plant capacity and transportation. Figure 9 (b) shows the geographic distribution of the cattle feedlots and quantity of solid cattle manure for each feedlot. The annual amount of cattle manure and locations has been generated using GIS. A cattle manure acquisition cost of $10/ton is used (Oklahoma State University, 2009).

4.5.2. Potential Biogas Plants

In this study, we identify 22 potential biogas sites by performing a land use suitability analysis, considering the various factors and criteria in Figure 9 (c). Table 13 presents the social,

geographic, and land use criteria that were used to identify their potentially suitable sites for ADSs in ND. The default values of the criteria are based on literatures, as well as some assumptions. All criteria employ GIS analysis, such as creating buffer from lines (road, railway, and gas grid) or point feature (urban), and clipping polygons (park and water area). Social factors include public areas that are defined as urban, geographic factor such as water (river and aquifer surface area), Bureau of Land Management (BLM), forest service, national park, and wildlife, and land use factor such as road and railway, gas grid, and well and rig (Silva, Alçada-Almeida, & Dias, 2014; Thompson, Wang, & Li, 2013). The criteria for wells and rigs is assumed because no studies have been found that studied suitability analysis of biogas plant within an oil producing area. This assumption can be reconsidered later by consulting considering expert opinion or actual survey.

Table 13. Factor and Criteria to Select Candidate Biogas Plant.

Factor	Criteria
Roads and railway	To exclude area which contain or are less than 200m away from major, county and rail network
Water (river and aquifer surface)	To exclude area which contain or are less than 150m away from water line
Bureau of Land Management (BLM)	To exclude area which contain or are less than 1km away from BLM surface land
Gas grid	To include area within 2km of gas pipeline
Forest service	To exclude area which contain or are less than 200m away from
Tribal land	To exclude area which contain or are less than 200m away from
National park	To exclude area which contain or are less than 200m away from
Wildlife	To exclude area which contain or are less than 150m away from wildlife area
Wells and rigs	To exclude area which contain or are less than 200m away from oil well and rig
Urban	To exclude area which contain or are less than 2km away

There are different types of biogas plants. Silva et al. (2017) classified biogas plant sizes into four groups: very small scale-facility biogas plant; small scale-facility biogas plant; medium scale- facility biogas plant; large scale-centralized/joint co-digestion plant. Locating plants in a centralized location is economically and environmentally beneficial (Osmani & Zhang, 2014). Therefore, this study considers that each plant could have one of four sizes, according to the amount of cattle manure processed and amount of natural gas produced. The four types of biogas plant are named very small, medium, large, and very large. In our model, we assumed that the four types of plant have different values for the initial investment and maintenance cost. The initial investment cost and life time maintenance cost of a biogas plant are subject to economies of scale. This work considered that annual operation and maintenance costs of a biogas plant represents on average 2% of the investment cost. Operation and maintenance costs were calculated for a plant with a life time of 20 years (Silva et al., 2017). The biogas production cost of \$4 per m^3 is used (USDA, 2007) with conversion efficiency of $23m^3$/ton (Abdeshahian, Lim, Ho, Hashim, & Lee, 2016).

4.5.3. Transportation Data

In this study, road transportation networks, including local, rural, urban, and highway, are used to estimate the cost of transporting cattle manure (see Figure 9 (a)). The shortest path based on Dijkstra's algorithm between each node is generated using the O-D cost matrix application in ArcGIS. The hauling cost per loaded mile for cattle manure is \$4/mile, the cost of loading and unloading a truck is \$5/ton, and tons per truck load is 25 tons. Therefore, transport cost per ton mile is \$4 per mile/25 tons according to Oklahoma State University (2009).

4.5.4. Environmental Impact Assessment

In terms of environmental impact analysis, the emission rate associated with biogas production, including feedstock acquisition, transportation, and production, is obtained from existing literature. The final CO_2-eq value is found to be 0.008ton CO_2-eq/ton of manure for acquisition (Favre, Bounaceur, & Roizard, 2009), 0.002 ton CO_2-eq/ ton manure for transportation (Esfandiari, Khosrokhavar, & Masih, 2011), and 0.08 ton CO_2-eq/ m^3 for biogas production (Esfandiari et al., 2011). The main components of biogas are carbon dioxide and methane; specifically, and biogas is 60 to 70 percent methane, and 30 to 40 percent carbon dioxide (CO_2) with a low amount of other gases including nitrogen, hydrogen and hydrogen sulphide. Biogas produced in anaerobic digesters is burned to generate clean, renewable energy (Kumar et al., 2016). Methane (CH_4) is one of the primary greenhouse gases associated with the agricultural sector. It is 21 times more effective at trapping heat in the atmosphere than CO_2 over a 100-year timeframe. In other words, it takes 21 tons of CO_2 to equal the effect of 1 ton of CH_4. Capturing methane with an ADs is beneficial because it reduces emissions of a harmful greenhouse gas. The following calculations were developed based on study from our sources and the rules of arithmetic. According to Abdeshahian et al. (2016), a 1 ton of manure will produce 23 m^3 of biogas. Therefore, equation 4.15 convert this figure to amount of CH_4 produced per ton of manure using the EPA's estimate that 60% of the biogas from anaerobic digestion is methane (U.S. EPA, 2011). Then, calculated the equivalent amount of CO_2 by assuming that 1 ton of methane is equivalent to 21 tons of carbon dioxide. Thus, multiplying the tons of methane produced per ton of manure by twenty one should provide a reasonable estimate of the amount of carbon dioxide equivalent gas (methane offset, e_j^{moff}). Captured methane qualifies as a carbon offset, which can be a source of carbon credits ($e_j^{moff}\alpha$).

$$e_j^{moff} = 0.6 \times \frac{23\ m^3}{1\ ton\ of\ manure} \times \frac{21\ tons\ of\ CO_2}{1\ ton\ CH_4} \times tons\ of\ manure\ converted\ into\ biogas \quad (4.16)$$

The carbon price (α) used in this case study is $40/ton of carbon-equivalent emissions (Tang et al., 2012). Environmental Protection Agency (EPA) indicated that 45% reduction in CO2 emissions from the 2005 level by 2030 will be achieved in North Dakota by replacing power plants with non-emitting generation resources. Using this rule, we set the initial carbon cap as 21 million metric tons of carbon emissions.

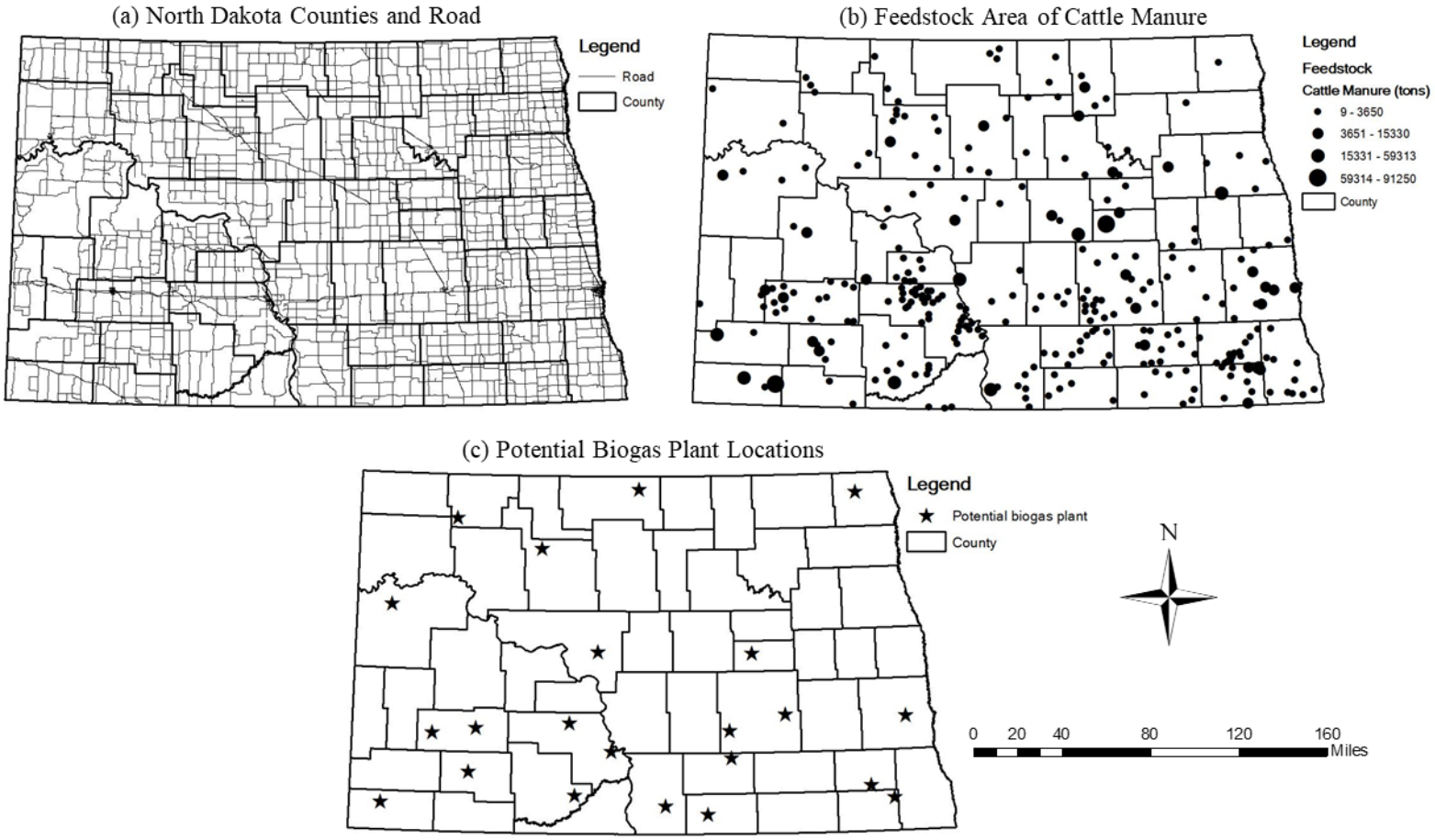

Figure 9. Geographic Distribution of Animal Manure Feedstock Resource and Potential Biogas Plants in North Dakota.

4.6. Results and Discussion

From Table 14, the cost-only and emission-only optimization scenarios without considering carbon price show what happens at the two extremes. From the analysis, it shows that the cost-only optimization (Z_1) and emissions-only optimization (Z_2) are two conflicting objectives. When cost-only optimization model is solved, a minimum supply chain cost of $310,015,893 occurs which is $60,25,757 less than when compared to the emission-only optimization. The reverse situation occurs in the emission-only optimization scenario where the minimum carbon emission of 2,245,564 tons emits at the maximum cost is incurred. The results clearly indicate that without a carbon pricing mechanism in place, the supply chain could be less costly to manage. We also observe the number of total ADs opened and their size and amount of biogas produced for each optimization scenario. Table 15 shows that the number of ADs opened increases in the emission-only optimization, which may stem from the fact that the model assigns more ADs to minimize the emissions. Also, the average size of ADs eventually decreases for emission-only optimization as the assigned demand decrease, therefore less product is allocated to the ADs.

Table 14. Numerical Results for the Optimizations.

	Cost-only optimization (Z_1)		Emission-only optimization (Z_2)	
	Total SC costs ($)	Total Emissions (tons)	Total SC costs ($)	Total Emissions (tons)
Transportation	12,859,893	647,880	9,124,530	405,444
Acquisition	8,000,000	584,000	7,160,000	522,680
Production	1,656,000	1,472,000	1,482,120	1,317,440
Investment	287,500,000	-	352,500,000	-
Total	310,015,893	2,703,880	370,266,650	2,245,564

Table 15. Number of AD Opened and Their Relative Size Variation.

	Cost-only optimization (Z_1)	Emission-only optimization (Z_2)
Number of ADs	9	20
Total ADs Size (ton)	690,000	716,000
Average ADs Size (ton)	76,666	35,800

Figure 10 illustrates the supply chain cost and emission reduction performance over the range of the carbon prices when a carbon trading scheme is in place. The y-axis values in figure 10 represent the supply chain cost percentage increase and emission percentage reduction at each carbon price when compared to the $0 price. This perspective allows for evaluating the schemes' effectiveness over a range of carbon prices. Figure 10 shows that the supply chain cost increases steadily, and relatively linearly, as the carbon price increases. However, the curve eventually flattens since, given the supply chain structure, there exist no more operational changes which impact emissions.

There is a very erratic, nonlinear pattern, to the emissions reductions until a carbon price of $100. As can be seen there is a rapid decrease in carbon emissions that occurs at the very low carbon prices of $0-$40 per ton. Interestingly, after this point, a slight emission reduction occurs until carbon prices reach $60 per ton. The next significant improvement in emission reductions occurs at a carbon price of over $60 per ton and continues to improve until carbon prices reach $80 per ton. Increasing the carbon price provides strong motivation to reduce emission level, and, as a result, reduces system costs by the sale of offset emission credits.

Figure 11 shows the cost of carbon purchased and sold at different levels of carbon cap. At a higher cap, the firm will sell less carbon and purchase more carbon. This indicates that a change in the carbon cap will have a greater impact on the amount of carbon sold and purchased.

One primary and broad-based policy question is to determine the carbon price at which the maximum environmental performance can be achieved, without substantial negative impacts on the economy and competitive position of the biogas industry. Therefore, from this analysis the price range of $60-$70 appears to be the most effective and efficient option in terms of emissions generation and cost escalation. Within this range, a dollar increase in supply chain costs has the greatest positive impact on carbon pollution reduction.

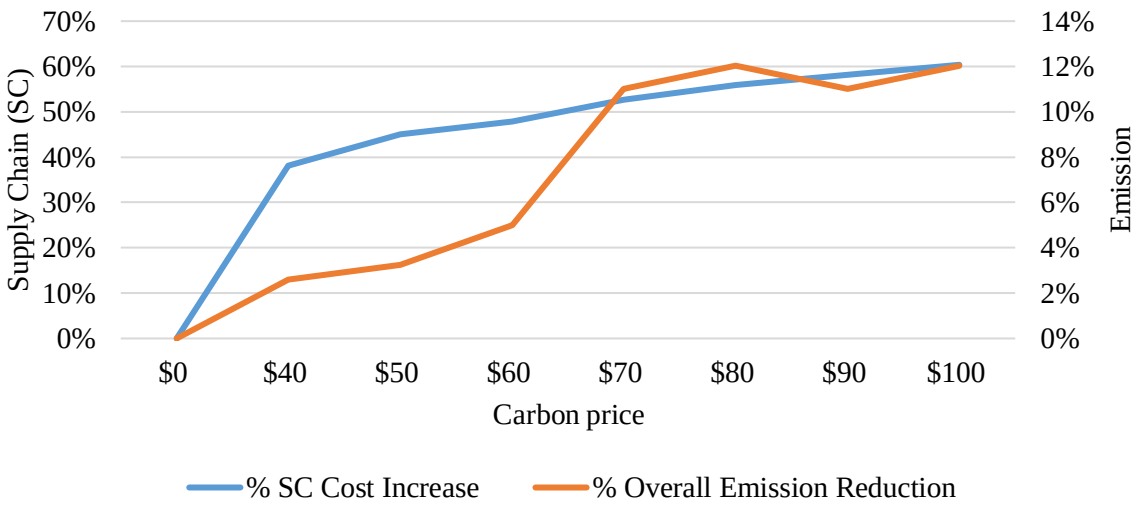

Figure 10. Cost Increase and Emission Reduction Performance.

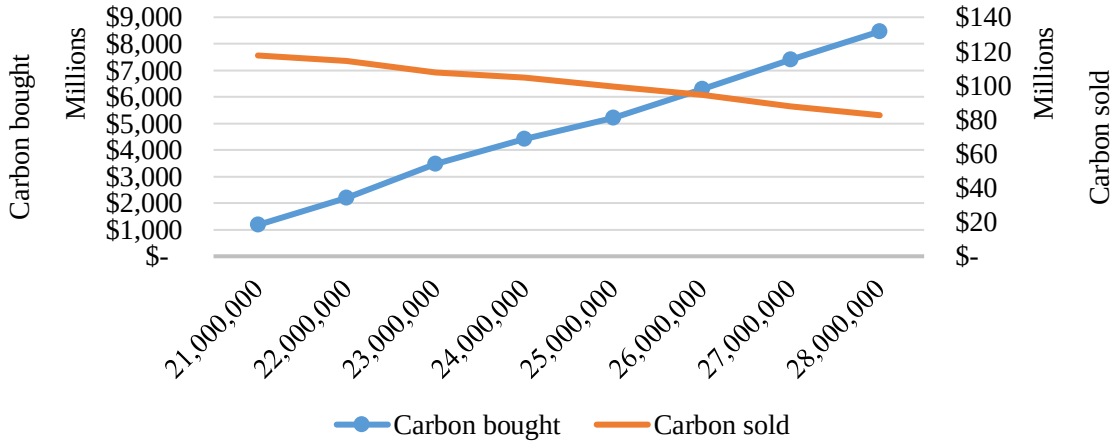

Figure 11. Carbon Bought and Sold with Carbon Cap Variations.

Table16 reports capacities of the plants and amounts of biogas production in each county when carbon price of $0 and carbon price of $40. The results suggest that Bowman and Foster are the counties in which the largest plant are constructed at carbon price of $0. On the other hand, when carbon price increased by $40, Stutsman maybe the county with the largest plant. Under cap and trade, the number of biogas plants is only determined by the carbon price. For a fixed carbon cap, the number of biogas plants and their relative sizes are highly dependent on carbon prices. As seen in Figure 12 and 13, as the carbon price increases, the number of biogas plants opened increases in order to minimize the carbon emission due to transportation. Also, the average size of the biogas plants will eventually decrease as less cattle manure is allocated to each biogas plant.

Figure 14 shows the geographical location of biogas plants in ND for carbon prices of $0, $40, $60, $80, and $100. The locations of biogas plants and their different optimal capacity levels are presented. As previously mentioned, having no carbon regulatory scheme in place (i.e. a carbon price of $0) results in 9 biogas plants being opened as the base scenario. Introducing a carbon price at the current national level of $40 per ton results in more biogas plants being opened. When carbon price increases to $100, the model opens 17 biogas plants in ND. An increase in the number of plants allows a reduction in transportation and emission costs, thus putting greater emphasis on more efficient and environmentally friendly transport and location decisions. It seems that the model locates biogas plant near the county that produces the largest amount of cattle manure. It can be concluded from the results that the location sites and plant capacities are highly dependent on carbon price and per unit transportation cost for manure.

Table 16. Total Manure Processing, Biogas Production in Each County at Carbon Price of $0 and Carbon Price of $40.

County	Carbon price	Total manure capacity (t/y)	Biogas production (m^3/y)
Bowman	$0	100,000	2,300,000
	$40	70,000	1,610,000
Stutsman	$0	70,000	1,610,000
	$40	140,000	3,220,000
Sargent	$0	-	-
	$40	70,000	1,610,000
Foster	$0	100,000	2,300,000
	$40	100,000	2,300,000
Stark,Morton, McLean, Emmons, Cass, Hettinger	$0	70,000	1,610,000
	$40	70,000	1,610,000

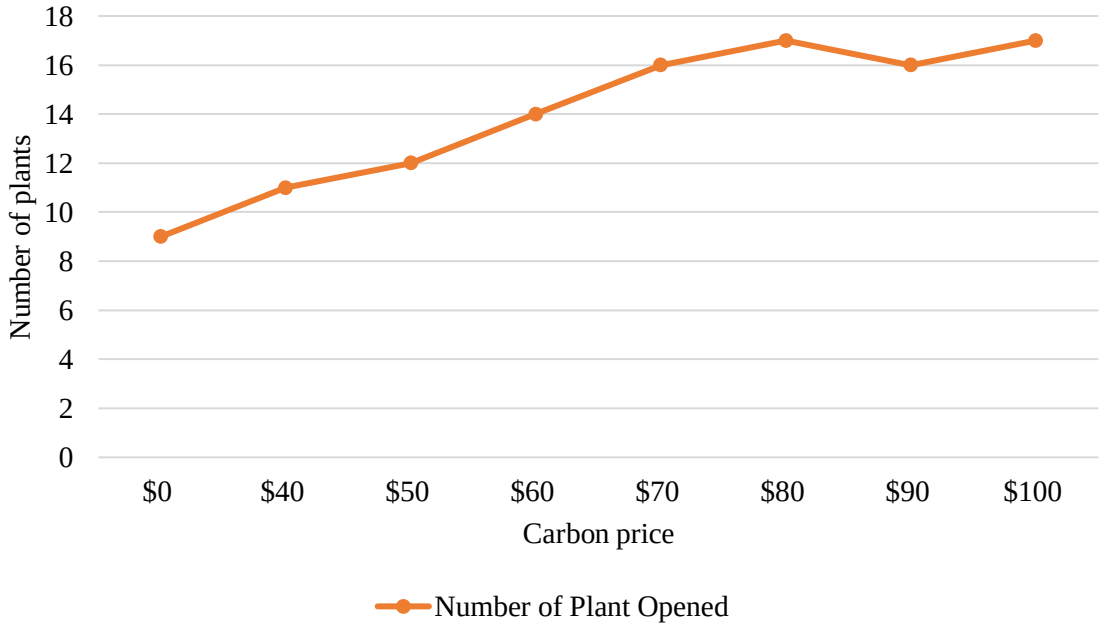

Figure 12. Number of Plants Opened with Carbon Price Variations.

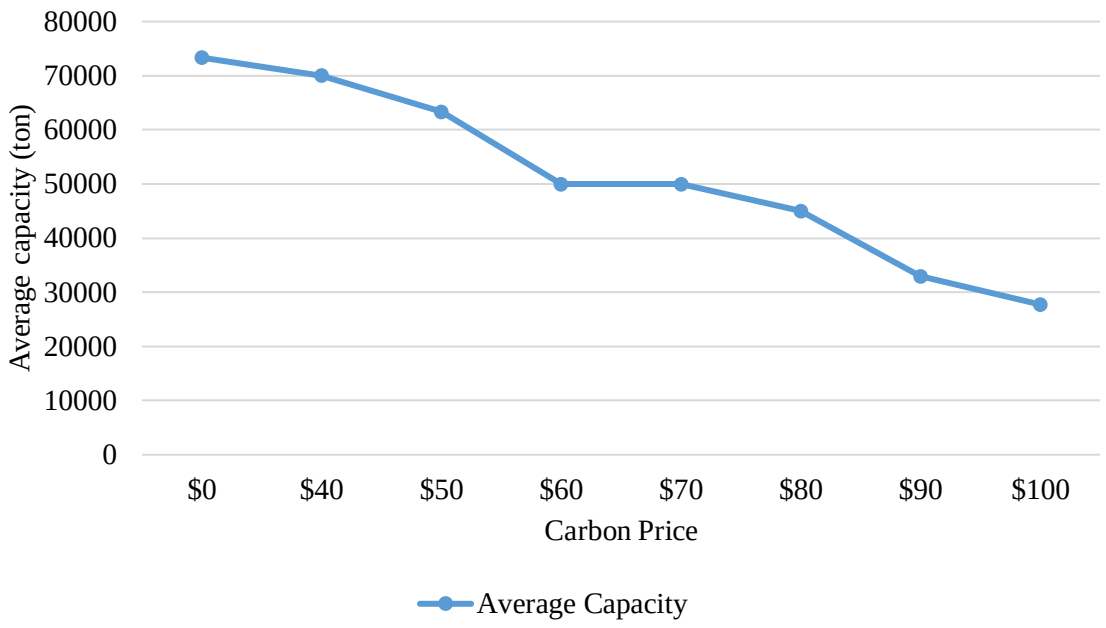

Figure 13. Average Size of Plants with Carbon Price Variations.

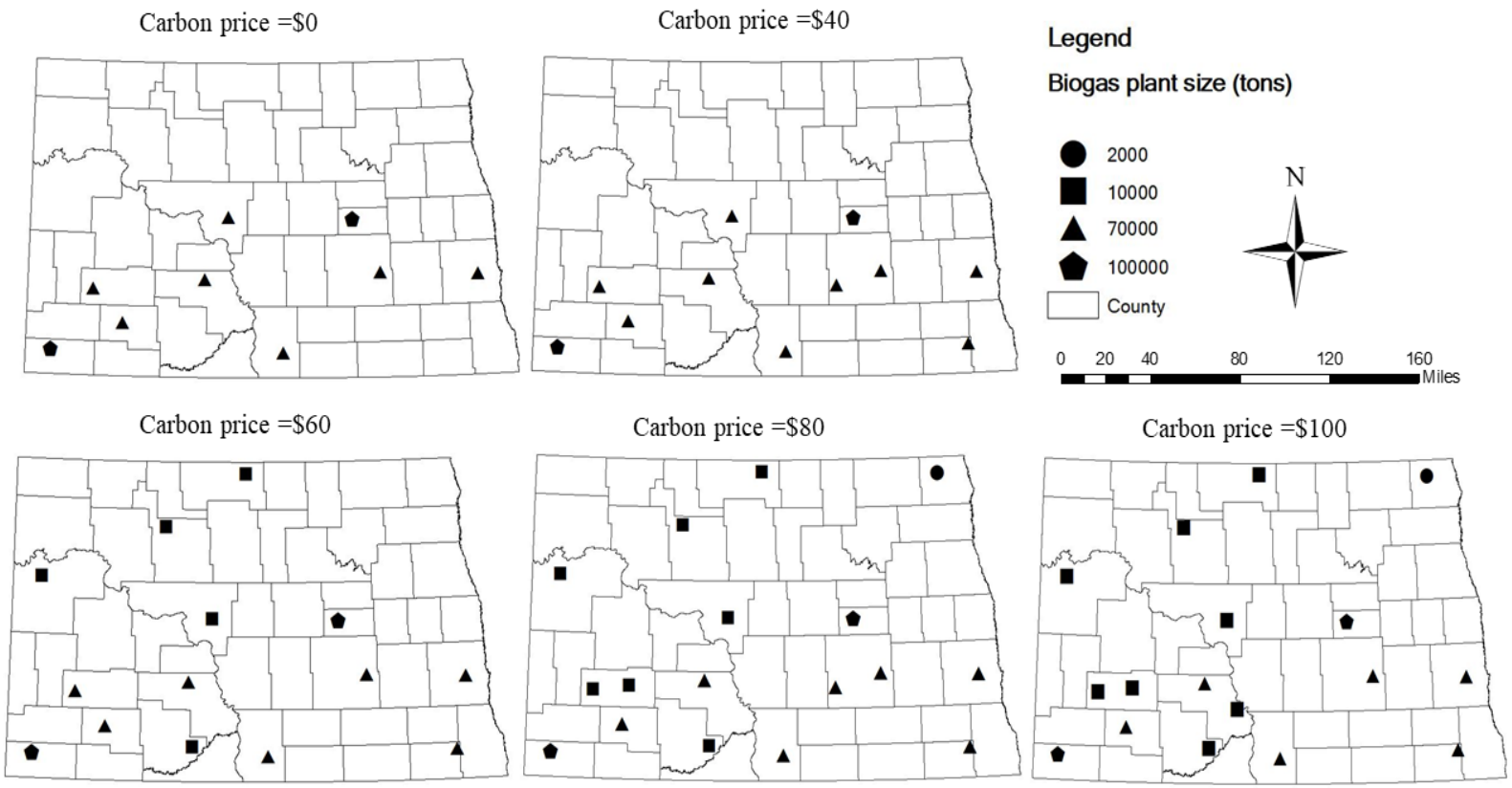

Figure 14. Impact of Carbon Price on Biogas Plant Locations and Sizes.

4.6.1. Sensitivity Analysis

In our model, we perform sensitivity analysis to identify the factors that are significant to the biogas supply chain, especially focusing on cost of biogas by comparing current carbon adjusted cost of natural gas. Thus, we measure cost of biogas delivered by dividing total supply chain cost by total amount of biogas produced in North Dakota as shown in Figure 15. This analysis also shows to determine the indifference point of carbon price at which unit cost of biogas and natural gas becomes equal. The cost of natural gas was calculated under carbon tax that is provided by Hafstead & Picciano (2017). The level of carbon price is varied from $0/ton of carbon –equivalent emission to $100/ ton of carbon-equivalent emissions. Figure 15 indicates that the carbon price significantly impacts on the unit cost of biogas. Low level of carbon price results in lower cost of biogas and high level of carbon price results in higher cost of biogas. However, as carbon price increases the cost of biogas become higher than the cost of natural gas. The indifference point is achieved once carbon price exceeds $160/ton of carbon –equivalent emissions.

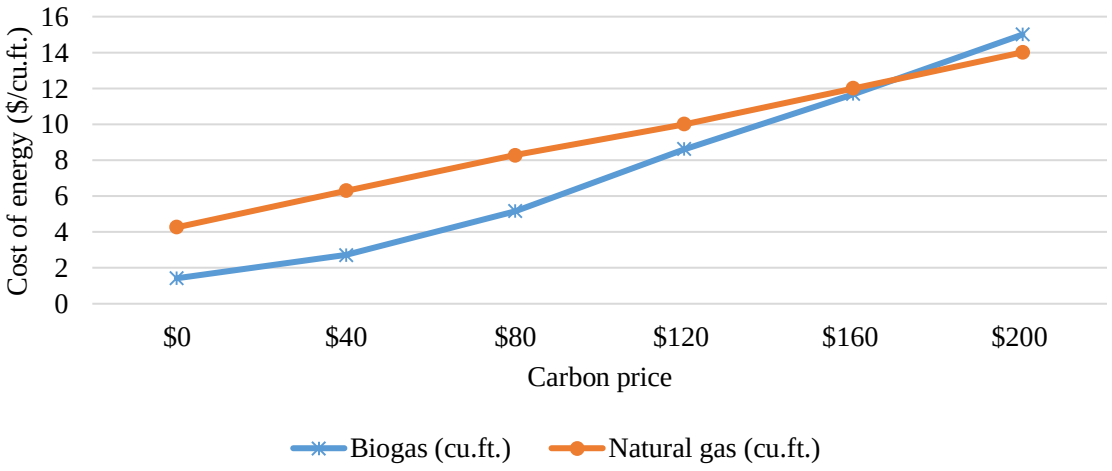

Figure 15. Impact of Carbon Price on Energy Cost using Biogas and Natural Gas.

In order to understand the increase in the cost of biogas as carbon price increases, we used break-even analysis to see the relationship between carbon price and the conversion efficiency, as well as natural gas demand and cattle manure acquisition cost. Figure 16 presents the break-even point for natural gas for different values of carbon price and rate of biogas production. The current conversion rate from animal manure to biogas production is relatively low, one ton of manure produces only 23 m^3 of biogas. In the baseline case, the conversion efficiency of biogas was 23 m^3 per ton of manure. The conversion efficiency rate increases up to 188 m^3 per ton of manure from baseline, because it was the maximum conversion efficiency level that would have impact on number of biogas plant and capacity level. It was assumed that there is no cost with improvement of conversion efficiency. When conversion efficiency is fixed, the cost of biogas increases as carbon price increases. When carbon price remains the same, the cost of biogas decreases as the conversion efficiency increases, meaning that the cost of biogas is higher with less efficient technology is employed and a higher carbon price is applied. The increase in the cost of biogas (as the conversion rate increases) is mainly due to the increase in transportation distance and processing costs. As the conversion rate increases, fewer biogas plants are needed in order to process cattle manure. Increasing the number of biogas plants will decrease the cost of transportation and the cost of processing additional manure while reducing carbon emissions as carbon price increases.

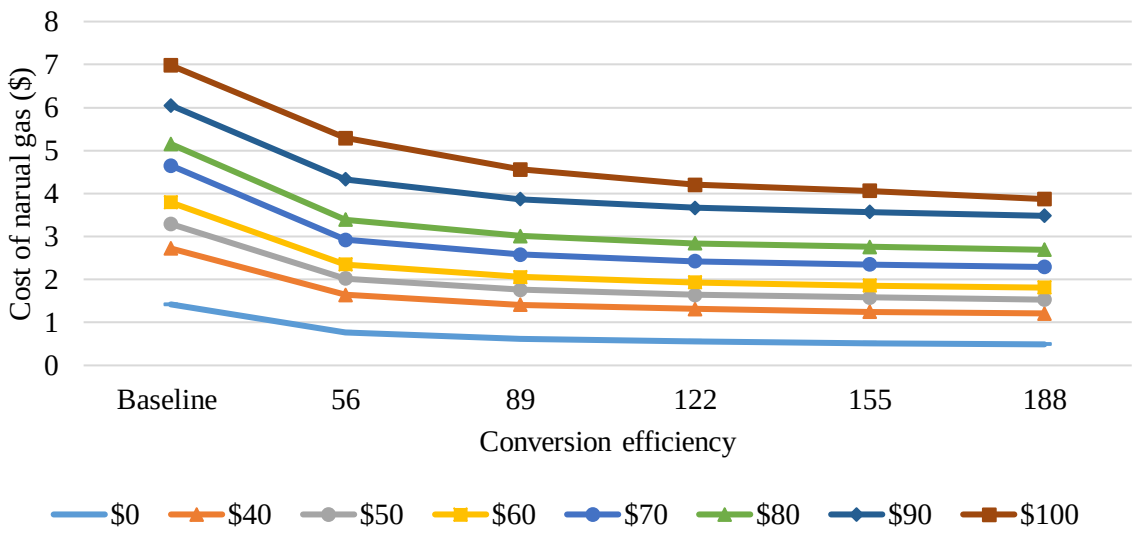

Figure 16. Cost of Biogas by Carbon Price and Conversion Efficiency (m^3/ton).

The change in the cost of biogas at different levels of demand and carbon prices was also investigated, see figure 17. This result presents the impact that an increase of manure supply and carbon price on cost of biogas. These experiments were inspired by the natural gas consumption trend in the United State in that natural gas consumption is expected to increase about 11% by 2040 from the 2016 level of natural gas consumption (U.S. EIA, 2017). Results show that when demand is fixed, the cost of biogas increases as carbon prices increase. It was found that the cost of biogas increases at the highest demand and at the highest carbon price. For example, the cost of biogas increases from $1.42 to $1.89 at carbon price of $0 and $6.98 to $7.81 at carbon price of $100. These results may stem from long-haul shipments that occur in high demand.

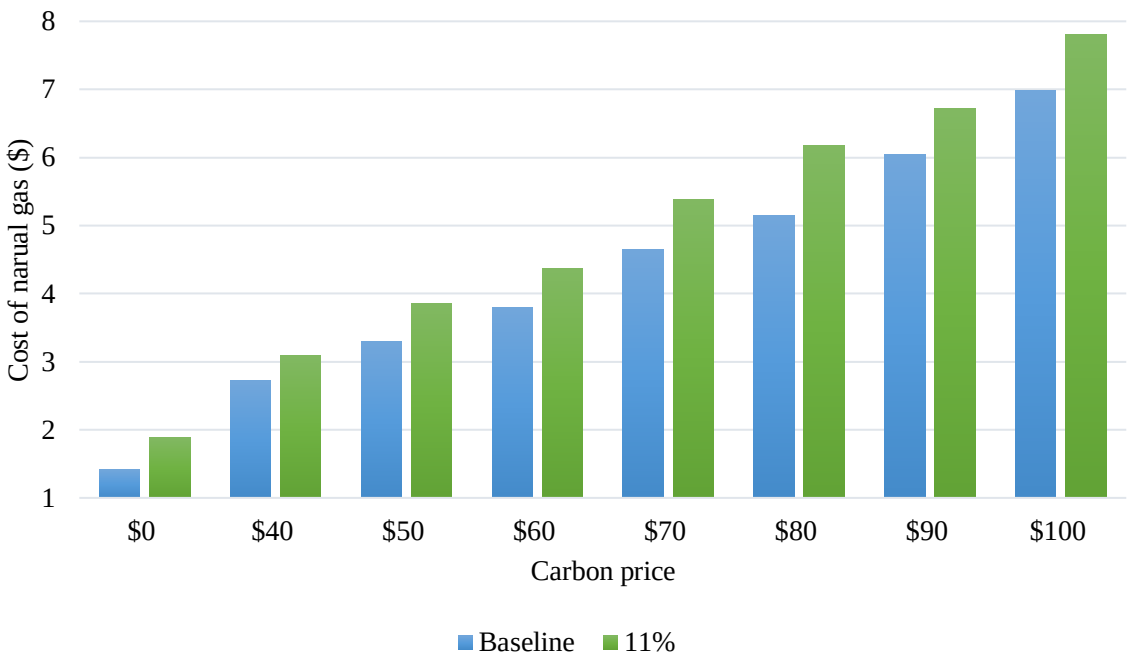

Figure 17. Analyzing the Impact of Demand Variation and Carbon Price on Cost of Biogas.

Study shows that overall supply chain cost of biomass related to biomass acquisition would be reduce by up to 25% with improved collecting and process technologies (ETSAP, 2013). Short-term biomass prices are driven by the cost of the raw material, while long-term bioenergy prices are driven by fossil fuel prices. Large scale animal manure supply is also affected by a raw material initial cost and fertilizer price. During the last few years, the current fertilizer price has decreased with a rate of about 3%. (USDA, 2018). The unit cost of cattle manure acquisition is highly sensitive to fertilizer price. Therefore, the impact of manure acquisition cost on unit cost of biogas was analyzed by increasing or decreasing unit cost of manure acquisition by 3% for a sensitivity analysis. In this analysis, the relationship between carbon price and cost of manure acquisition was also investigated, as presented in Figure 18. The results show that the cost of biogas is highly dependent on manure acquisition cost. Without carbon price is added, the unit cost of biogas is decreased by 1.8% and increased by 2.5% from

base case scenario. It is also found that the unit cost of biogas increases linearly as carbon price increases.

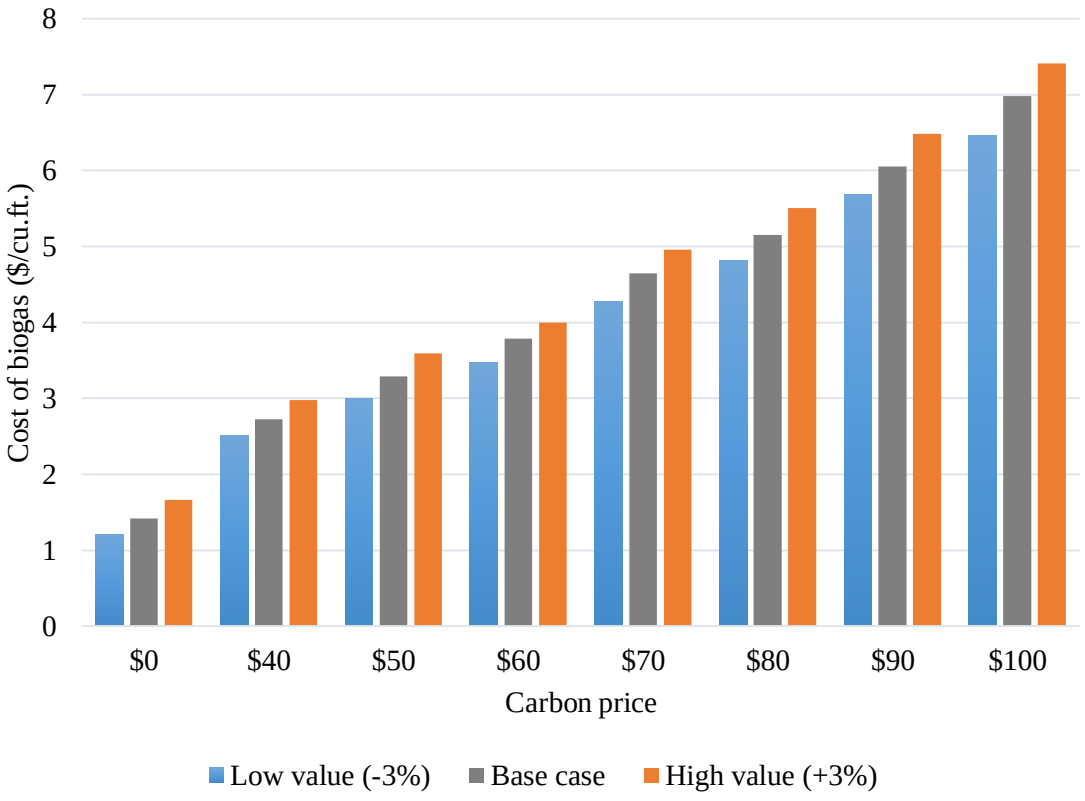

Figure 18. Impact of Manure Acquisition Cost and Carbon Price on Cost of Biogas.

This study further evaluates the impact of critical parameters on system design and cost. The effects of wet and dry content of manure is analyzed with two carbon price scenarios by assigning weight for each type of manure (e.g., 15% for dry basis and 85% for wet basis). The result of sensitivity analysis of wet versus dry manure content is presented in Table 17. The results indicate that wet and dry content of manure and carbon price have significant impacts on the total supply chain costs, carbon credit, and cost of biogas. There is a dramatic change in the number of biogas plants while the average capacity of plants remains the same.

Table 17. Impact of Wet Versus Dry Manure Content

Types of manure	Wet basis		Dry basis	
Scenario	Carbon price at $0	Carbon price at $40	Carbon price at $0	Carbon price at $40
Total cost (in $m)	464.5	579.2	45.5	348.1
Acquisition cost (in $m)	7.7	7.7	1.0	0.7
Investment cost (in $m)	385.0	385.0	35.0	52.5
Production cost (in $m)	70.8	70.8	9.2	1.8
Transport cost (in $m)	0.9	0.8	0.3	0.3
Emission cost (in $m)	-	114.9	-	61.0
Carbon credit (in $m)	-	8925.8	-	231.8
Cost of biogas ($/cu.ft.)	0.88	1.07	9.02	10.58
Number of plants	11	11	2	3
Average capacity (tons)	70,000	70,000	70,000	70,000

4.7. Summary and Conclusion

The optimization of a green supply chain for biogas production from animal manure is a relatively unexplored field from a renewable energy supply chain point of view. In this study, we address greening the biomass supply chain for animal manure through consideration of the carbon emissions along the SC and carbon strategy to provide tactical and strategic SC decisions.

This study contributes to the current literature in several ways. It proposes a mathematical model for design and management of a biomass to biogas supply chain, including anaerobic digestion as a source of renewable energy production. This study also contributes to the related body of knowledge by considering mainly waste biomass in the supply chain design model, while most of the studies focus on energy crops as a source of biomass. Therefore, waste

management issues are handled by incorporating carbon policy into the biomass supply chain with due consideration accorded to both monetary and environmental factors. Thus, various performance measures for carbon policies that can be used in biomass supply chain planning decisions are studied.

To validate the proposed model, computational experiments were performed on a case study using North Dakota, which is one of the significant cattle manure producers in the U.S. The experimental analysis shows that the biogas industry tends to reduce their carbon emissions significantly with introduction of a carbon price by decentralizing supply chain to minimize the emissions from transportation and production. From sensitivity analysis, cost of biogas was very responsive to different carbon prices, advanced conversion technological efficiencies, types of manure, and manure acquisition cost. This model can help supply chain practitioners devise and implement a strategy based on future expectations of a carbon policy. This model was developed mainly to determine the impact of carbon policies on biogas supply chains. For future work, developing dedicated transportation mode, trade-off between logistics costs of manure loss and collection of manure and the cost of transport, that address vertical and horizontal relationship in supply chain management would be key area to improve the comprehensive nature of the model (Svanberg, Finnsgard, Floden, & Lundgren, 2016). The proposed model can also be further improved by modeling animal waste with other biomass commodities (wood, industrial waste, and crops etc.) or using a multiple objective optimization of supply chain costs and social impact with a more comprehensive life cycle assessment.

REFERENCES

Abdallah, T., Diabat, A., & Simchi-Levi, D. (2010). A carbon sensitive supply chain network problem with green procurement. *40th International Conference on Computers and Industrial Engineering: Soft Computing Techniques for Advanced Manufacturing and Service Systems, CIE40 2010*. https://doi.org/10.1109/ICCIE.2010.5668278

Abdallah, T., Farhat, A., Diabat, A., & Kennedy, S. (2012). Green supply chains with carbon trading and environmental sourcing: Formulation and life cycle assessment. *Applied Mathematical Modelling*, *36*(9), 4271–4285. https://doi.org/10.1016/j.apm.2011.11.056

Abdeshahian, P., Lim, J. S., Ho, W. S., Hashim, H., & Lee, C. T. (2016). Potential of biogas production from farm animal waste in Malaysia. *Renewable and Sustainable Energy Reviews*. https://doi.org/10.1016/j.rser.2016.01.117

Ahi, P., & Searcy, C. (2013). A comparative literature analysis of definitions for green and sustainable supply chain management. *Journal of Cleaner Production*, *52*, 329–341. https://doi.org/10.1016/j.jclepro.2013.02.018

Akgul, O., Zamboni, A., Bezzo, F., Shah, N., & Papageorgiou, L. G. (2010). Optimization based approaches for bioethanol supply chains. *Industrial & Engineering Chemistry Research*, 4927–4938.

Akgul, O., Shah, N., & Papageorgiou, L. G. (2012). Economic optimisation of a UK advanced biofuel supply chain. *Biomass and Bioenergy*, *41*, 57–72. https://doi.org/10.1016/j.biombioe.2012.01.040

Akgul, O., Zamboni, A., Bezzo, F., Shah, N., & Papageorgiou, L. G. (2011). Optimization-based approaches for bioethanol supply chains. *Industrial and Engineering Chemistry Research*, *50*(9), 4927–4938. https://doi.org/10.1021/ie101392y

Alex Marvin, W., Schmidt, L. D., Benjaafar, S., Tiffany, D. G., & Daoutidis, P. (2012). Economic Optimization of a Lignocellulosic Biomass-to-Ethanol Supply Chain. *Chemical Engineering Science*, *67*(1), 68–79. https://doi.org/10.1016/j.ces.2011.05.055

American Biogas Council. (2015). *Biogas State Profile: North Dakota*. Retrieved from https://www.americanbiogascouncil.org/State Profiles/ABCBiogasStateProfile_ND.pdf

An, H., Wilhelm, W. E., & Searcy, S. W. (2011). A mathematical model to design a lignocellulosic biofuel supply chain system with a case study based on a region in Central Texas. *Bioresource Technology*, *102*(17), 7860–7870. https://doi.org/10.1016/j.biortech.2011.05.060

Balaman, Ş. Y., Selim, H., ßebnem, S., Balaman, Y., Selim, H., Balaman, Ş. Y., & Selim, H. (2014). A network design model for biomass to energy supply chains with anaerobic digestion systems. *Applied Energy*, *130*, 289–304. https://doi.org/10.1016/j.apenergy.2014.05.043

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Barba-Gutiérrez, Y. (2009). Eco-efficiency of electric and electronic appliances: a data envelopment analysis (DEA). *Environmental Modeling & Assessment*, *14*(4), 439–447. Retrieved from http://link.springer.com/article/10.1007/s10666-007-9134-2

Benjaafar, S., & Savelsbergh, M. (2014). Carbon-aware transport and logistics. *EURO Journal on Transportation and Logistics*, *3*(1), 1–3. https://doi.org/10.1007/s13676-014-0049-1

Berwick, M., Bitzan, J., Chi, J., & Lofgren, M. (2002). *North Dakota Strategic Freight Analysis: The Role of Intermodal Container Transportation in North Dakota*. Retrieved from https://www.ugpti.org/pubs/pdf/DP150.pdf

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management: Developments and directions. *European Journal of Operational Research*, *233*(2), 299–312. https://doi.org/10.1016/j.ejor.2013.09.032

C2ES. (2012). Transportation Overview. Retrieved November 3, 2016, from http://www.c2es.org/energy/use/transportation#_edn3

Cambero, C., & Sowlati, T. (2014). Assessment and optimization of forest biomass supply chains from economic, social and environmental perspectives - A review of literature. *Renewable and Sustainable Energy Reviews*, *36*, 62–73. https://doi.org/10.1016/j.rser.2014.04.041

Carter, C. R., & Easton, P. L. (2011). Sustainable supply chain management: evolution and future directions. *International Journal of Physical Distribution & Logistics Management*, *41*, 46–62. https://doi.org/10.1108/09600031111101420

Caves, D. W. D. W., Christensen, L. R. L. R., & Diewert, W. E. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers. *Economic Journal*, *92*(365), 73–86. https://doi.org/10.2307/2232257

Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. *International Journal of Production Economics*, *135*(1), 37–49. https://doi.org/10.1016/j.ijpe.2010.10.025

Chang, Y.-T. (2013). Environmental efficiency of ports: a Data Envelopment Analysis approach. *Maritime Policy & Management*, *40*(5), 467–478. https://doi.org/10.1080/03088839.2013.797119

Chang, Y.-T., Zhang, N., Danao, D., & Zhang, N. (2013). Environmental efficiency analysis of transportation system in China: A non-radial DEA approach. *Energy Policy*, *58*(2013), 277–283. https://doi.org/10.1016/j.enpol.2013.03.011

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Charnes, A., Haag, S., Jaska, P., & Semple, J. (1992). Sensitivity of efficiency classifications in the additive model of data envelopment analysis. *International Journal of Systems Science*, *23*(5), 789–798. https://doi.org/10.1080/00207729208949248

Charnes, A., Roussea, J. J., & Semple, J. H. (1996). Sensitivity and stability of efficiency classifications in data envelopment analysis. *Journal of Productivity Analysis*, *7*(1), 5–18. https://doi.org/Doi 10.1007/Bf00158473

Chen, C.-W., & Fan, Y. (2012). Bioethanol supply chain system planning under supply and demand uncertainties. *Transportation Research Part E: Logistics and Transportation Review*, *48*(1, SI), 150–164. https://doi.org/10.1016/j.tre.2011.08.004

Choi, J., Park, Y. S., & Park, J. D. (2015). Development of an Aggregate Air Quality Index Using a PCA-Based Method : A Case Study of the US Transportation Sector. *American Journal of Industrial and Business Management*, *5*, 53–65.

Connolly, D., Mathiesen, B. V., & Ridjan, I. (2014). A comparison between renewable transport fuels that can supplement or replace biofuels in a 100% renewable energy system. *Energy*, *73*, 110–125. https://doi.org/10.1016/j.energy.2014.05.104

Cook, W., & Seiford, L. (2009). Data envelopment analysis (DEA)–Thirty years on. *European Journal of Operational Research*, *192*(1), 1–17.

Cooper, W., Seiford, L., & Tone, K. (2007). *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*. Springer Science & Business Media.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software: Second edition*. *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software: Second Edition*. https://doi.org/10.1007/978-0-387-45283-8

Cundiff, J. S., Dias, N., & Sherali, H. D. (1997). A linear programming approach for designing a herbaceous biomass delivery system. *Bioresource Technology*, *59*(1), 47–55. https://doi.org/10.1016/S0960-8524(96)00129-0

Dal Mas, M., Giarola, S., Zamboni, A., & Bezzo, F. (2010). Capacity planning and financial optimization of the bioethanol supply chain under price uncertainty. *Computer Aided Chemical Engineering*, *28*(C), 97–102. https://doi.org/10.1016/S1570-7946(10)28017-3

Egilmez, G., Kucukvar, M., & Tatari, O. (2013). Sustainability assessment of U.S. manufacturing sectors: An economic input output-based frontier approach. *Journal of Cleaner Production*, *53*, 91–102. https://doi.org/10.1016/j.jclepro.2013.03.037

Egilmez, G., & Park, Y. S. (2014). Transportation related carbon, energy and water footprint analysis of U.S. manufacturing: An eco-efficiency assessment. *Transportation Research Part D: Transport and Environment*, *32*. https://doi.org/10.1016/j.trd.2014.07.001

Ekşioğlu, S., Li, S., Zhang, S., Sokhansanj, S., & Petrolia, D. (2010). Analyzing Impact of Intermodal Facilities on Design and Management of Biofuel Supply Chain. *Transportation Research Record: Journal of the Transportation Research Board*, *2191*, 144–151. https://doi.org/10.3141/2191-18

Elhedhli, S., & Merrick, R. (2012). Green supply chain network design to reduce carbon emissions. *Transportation Research Part D: Transport and Environment*, *17*(5), 370–379. https://doi.org/10.1016/j.trd.2012.02.002

Esfandiari, S., Khosrokhavar, R., & Masih, S. (2011). Greenhouse Gas Emissions Reduction through a Biogas Plant: A Case Studey of Waste Management Systems at FEKA Dairy Farm. *2011 2nd International Conference on Environmental Science and Technology IPCBEE*, *6*, 445–448.

ETSAP. (2013). *Biomass Production and Logistics*. Retrieved from https://iea-etsap.org/E-TechDS/PDF/P09_Biomass prod&log_ML_Dec2013_GSOK.pdf

Faere, R., Grosskopf, S., Lovell, C. A. K., & Pasurka, C. (1989). Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach. *The Review of Economics and Statistics*, *71*(1), 90. https://doi.org/10.2307/1928055

Fahimnia, B., Sarkis, J., Boland, J., Reisi, M., & Goh, M. (2015). Policy insights from a green supply chain optimisation model. *International Journal of Production Research*, *53*(21), 6522–6533. https://doi.org/10.1080/00207543.2014.958592

Färe, R., & Grosskopf, S. (2003). Modeling undesirable factors in efficiency evaluation: Comment. *American Journal of Agricultural Economics*, *85*(4), 1070–1074.

Favre, E., Bounaceur, R., & Roizard, D. (2009). Biogas, membranes and carbon dioxide capture. *Journal of Membrane Science*, *328*(1–2), 11–14. https://doi.org/10.1016/j.memsci.2008.12.017

Federal Reserve Bank of St. Louis. (2014). Federal Reserve Bank of St. Louis, Undated. NBER based Recession Indicators for the United States from the Period following the Peak through the Trough. Retrieved from https://research.stlouisfed.org/fred2/series/USREC

Frey, H., & Kuo, P. (2007). Assessment of potential reduction in greenhouse gas (GHG) emissions in freight transportation. *Emission Inventory Conference, US*, 15–17. Retrieved from http://www.researchgate.net/publication/229053869_Assessment_of_Potential_Reduction_in_Greenhouse_Gas(GHG)_Emissions_in_Freight_Transportation/file/50463519fc89ca7d99.pdf

Fukuyama, H., & Weber, W. L. (2009). A directional slacks-based measure of technical inefficiency. *Socio-Economic Planning Sciences*, *43*(4), 274–287.

Füsun, Boysan, Cigdem Özer, Kagan Bakkaloglu, M. T. B. (2015). Biogas Production from Animal Manure. *Procedia Earth and Planetary Science*, *15*(6), 908–911. https://doi.org/10.1016/j.proeps.2015.08.144

Giarola, S., Shah, N., & Bezzo, F. (2012). A comprehensive approach to the design of ethanol supply chains including carbon trading effects. *Bioresource Technology*, *107*, 175–185. https://doi.org/10.1016/j.biortech.2011.11.090

Goldman, T., & Gorham, R. (2006). Sustainable urban transport: Four innovative directions. *Technology in Society*, *28*(1–2), 261–273. https://doi.org/10.1016/j.techsoc.2005.10.007

Hafstead, M., & Picciano, P. (2017). Calculating Various Fuel Prices under a Carbon Tax. Retrieved from http://www.rff.org/blog/2017/calculating-various-fuel-prices-under-carbon-tax

Hailu, A., & Veeman, T. S. (2001). Non-parametric productivity analysis with undesirable outputs: An application to the Canadian pulp and paper industry. *American Journal of Agricultural Economics*, *83*(3), 605–616. https://doi.org/10.1111/0002-9092.00181

Haque, M., & Epplin, F. M. (2012). Cost to produce switchgrass and cost to produce ethanol from switchgrass for several levels of biorefinery investment cost and biomass to ethanol conversion rates. *Biomass and Bioenergy*, *46*, 517–530. https://doi.org/10.1016/j.biombioe.2012.07.008

Hendrickson, C., Cicas, G., & Matthews, H. S. (2006). Transportation sector and supply chain performance and sustainability. *Transportation Research Record*, (1983), 151–157.

Hernández-Sancho, F., Molinos-Senante, M., & Sala-Garrido, R. (2011). Energy efficiency in Spanish wastewater treatment plants: A non-radial DEA approach. *Science of the Total Environment*, *409*(14), 2693–2699. https://doi.org/10.1016/j.scitotenv.2011.04.018

Höhn, J., Lehtonen, E., Rasi, S., & Rintala, J. (2014). A Geographical Information System (GIS) based methodology for determination of potential biomasses and sites for biogas plants in southern Finland. *Applied Energy*, *113*(2014), 1–10. https://doi.org/10.1016/j.apenergy.2013.07.005

Hu, J., & Wang, S. (2006). Total-factor energy efficiency of regions in China. *Energy Policy*, *34*(17), 3206–3217.

Huang, Y., Chen, C. W., & Fan, Y. (2010). Multistage optimization of the supply chains of biofuels. *Transportation Research Part E: Logistics and Transportation Review*, *46*(6), 820–830. https://doi.org/10.1016/j.tre.2010.03.002

J. Javid, R., Nejat, A., & Hayhoe, K. (2014). Selection of CO2 mitigation strategies for road transportation in the United States using a multi-criteria approach. *Renewable and Sustainable Energy Reviews*, *38*, 960–972. https://doi.org/10.1016/j.rser.2014.07.005

Jin, M., Granda-Marulanda, N. A., & Down, I. (2014). The impact of carbon policies on supply chain design and logistics of a major retailer. *Journal of Cleaner Production*, *85*, 453–461. https://doi.org/10.1016/j.jclepro.2013.08.042

Kanzian, C., Kühmaier, M., Zazgornik, J., & Stampfer, K. (2013). Design of forest energy supply networks using multi-objective optimization. *Biomass and Bioenergy*, *58*, 294–302. https://doi.org/10.1016/j.biombioe.2013.10.009

Kizil, U. (2017). North Dakota State Feedlot Database. Retrieved from https://www.ag.ndsu.edu/archive/dickinso/staff/radtke/index.html

Kumar, K., Lopez, C. J. C., Sanchez, O. A. T., Gupta, A., Péton, O., Yeung, T. G., & Vanuxem, A. (2016). Integrated strategic and tactical optimization of animal-waste sourced biopower supply chains. *Proceedings of 2015 International Conference on Industrial Engineering and Systems Management, IEEE IESM 2015*, 1367–1373. https://doi.org/10.1109/IESM.2015.7380330

Kuramochi, T. (2017). *Greenhouse gas mitigation scenarios for major emitting countries*. Retrieved from https://newclimate.org/2017/11/01/greenhouse-gas-mitigation-scenarios-for-major-emitting-countries-2017/

Larson, J. a., Yu, T.-H., English, B. C., Mooney, D. F., & Wang, C. (2010). Cost evaluation of alternative switchgrass producing, harvesting, storing, and transporting systems and their logistics in the Southeastern USA. *Agricultural Finance Review*, *70*(2), 184–200. https://doi.org/10.1108/00021461011064950

Lautala, P., Pouryousef, H., Handler, R., & Chartier, S. (2012). The Role of Railroads in Multimodal Woody Biomass Transportation in Michigan. *ASME Proceedings*, 473. https://doi.org/10.1115/JRC2012-74131

Lawrence H, G., & Schein, A. (2013a). *Carbon taxes vs. cap and trade: A critical review* (No. No. w19338). https://doi.org/10.3386/w19338

Lawrence H, G., & Schein, A. (2013b). Carbon taxes vs. cap and trade: A critical review. *National Bureau of Economic Research*.

Lee, K. H., & Wu, Y. (2014). Integrating sustainability performance measurement into logistics and supply networks: A multi-methodological approach. *British Accounting Review*, *46*(4), 361–378. https://doi.org/10.1016/j.bar.2014.10.005

Leggett, J. A. (2014). *President Obama's Climate Action Plan*. Retrieved from https://www.whitehouse.gov/sites/default/files/image/president27sclimateactionplan.pdf

Li, H., Fang, K., Yang, W., Wang, D., & Hong, X. (2013). Regional environmental efficiency evaluation in China: Analysis based on the Super-SBM model with undesirable outputs. *Mathematical and Computer Modelling*, *58*(5–6), 1018–1031. https://doi.org/10.1016/j.mcm.2012.09.007

Lim, C. H., & Lam, H. L. (2016). Biomass supply chain optimisation via novel Biomass Element Life Cycle Analysis (BELCA). *Applied Energy*, *161*, 733–745. https://doi.org/10.1016/j.apenergy.2015.07.030

Lin, L. C., & Hong, C. H. (2006). Operational performance evaluation of international major airports: An application of data envelopment analysis. *Journal of Air Transport Management*, *12*(6), 342–351. https://doi.org/10.1016/j.jairtraman.2006.08.002

Liu, Q., & Hoon Lim, S. (2017). Toxic air pollution and container port efficiency in the USA oa. *Maritime Economics and Logistics*, *19*(1), 94–105. https://doi.org/10.1057/mel.2015.29

Lozano, S., & Gutiérrez, E. (2011). Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs. *Computers & Operations Research*, *38*(1), 131–139.

Mahmudi, H., & Flynn, P. C. (2006). Rail vs truck transport of biomass. *Applied Biochemistry and Biotechnology*, *129–132*, 88–103. https://doi.org/10.1385/ABAB:129:1:88

Mansoornejad, B., Chambost, V., & Stuart, P. (2010). Integrating product portfolio design and supply chain design for the forest biorefinery. *Computers and Chemical Engineering*, *34*(9), 1497–1506. https://doi.org/10.1016/j.compchemeng.2010.02.004

Marufuzzaman, M., & Ekşioğlu, S. D. (2017). Managing congestion in supply chains via dynamic freight routing: An application in the biomass supply chain. *Transportation Research Part E: Logistics and Transportation Review*, *99*, 54–76. https://doi.org/10.1016/j.tre.2017.01.005

Marufuzzaman, M., Ekşioğlu, S. D., & Hernandez, R. (2014). Environmentally Friendly Supply Chain Planning and Design for Biodiesel Production via Wastewater Sludge. *Transportation Science*, *48*(4), 555–574. https://doi.org/10.1287/trsc.2013.0505

Marufuzzaman, M., Eksioglu, S. D., Li, X., & Wang, J. (2014). Analyzing the impact of intermodal-related risk to the design and management of biofuel supply chain. *Transportation Research Part E: Logistics and Transportation Review*, *69*, 122–145. https://doi.org/10.1016/j.tre.2014.06.008

Merkert, R., & Hensher, D. A. (2011). The impact of strategic management and fleet planning on airline efficiency – A random effects Tobit model based on DEA efficiency scores. *Transportation Research Part A: Policy and Practice*, *45*(7), 686–695. https://doi.org/10.1016/j.tra.2011.04.015

Morrow, W. R., Griffin, W. M., & Matthews, H. S. (2006). Modeling switchgrass derived cellulosic ethanol distribution in the United States. *Environmental Science and Technology*, *40*(9), 2877–2886. https://doi.org/10.1021/es048296m

Nagurney, A., Liu, Z., & Woolley, T. (2007). Sustainable supply chain and transportation networks. *International Journal of Sustainable Transportation*, *1*(1), 29–51. https://doi.org/10.1080/15568310601060077

National Academy of Sciences. (2009). *Liquid Transportation Fuels from Coal and Biomass: Technological Status, Costs, and Environmental Impacts*. *Energy*. https://doi.org/ISBN-10: 0-309-13712-8

ND.gov. (2016). Biomass/Biofuels. Retrieved August 9, 2016, from http://ndstudies.gov/energy/level1/module-5-biofuels-geothermal-recovered/biomassbiofuels

Oklahoma State University. (2009). Value of Animal Waste Calculator. Retrieved from http://agecon.okstate.edu/faculty/publications_results.asp?page=1

Osmani, A., & Zhang, J. (2013). Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol supply chain under multiple uncertainties. *Energy*, *59*, 157–172. https://doi.org/10.1016/j.energy.2013.07.043

Osmani, A., & Zhang, J. (2014). Economic and environmental optimization of a large scale sustainable dual feedstock lignocellulosic-based bioethanol supply chain in a stochastic environment. *Applied Energy*, *114*, 572–587. https://doi.org/10.1016/j.apenergy.2013.10.024

Palak, G., Ekşioğlu, S. D., & Geunes, J. (2014). Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: An application to a biofuel supply chain. *International Journal of Production Economics*, *154*, 198–216. https://doi.org/10.1016/j.ijpe.2014.04.019

Park, Y., Egilmez, G., & Kucukvar, M. (2015). A Novel Life Cycle-based Principal Component Analysis Framework for Eco-efficiency Analysis: Case of the US Manufacturing and Transportation Nexus. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2014.12.057

Park, Y. S., Lim, S. H., Egilmez, G., & Szmerekovsky, J. (2015). Environmental efficiency assessment of U.S. transport sector: A slack-based data envelopment analysis approach. *Transportation Research Part D: Transport and Environment*. https://doi.org/10.1016/j.trd.2016.09.009

Park, Y. S., Szmerekovsky, J., Osmani, A., & Aslaam, N. M. (2017). Integrated Multimodal Transportation Model for a Switchgrass-Based Bioethanol Supply Chain. *Transportation Research Record: Journal of the Transportation Research Board*, *2628*, 32–41. https://doi.org/10.3141/2628-04

Parker, N., Tittmann, P., Hart, Q., Nelson, R., Skog, K., Schmidt, A., … Jenkins, B. (2010). Development of a biorefinery optimized biofuel supply curve for the Western United States. *Biomass and Bioenergy*, *34*(11), 1597–1607. https://doi.org/10.1016/j.biombioe.2010.06.007

Pittman, R. (1983). Multilateral productivity comparisons with undesirable outputs. *The Economic Journal*, 883–891.

Ramudhin, A., Chaabane, A., & Paquet, M. (2013). Carbon market sensitive sustainable supply chain network design. *International Journal of Management Science and Engineering Management*, *5*(1), 30–38.

Ren, J., An, D., Liang, H., Dong, L., Gao, Z., Geng, Y., … Zhao, W. (2016). Life cycle energy and CO2 emission optimization for biofuel supply chain planning under uncertainties. *Energy*, *103*, 151–166. https://doi.org/10.1016/j.energy.2016.02.151

Rezaee, A., Dehghanian, F., Fahimnia, B., & Beamon, B. (2015). Green supply chain network design with stochastic demand and carbon price. *Annals of Operations Research*, 1–23.

RITA. (2014). National Transportation Statistics 2014 | Bureau of Transportation Statistics. Retrieved July 11, 2014, from http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/index.html

Rodrigue, J.-P., Comtois, C., & Slack, B. (2013). *The geography of transport systems*. Routledge.

Rodrigue, J. P., Comtois, C., & Slack, B. (2016). *The geography of transport systems*. *The Geography of Transport Systems*. https://doi.org/10.4324/9781315618159

Roni, M. S., Eksioglu, S. D., Cafferty, K. G., & Jacobson, J. J. (2017). A multi-objective, hub-and-spoke model to design and manage biofuel supply chains. *Annals of Operations Research*, *249*(1–2), 351–380. https://doi.org/10.1007/s10479-015-2102-3

Roni, M. S., Eksioglu, S. D., Searcy, E., & Jha, K. (2014). A supply chain network design model for biomass co-firing in coal-fired power plants. *Transportation Research Part E: Logistics and Transportation Review*, *61*, 115–134. https://doi.org/10.1016/j.tre.2013.10.007

Rousseau, J. J., & Semple, J. H. (1995). Radii of Classification Preservation in Data Envelopment Analysis: A Case Study of "Program Follow-Through." *The Journal of the Operational Research Society*, *46*(8), 943–957.

Sarder, M., Adnan, Z., & Miller, C. (2013). Biomass Transportation Model for Intermodal Network. *Journal of Supply Chain Management*, *2*(2), 7–18. Retrieved from http://www.ojs.excelingtech.co.uk/index.php/IJSCM/article/view/749

Scheraga, C. A. (2004). Operational efficiency versus financial mobility in the global airline industry: a data envelopment and Tobit analysis. *Transportation Research Part A: Policy and Practice*, *38*(5), 383–404. https://doi.org/10.1016/j.tra.2003.12.003

Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, *142*(1), 16–20.

Shinners, K. J., & Binversie, B. N. (2007). Fractional yield and moisture of corn stover biomass produced in the Northern US Corn Belt. *Biomass and Bioenergy*, *31*(8), 576–584. https://doi.org/10.1016/j.biombioe.2007.02.002

Silva, S., Alcada-Almeida, L., & Dias, L. C. (2017). Multiobjective programming for sizing and locating biogas plants: A model and an application in a region of Portugal. *Computers and Operations Research*, *83*, 189–198. https://doi.org/10.1016/j.cor.2017.02.016

Silva, S., Alçada-Almeida, L., & Dias, L. C. (2014). Biogas plants site selection integrating Multicriteria Decision Aid methods and GIS techniques: A case study in a Portuguese region. *Biomass and Bioenergy*, *71*, 58–68. https://doi.org/10.1016/j.biombioe.2014.10.025

Simsek, N. (2014). Energy Efficiency with Undesirable Output at the Economy-Wide Level: Cross Country Comparison in OECD Sample. *American Journal of Energy Research*, *2*(1), 9–17. https://doi.org/10.12691/ajer-2-1-2

Sokhansanj, S., Mani, S., Turhollow, S., Kumar, A., Bransby, D., Lynd, L., & Laser, M. (2009). Large-scale production, harvest and logistics of switchgrass (Panicum virgatum L.) - Current technology and envisioning a mature technology. *Biofuels, Bioproducts and Biorefining*, *3*(2), 124–141. https://doi.org/10.1002/bbb.129

Svanberg, M., Finnsgard, C., Floden, J., & Lundgren, J. (2016). Analyzing animal waste-to-energy supply chains: The case of horse manure. *Renewable Energy*, 1–8. https://doi.org/10.1016/j.renene.2017.04.002

Tang, A., Chiara, N., & Taylor, J. E. (2012). Financing renewable energy infrastructure: Formulation, pricing and impact of a carbon revenue bond. *Energy Policy*, *45*, 691–703. https://doi.org/10.1016/j.enpol.2012.03.022

Thompson, E., Wang, Q., & Li, M. (2013). Anaerobic digester systems (ADS) for multiple dairy farms: A GIS analysis for optimal site selection. *Energy Policy*, *61*, 114–124. https://doi.org/10.1016/j.enpol.2013.06.035

Tognetti, A., Grosse-Ruyken, P. T., & Wagner, S. M. (2015). Green supply chain network optimization and the trade-off between environmental and economic objectives. *International Journal of Production Economics*, *170*, 385–392. https://doi.org/10.1016/j.ijpe.2015.05.012

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research*, *130*(3), 498–509.

U.S. DOE. (2016). Ethanol Production and Distribution. Retrieved from http://www.afdc.energy.gov/fuels/ethanol_production.html

U.S. EIA. (2014). Energy Use for Transportation. Retrieved from http://www.eia.gov/Energyexplained/?page=us_energy_transportation

U.S. EIA. (2015). Petroleum & Other Liquids. Retrieved November 3, 2016, from http://www.eia.gov/petroleum/data.cfm

U.S. EIA. (2016). Energy Use for Transportation. Retrieved November 3, 2016, from http://www.eia.gov/energyexplained/?page=us_energy_transportation

U.S. EIA. (2017). *Annual Energy Outlook*. Washington. Retrieved from https://www.eia.gov/outlooks/aeo/

U.S. EIA. (2018). Natural Gas Consumption by End Use. Retrieved from https://www.eia.gov/dnav/ng/ng_cons_sum_dcu_SND_m.htm

U.S. EPA. (2005). Summary of the Energy Policy Act. Retrieved April 5, 2018, from https://www.epa.gov/laws-regulations/summary-energy-policy-act

U.S. EPA. (2011). *Basic Anaerobic Digester System Flow Diagram*. Retrieved from http://www.epa.gov/agstar/documents/digester_flow_diagram.pdf

U.S. EPA. (2014). *Inventory of U.S. Greenhouse Gas Emissions and Sinks*. Retrieved from https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

U.S. EPA. (2016). Renewable Fuel Standard Program. Retrieved from https://www.epa.gov/renewable-fuel-standard-program

US EPA. (2014). Inventory of U.S. Greenhouse Gas Inventory Report: 1990–2014. Retrieved from http://www.epa.gov/climatechange/ghgemissions/usinventoryreport.html

USDA. (2007). *An Analysis of Energy Production Costs from Anaerobic Digestion System on U.S. Livestock Production Facilities*. Retrieved from http://www.agmrc.org/media/cms/manuredigesters_FC5C31F0F7B78.pdf

USDA. (2012). 2012 Census Publications. Retrieved from https://www.agcensus.usda.gov/Publications/2012/Full_Report/Census_by_State/North_Dakota/index.asp

USDA. (2018). Fertilizer Use and Price. Retrieved April 5, 2018, from https://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx

Vanek, F. M., & Morlok, E. K. (2000). Improving the energy efficiency of freight in the United States through commodity-based analysis: Justification and implementation. *Transportation Research Part D: Transport and Environment*, *5*(1), 11–29. https://doi.org/10.1016/S1361-9209(99)00021-8

Wakeley, H. L., Hendrickson, C. T., Griffin, W. M., & Matthews, H. S. (2009). Economic and environmental transportation effects of large-scale ethanol production and distribution in the United States. *Environmental Science & Technology*, *43*(7), 2228–2233. https://doi.org/doi:10.1021/es8015827

Wallace, R., Ibsen, K., McAloon, A. and Yee, W. (2005). Feasibility Study for Co-Locating and Integrating Ethanol Production Plants from Corn Starch and Lignocellulosic Feedstocks. *National Renewable Energy Laboratory*, 1–58. https://doi.org/10.2172/15011708

Walther, G., Schatka, A., & Spengler, T. S. (2012). Design of regional production networks for second generation synthetic bio-fuel - A case study in Northern Germany. *European Journal of Operational Research*, *218*(1), 280–292. https://doi.org/10.1016/j.ejor.2011.09.050

WCED. (1987). *world commision on environment and development*. *1987*. Retrieved from www.un-documents.net/our-common-future.pdf

Wilkes, H. L. (2007). *ESTIMATED PRODUCTION COST BUDGETS FOR BIOMASS : Switchgrass , " Highlander " Eastern Gamagrass , Indiangrass , and Big Bluestem*.

Xie, F., Huang, Y., & Eksioglu, S. (2014). Integrating multimodal transport into cellulosic biofuel supply chain design under feedstock seasonality with a case study based on California. *Bioresource Technology*, *152*, 15–23. https://doi.org/10.1016/j.biortech.2013.10.074

You, F., Graziano, D. J., & Snyder, S. W. (2012). Optimal Design of Sustainable Cellulosic Biofuel Supply Chains : Multiobjective Optimization Coupled with Life Cycle Assessment and Input – Output Analysis. *AIChE Journal*, *58*(4), 1157–1180. https://doi.org/10.1002/aic

Zakeri, A., Dehghanian, F., Fahimnia, B., & Sarkis, J. (2015). Carbon pricing versus emissions trading: A supply chain planning perspective. *International Journal of Production Economics*, *164*, 197–205. https://doi.org/10.1016/j.ijpe.2014.11.012

Zhang, B., Bi, J., Fan, Z., Yuan, Z., & Ge, J. (2008). Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach. *Ecological Economics*, *68*(1–2), 306–316.

Zhang, F., Johnson, D. M., & Wang, J. (2016). Integrating multimodal transport into forest-delivered biofuel supply chain design. *Renewable Energy*, *93*, 58–67. https://doi.org/10.1016/j.renene.2016.02.047

Zhang, H., Su, X., & Ge, S. (2011). A slacks-based measure of efficiency of electric arc furnace activity with undesirable outputs. *Journal of Service Science and Management*. Retrieved from http://file.scirp.org/Html/5238.html

Zhang, J., Osmani, A., Awudu, I., & Gonela, V. (2013). An integrated optimization model for switchgrass-based bioethanol supply chain. *Applied Energy*, *102*, 1205–1217. https://doi.org/10.1016/j.apenergy.2012.06.054

Zhang, N., & Kim, J. D. (2014). Measuring sustainability by energy efficiency analysis for Korean Power Companies: A sequential slacks-based efficiency measure. *Sustainability (Switzerland)*, *6*(3), 1414–1426. https://doi.org/10.3390/su6031414

Zhong, J., Yu, T. E., Larson, J. A., English, B. C., Fu, J. S., & Calcagno, J. (2016). Analysis of environmental and economic tradeoffs in switchgrass supply chains for biofuel production. *Energy*, *107*, 791–803. https://doi.org/10.1016/j.energy.2016.04.086

Zhou, G., Chung, W., & Zhang, Y. (2014). Measuring energy efficiency performance of China's transport sector: A data envelopment analysis approach. *Expert Systems with Applications*, *41*(2), 709–722. https://doi.org/10.1016/j.eswa.2013.07.095

Zhou, P., & Ang, B. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy*, *36*(8), 2911–2916.

Zhou, P., Ang, B., & Poh, K. (2006). Slacks-based efficiency measures for modeling environmental performance. *Ecological Economics*, *60*(1), 111–118.

Zhou, P., Poh, K., & Ang, B. (2007). A non-radial DEA approach to measuring environmental performance. *European Journal of Operational Research*, *178*(1), 1–9.

Zhou, P., Poh, K. L., & Ang, B. W. (2007). A non-radial DEA approach to measuring environmental performance. *European Journal of Operational Research*, *178*, 1–9. https://doi.org/10.1016/j.ejor.2006.04.038

Zhu, X., & Yao, Q. (2011). Logistics system design for biomass-to-bioenergy industry with multiple types of feedstocks. *Bioresource Technology*, *102*(23), 10936–10945. https://doi.org/10.1016/j.biortech.2011.08.121