Lignocellulosic biomass-to-biofuel supply chain optimization with mobile densification and farmers' choices

by

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B.S., Jordan University of Science and Technology, 2006
M.S., Jordan University of Science and Technology, 2010

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Industrial and Manufacturing Systems Engineering
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Abstract

This dissertation focuses on logistics challenges arising in the biofuels industry. Studies have found that logistics costs in the biomass-to-biofuel supply chain (BBSC) account for 35%-65% of total biofuel production cost. This is mainly due to the low density of biomass that results in high costs associated with biomass transportation, storage, and handling in the biomass-to-biofuel supply chain. Densification provides an as-yet-unexplored opportunity to reduce logistic costs associated with biomass-to-biofuel supply chains.

This research advances understanding about biomass-to-biofuel supply chain management through new optimization models. As a first step, the author presents an extensive overview of densification techniques and BBSC optimization models that account for biomass densification. This literature review helps the author to recognize the gaps and future research areas in BBSC studies. These gaps direct the author toward the remaining components of the dissertation. In particular, the literature review highlights two research gaps. First, the review indicates that mobile pelleting holds promise for improved BBSC management, but that there is no mathematical optimization model that addresses this opportunity. Second, currently, there does not exist a model that explicitly accounts for farmers' objectives and their probability to sell biomass to the bioenergy plant in BBSC optimization.

To fill the first gap, the author focuses on managing the BBSC considering mobile densification units to account for chances to minimize logistics costs. A mixed integer linear programming model is proposed to manage the BBSC with different types and forms of biomass feedstock and mobile densification units. Sensitivity analysis and scenario analysis are presented to quantify conditions that make mobile densification an attractive choice. The author conducts a case study to demonstrate model applicability and type of analysis that can be drawn from this

type of models. The result indicates that mobile pelleting is not an attractive choice under the current economic status. However, modest changes in pelleting cost, satellite storage location fixed cost, and/or travel distances are enough to make mobile pelleting an attractive choice.

To fill the second gap, the author introduces a model that explicitly accounts for mobile densification and farmers' probability to supply a bioenergy plant with biomass feedstock. Farmers' probability to provide biomass to the bioenergy plant depends on contract attributes, including expected net return and services provided by the bioenergy plant. The proposed model helps the bioenergy plant to meet biofuel demand while considering farmers' choices that satisfy their own objectives and preferences. The model makes it possible to determine most important factors that influence type of contract offered to each supplier and optimal BBSC design. A case study based on the state of Kansas is conducted to demonstrate how bioenergy plant can benefit from this type of model.

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Table of Contents

List of Figures

List of Tables

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Last but not least, this dissertation is dedicated to my late father who sacrificed everything to help me to come to Kansas State University to have a PhD. Papa, this is for you.

Dedication

This dissertation is dedicated to my father's soul, for his endless love, encouragement, and support.

Chapter 1 - Introduction

Biofuels are environmentally friendly renewable energy sources that could potentially reduce energy dependence on fossil fuels. Considerable research has focused on increasing understanding and improving management of logistics challenges in the biomass-to-biofuel supply chain (BBSC). The low bulk density of biomass is the most pressing challenge because it increases costs associated with biomass transportation, storage, and handling. Densification techniques such as baling, pelleting, and pyrolysis help mitigate these costs, but the role of densification within the overall supply chain context is not yet well understood. This dissertation provides new insights into the effect of densification, especially mobile densification, on minimizing logistic costs of BBSC. Literature shows that using mobile densification to densify close to the biomass source instead of transporting low-density biomass to fixed densification facilities could improve BBSC management. However, no mathematical optimization model addresses this opportunity. Furthermore, biomass supply depends on farmers' choices and their willingness to provide biomass feedstocks to a bioenergy plant. No optimization model considers farmers' decisions in conjunction with mobile densification.

Optimization models that consider multiple biomass types, multiple densification forms, mobile densification units, and farmers' choices are essential for reflecting BBSC reality and complexity. Mobile pelleting could potentially minimize logistics costs caused by the low bulk density of lignocellulosic biomass (LB). Moreover, because farmers differ in their willingness to collaborate with bioenergy plants, consideration of farmers' choices under various contract features provides an accurate estimate of supply and contract payments.

This dissertation addresses gaps in previous BBSC studies by (1) describing issues and challenges related to BBSC modeling with densification, (2) introducing new mathematical models that incorporate mobile densification, and (3) introducing new mathematical models that consider farmers' willingness to supply biomass for ethanol production. Section 1.1 of this chapter introduces research motivation, Section 1.2 summarizes in detail the dynamic facility location problem and distinguishes the author's research from previous related literature, and Section 1.3 describes the contributions and organization of the dissertation.

1.1 Research Motivation

The research described in this dissertation aims to advance knowledge related to the management of BBSC challenges. The author considers two factors that are absent from prior literature: the option to densify biomass at satellite storage locations (SSLs) using mobile pelleting machines (MPMs), and farmers' choices and their probability to provide biomass feedstock to the bioenergy plant.

The low bulk density of LB results in high costs associated with biomass transportation, storage, and handling in the BBSC [1, 2]. Densification is considered essential for reducing total BBSC cost because it produces a dense intermediate product that has low storage and transportation costs [3, 4, 5, 6, 7, 8, 9, 10, 11]. In addition to traditional densification techniques in which biomass is densified at a fixed location, researchers suggest utilizing mobile densification machines that move between SSLs to densify biomass before being transported to the bioenergy plant [4, 10, 12, 13, 14]. Prior literature focuses mainly on densification at fixed locations, and currently no model explicitly accounts for optimizing BBSC with mobile densification [11, 15, 16]. Therefore, the author proposes a mathematical model that optimizes MPM movement in the BBSC.

BBSC research studies typically focus on bioenergy plant objectives [17, 18, 19, 20, 21, 22, 23, 24, 25], although a few studies consider farmers' choices and their willingness to participate in the BBSC [26, 27, 28, 29, 30]. Because farmers' decisions directly impact BBSC operations, omitting farmers' choice results in inaccurate estimates of available supply for biofuel. However, no current optimization model explicitly accounts for optimizing BBSC with mobile densification and farmers' choices and their probability to sell biomass to the bioenergy plant.

The research described in this dissertation is expected to benefit society because it optimizes the utilization of a nonfood source of biomass (LB) to produce an environmentally friendly renewable energy source (ethanol). BBSC is characterized by low bulk density biomass and multiple decision makers (bioenergy plant and farmers' choices). Failure to manage these characteristics can significantly increase the total cost of the BBSC and the ability to meet biofuel demand. This research is compatible with worldwide efforts to produce a renewable energy source that could decrease dependency on fossil fuels and reduce greenhouse gas (GHG) emissions. The proposed research also is in agreement with the United States' Revised Renewable Fuel Standard (RFS2) that establishes a goal to consume a 36 billion gallons of biofuel per year by 2022, of which at least 16 billion gallons per year of biofuel consumption should be from LB [31].

1.2 Background

The problem considered in this dissertation is related to the dynamic facility location problem. Researchers have studied facility location, including dynamic aspects, before. This section summarizes existing literature on dynamic facility location and the importance of the existing literature to the work presented in this dissertation.

1.2.1 Facility location

Facility location decisions are typically strategic decisions designed to serve the supply chain for a long planning horizon; therefore, the decision must be robust. Facility location decisions are costly and difficult to change once they are made. Many research studies have considered facility location optimization in a variety of applications and proposed optimization models to determine optimal number and location of facilities in the supply chain to minimize facilities' fixed costs and transportation costs. Numerous reviews have summarized various models for facility location considering different key aspects [32, 33, 34, 35, 36, 37, 38, 39].

1.2.2 Dynamic facility location

Modeling the facility location decision as a strategic decision is useful in a static environment, but in a dynamic environment, where model parameters vary by time period, facility location may be a tactical or operational decision that can change annually, semiannually, monthly, weekly, or even daily. Because supply and demand in the supply chain vary per time period, idle facilities that do not efficiently utilize their capacity must be relocated to areas with high supply or demand. In addition, facility location must be modeled as a dynamic facility location problem to account for the dynamic nature of parameters. A dynamic facility location problem enables a decision maker to model facility location as a time-dependent decision by considering facility relocation and/or capacity relocation per time period. Dynamic facility location problems are complicated. Various techniques have been developed to solve this problem; some researchers used heuristics [40, 41, 42, 43, 44, 45, 46, 47], others utilized integer programming [48, 49], and others used mixed integer linear programming [50, 51, 52, 53, 54, 55]. Since this dissertation proposes optimization tool to manage dynamic supply chain, the author did extensive literature review on optimizing dynamic facility location using integer and mixed integer linear programming models.

Dynamic facility location problems have been extensively studied by researchers throughout various disciplines since Ballou [56] first introduced a dynamic unconstrained multi-period facility location problem with one facility. His model objective, which was to maximize profit for the planning horizon, was extended by Scott [57] to include multiple facilities. Wesolowsky [58] proposed a dynamic unconstrained model for the single-facility location problem considering relocation cost in the objective function. Wesolowsky and Truscott [50] then proposed a multi-period mixed integer linear programming (MILP) model that allows facilities to be relocated based on demand change. Their model aims to minimize the cost associated with assigning facility node to demand node and cost associated with relocation of facilities, including facility removal and establishment cost. However, their multi-period location-allocation model restricts the number of relocations. Chardaire et al. [44], Galvão and Santibañez-Gonzalez [45], Kelly and Marucheck [59], Khumawala and Whybark [60], Roodman and Schwarz [46, 61], and Van Roy and Erlenkotter [62] produced relevant early works on managing the dynamic facility location problem, but the proposed models assume that facilities have unlimited capacity, meaning no capacity constraints.

Many studies account for dynamic parameters by assuming that facility location is a strategic decision but that associated capacity is a tactical decision that can be partially or completely relocated between facilities. The capacity relocation was early studied, amongst others, by Fong and Srinivasan [47, 63], Jacobsen [64], and Lee and Luss [65]. These studies manage the dynamic facility location problem by considering operating capacity expansion and reduction. These papers, however, consider only a single commodity. Melo et al. [51] first presented an optimization model that combined dynamic facility location and multiple commodities in a comprehensive mixed integer linear programming model for a dynamic multi-commodity facility location problem. The study managed demand fluctuation by considering capacity relocation, which is capacity expansion or reduction, instead of facility relocation; facility capacity could be completely or partially relocated. If facility capacity is completely relocated to another facility, then the original facility is closed permanently. Their model considers several realistic aspects, such as external supply and holding products at inventory.

As stated, dynamic modeling of facilities and machine locations allows decision makers to efficiently respond to daily or hourly fluctuations in model parameters. Previously mentioned papers addressed the facility location problem by assuming that facilities are immobile and that facility location and capacity should be reconfigured to handle parameter changes [52]. Another practice associated with dynamic facility location considers utilization of mobile facilities or machines that move to new locations instead of closing a facility in one location and opening a new facility in a new location. Both practices are similarly modeled.

Prior studies have introduced models to optimize the location and relocation of mobile facilities [53, 66, 67, 68], as well as to consider mobile and immobile facilities simultaneously [54]. Location-allocation of ambulances is an important application dynamic facility location models, assuming facilities (in this case, ambulances and station) are mobile. Gendreau et al. [43] proposed a multi-period MILP model for ambulance relocation that includes consideration of penalty cost per relocation in the objective function to minimize the number of relocations. Degel et al. [55] developed a data-driven optimization model for locating and relocating ambulance stations according to the daily change in demand, travel time, speed of ambulances, and areas of coverage.

Researchers have modeled and solved problems in all categories using different methods, such as single-stage [51, 52, 54], two-stages [53, 69, 70], or rolling horizon facility location model [71, 72, 73].

Managing the BBSC considering mobile densification and farmers' choices is a dynamic facility location problem. Dynamic aspects of a BBSC are considered in this dissertation. Because facility relocation based on biomass supply is expensive, this dissertation assumes that locating SSLs is a strategic decision that must account for the dynamic environment associated with biomass supply. However, this study copes with fluctuating biomass supply by utilizing mobile densification units that change location based on biomass availability at each time period. There are specific features that need to be considered in the model to be able to solve the BBSC problem presented in this dissertation. The model needs to simultaneously consider multiple periods, multiple commodities, facilities' relocation, losses in transportation and inventory arcs, facilities that change product characteristic in middle stage, and stakeholders' choices. There are no prior studies that simultaneously consider all of these conditions, thus, this dissertation advances the field of dynamic facility location.

1.3 Research Contribution and Organization of the Dissertation

The research described in this dissertation utilizes optimization to advance knowledge about BBSC design and management and provides insights for minimizing BBSC logistic costs. The following subsections summarize the research contributions of each chapter.

1.3.1 State of Current Literature

Chapter 2 contains the author's summary of current academic literature related to BBSC management with densification and a comprehensive literature review of modeling and optimization studies of LB supply chains with densification processes. The literature review focuses on ethanol, a prevalent biofuel in the United States, and two promising LB feedstocks for commercial ethanol production, corn stover and switchgrass. Research in academic journals, books, and trade publications is classified based on densification method, analytical methodology, feedstock type, and mobility. Baling is the most-studied densification technique, while cost analysis is the most common analysis method. This review identifies gaps and future research areas in BBSC studies. Major contributions of the review include the following:

- The author considers models that include densification as a decision variable and finds that most existing literature shows biomass densification reduces BBSC cost. However, some studies determine that biomass densification is not always cost-effective.
- The author finds that mobile pelleting holds promise for improved BBSC management, but no mathematical optimization model addresses this opportunity.
- The review identifies opportunities to improve BBSC management. The author suggests that farmers' objectives and choices be considered in the BBSC since no model explicitly accounts for these objectives in BBSC optimization.

1.3.2 Mobile Densification

In Chapter 3, the author analyzes the effect of densifying biomass on the BBSC design with the objective of quantifying conditions that make mobile densification economically attractive. An optimization model is proposed to design the BBSC with mobile densification units that move between satellite storage locations to densify biomass. The proposed model addresses the unique challenges of different LB types and baling forms at production fields and potential use of MPMs.

Chapter 3 contains the following:

- A new optimization model is proposed to design the BBSC with mobile densification. The design includes strategic level decisions represented by supplier selection (production fields), storage site location, and bioenergy plant capacity. It also includes tactical level decisions that determine the flow of biomass between farms, the amount of biomass stored at various BBSC facilities, the amount of biomass processed and densified, and MPM movement.

- A computational study based on the state of Kansas is performed to illustrate the types of analysis that can be performed with the model. The case study is based on data obtained from the United States Department of Agriculture (USDA) and academic journals. Results indicates that mobile densification is not preferable under current economic conditions.
- A sensitivity analysis is presented to identify the impact of parameter changes on the amount of pelleted biomass. Sensitivity analysis results indicate that modest changes in pelleting cost, SSL fixed cost, or travelling distance make mobile densification economically attractive.
- A scenario analysis is performed to examine simultaneous changes in parameters to understand conditions under which mobile densification is economically viable. Scenario analysis results indicate that increasing number of MPMs in the BBSC makes densification more attractive. The high fixed cost associated with establishing SSL can be offset by decreasing logistics costs.
- Break-even analysis is presented to enable rapid decision making about densification for a specific production field. The analysis calculates the distance for which mobile densification and baling have the same cost, and it provides insight into conditions that make mobile pelleting appealing to reduce BBSC logistic costs.

1.3.3 Mobile Densification and Farmers' Choices

In Chapter 4, the author adjusts the model proposed in Chapter 3 to account for farmers' objectives and their probability to sell biomass to the bioenergy plant. The optimization model proposed in Chapter 3 assumes that farmers immediately and unconditionally provide the bioenergy plant with all needed biomass, omitting farmers' objectives and preferences. However, this scenario is often unrealistic, because farmers' choices and their willingness to participate in the BBSC differ based on different factors such as their favorability to contract payment or other contract options, conservation and environmental concerns, and demographic factors such as age and education.

The research described in Chapter 4 is designed to answer the following fundamental question: How do factors, such as location, yield, weather, and farmers' probabilities to supply biomass under different contract types, influence the optimal BBSC design? In response to this question, Chapter 4 provides the following contributions:

- The author updates the optimization model proposed in Chapter 3 to account for farmers' choices and mobile densification. To do so, the author utilizes a study performed in Kansas that estimates farmers' probability to provide biomass under various contract options.
- A computational study is performed based on the state of Kansas. Results indicate the biomass yield, farmers' probability to sell biomass to the bioenergy plant, and distances between supplier and SSLs and bioenergy plant affect the type of contract offered to each supplier.

1.4 Summary

This research advances dynamic facility location modeling by proposing an optimization model that manages a multi-commodity supply chain, while simultaneously considering stakeholders' choices, losses on transportation and storage arcs, and the potential to relocate facilities to cope with dynamic supply. For the area of managing the biomass-to-biofuel supply chain, the research described in this dissertation advances knowledge in managing the logistic challenges in the BBSC, especially the complexities caused by biomass low bulk density and farmers' choices. This dissertation not only fill the gaps in previous BBSC studies, it also demonstrates real life examples that can benefit from models proposed in the study. In Chapter 5 the author describes conclusions and future research.

Chapter 2 - Optimization of Lignocellulosic Biomass-To-Biofuel Supply Chains with Densification: Literature Review

Chapter 2 is based on the manuscript, "Optimization of Lignocellulosic Biomass-To-Biofuel Supply Chains with Densification: Literature Review," which is in preparation for submission to a peer-reviewed journal.

2.1 Introduction

The growing world population and rapid industrial development have considerably increased global energy demand. The search for economically viable, environmentally friendly renewable energy sources has been stimulated by non-renewable fossil fuel depletion, high prices, and recognition of environmental consequences. Biofuels, derived from plants and other biological materials (termed feedstock or biomass), are being developed as part of the solution to current energy challenges. Biofuels are garnering attention as promising renewable energy sources that not only could decrease fossil fuel dependence and protect the environment by reducing greenhouse gas (GHG) emissions, but also could improve the economy by bringing business to rural regions [74, 75]. The revised renewable fuel standard (RFS2) established a mandate that the U.S. consume 36 billion gallons of biofuel per year by 2022, of which at least 16 billion gallons per year must be produced from cellulosic biomass [31].

This study focuses on ethanol as an important liquid transportation biofuel in the U.S. Although ethanol can be produced from multiple sources, this study focuses primarily on corn stover and switchgrass, two promising lignocellulosic feedstocks for commercial ethanol production. Corn stover is the biomass that remains after harvesting corn grain, an annual crop. In the U.S. every year, more than 238 million tons of dry corn stover are available that can potentially be used to produce ethanol [76]. On the other hand, switchgrass is a perennial bioenergy crop. It is among the most favorable biofuel feedstocks because it is abundant and relatively inexpensive compared to other feedstocks [77, 78]. Switchgrass is considered a sustainable feedstock for ethanol production [79].

Realizing biofuels' potential benefits requires effective management of the biomass-to-biofuel supply chain, which includes the processes associated with growing, harvesting, storing, and transporting biomass feedstock from the source to the biofuel conversion point at the bioenergy plant. Modeling and optimizing the BBSC is an important research area that has recently received great attention from researchers. We briefly summarize research related to key BBSC design and operational planning decisions in Section 2.

Studies have found that biomass collection, storage, preprocessing, and transportation from fields to the bioenergy plant account for 35 – 65% of total biofuel production cost [1, 2]. However, studies indicate that BBSC logistics costs should not exceed 25% of the biofuel production cost in an economically viable supply chain [80]. A key contributing factor to the high logistics costs is the low bulk density of biomass. To minimize total supply chain costs, researchers recommend densifying biomass feedstocks to produce a dense intermediate product before transportation to the bioenergy plant for final processing [3, 4, 5, 6, 7, 8, 9]. Introducing densification affects BBSC design, including facility locations, biomass flow, and the amount of biomass densified or processed. Decisions about densification, such as densification unit type, location, and capacity, add complexity to BBSC management. Although an increasing number of studies model BBSC decisions related to biomass densification, to date there has been no comprehensive review describing densification mechanisms, quality attributes, or efforts to incorporate densification into holistic BBSC models. Our study addresses this gap by surveying work that integrates densification techniques, including baling, pelleting, and pyrolysis, into BBSC models (Section 3). We further discuss the promising trend of mobile densification (Section 4). The study concludes by summarizing the current state of the research in BBSC models that incorporate densification and highlighting important opportunities for future research.

2.2 Biomass-To-Biofuel Supply Chain

A BBSC network consists of production fields, satellite storage locations (SSLs), and bioenergy plants. Biomass is purchased from production fields, and then it is either transported directly to bioenergy plants or to a SSL. At a SSL, biomass is stored and densified (if required) before being transported as needed to the bioenergy plant. Figure 2.1 illustrates a typical biomass-to-biofuel supply chain structure on a time-expanded network. Solid arcs that connect different facilities within the BBSC in different time periods represent transportation decisions. Dashed arcs that connect the same facility in different time periods represent inventory holding decisions.

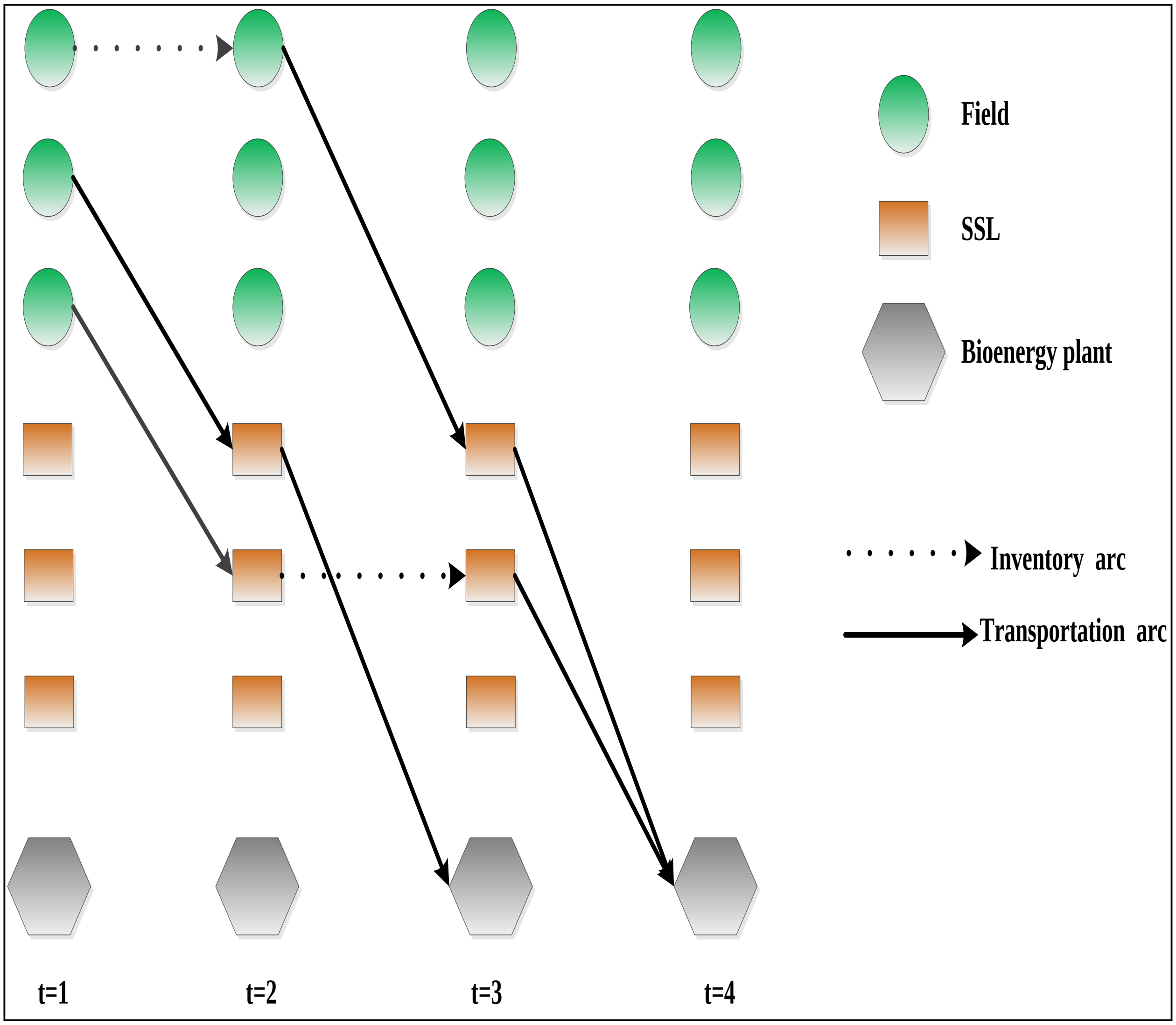


Figure 2.1: Biomass-to-biofuel supply chain structure

Effective, efficient supply chain design and management are challenging in any circumstance. However, biomass feedstocks have unique characteristics that amplify this complexity, such as low bulk density and uncertain, seasonal supply [17]. These characteristics prompt important research questions and encourage researchers to model BBSCs. Table 2.1 shows basic elements of biomass feedstock systems, decision variables to be optimized, and major logistical hurdles to deliver material from the field to the bioenergy plant. Supply chain decisions occur at strategic, tactical, and operational planning levels, distinguished by time frame and scope [19, 20, 21].

Table 2.1: Decisions and logistical challenges for BBSC elements

	Fields	**Satellite storage locations**	**Preprocessing**	**Transportation**
Decision variables	• Supplying fields • Biomass type • Baling type • Pretreatment at field • Harvesting time • Storage type at field: covered, uncovered, on wooden pallet or gravel surface	• SSL optimal locations • SSL capacity • Type of storage: indoor, outdoor	• Stationary or mobile • Preprocessing and densification techniques • Preprocessing optimal location	• Transportation mode • Biomass flow between BBSC facilities
Logistical challenges	• Harvesting machines' capacity and efficiency • Pretreatment and drying efficiency	• Shrinkage impact • Pretreatment impacts • High moisture content and variable moisture content • Dry matter loss	• Preprocessing efficiency • Biomass low bulk density • Pretreatment impact	• Transportation mode capacity • Biomass form • Biomass low bulk density

2.2.1 Strategic Level Decisions

For the biofuel industry, strategic level decisions have a long-term impact (years to decades) and are oriented toward achieving overall BBSC objectives [81]. Strategic decisions include but are not limited to production technology selection, biomass and baling type(s), location and capacity of bioenergy plant and satellite storage locations, and transportation mode [17, 81, 82, 83, 84].

Facility location is one of the most-studied strategic decisions [85]. Facility location is a crucial decision due to its long-term influence on the entire supply chain and the difficulty of changing the decision once it has been made. Transporting cheap bulky biomass between BBSC facilities represents a high percentage of the final cost of delivered biomass to the bioenergy plant

[86]. As a result, facility location decisions should be robust; the solution should remain near optimal even if input parameters, such as customer demands, transportation costs, raw material prices, or environmental conditions, change [87]. Researchers have used various methods, the most common of which are geographical information system (GIS) analysis and mixed integer linear programming (MILP), to select locations for BBSC facilities. We summarize this work here.

GIS software provides a spatial representation of supply chain locations, capturing facilities' proximity to each other and to transportation routes [88]. It also enables researchers to compute distances between BBSC facilities with great precision [86, 89, 90], although large study areas may require long computation times [85, 91]. GIS analysis can be an essential step for selecting candidate facility sites before implementing optimization and simulation [88]. GIS has been used to determine potential locations for bioenergy plants [91, 92], collection and storage sites [93], and biomass production fields [94]. Despite the fact that GIS analysis does not guarantee optimality [91], its visualization capabilities are important for decision support. GIS is used to optimize

MILP is another tool to design the supply chain and manage BBSC logistics. This approach has been used to determine the optimal location of collection facilities [18, 17, 95], bioenergy plants [17, 19, 20, 21, 96, 97, 98, 99], and supply zones among potential fields [99].

Introducing densification may change BBSC facility location decisions [15]. Balance should be achieved between transporting low-density biomass to nearby densification locations and transporting high-density densified biomass from densification sites to a more distant bioenergy plant. Utilizing densification techniques may also make it economically attractive to locate bioenergy plants closer to biofuel demand zones rather than biomass supply zones.

2.2.2 Tactical and Operational Level Decisions

Tactical level decisions are medium-term decisions (e.g., monthly, quarterly) that help achieve BBSC strategic objectives, such as determining the biomass quantity to purchase, store, and process; optimizing material flow within the BBSC network; and scheduling machines and vehicles [17, 82, 83, 84].

Many studies have analyzed the number of machines needed within BBSC, such as harvesting units [25, 95, 97, 98] and transportation units [19, 24, 100, 101]. A significant number of papers examine biomass and biofuel flow within the BBSC, considering decisions related to harvested, stored, and transported biomass quantities over time across the entire BBSC network [17, 20, 97, 98, 100, 101, 102, 103, 104, 105, 106]. Three interesting studies [105, 106, 107],] proposed MILP models that take into account densification and intermediate products before transporting biomass for final processing at a bioenergy plant. Introducing densification techniques into the BBSC could positively affect most tactical level decisions. For example, densification makes transportation of larger biomass quantities over longer distances more economically viable, thereby altering sourcing decisions.

Operational level decisions are short-term decisions (e.g., hourly, daily, or weekly) made by facility managers that aim to satisfy demand [81]. Examples include weekly, daily, or hourly production scheduling decisions, fleet management, and inventory review and management [82, 84, 108, 109]. Utilizing densification techniques may impact operational decisions since fewer trucks will be required to transport biomass to the bioenergy plant. Densification may also introduce new operational decisions, such as scheduling for densification operations.

2.2.3 Uncertainties in the Biomass-to-Biofuel Supply Chain

The previously-mentioned papers use deterministic methods to inform supply chain decisions under the assumption that all problem parameters are well-known in advance. This work has led to important insights regarding supply chain costs and operations. However, BBSC managers face uncertainty. Various papers have discussed uncertainties in supply [110, 111, 112, 113, 114], transportation [17, 114], biofuel demand [115], biomass price [116, 117], or biofuel price [116].

Kim et al. [103] studied BBSC logistics under uncertainty for a system converting woody biomass to biofuel and demonstrated their method using data from an industrial partner in the Southeast U.S. Among 14 uncertain parameters, the authors first identified five that are most influential: biomass availability, maximum demand, final product sale price, intermediate product yield, and final product yield. Scenarios were constructed by taking all combinations of these five parameters at high (+20%) and low (-20%) values. The authors then introduced a two-stage mixed integer stochastic model to identify the supply chain design that optimized expected profit over all scenarios. First stage decisions were strategic, such as facility location and capacity. The second stage incorporated tactical and operational level decisions such as determining biomass, intermediate products, and biofuel flow. Robustness analysis indicated that the scenario-based approach using a subset of the uncertain parameters was effective at identifying a supply chain design that performed well under the full range of uncertainty.

Marufuzzaman and Ekşioğlu [114] consider potential BBSC disruption by natural disasters. The proposed mixed integer nonlinear programming model adopts a rolling horizon framework to account for the dynamic nature of decision making in such contexts. It also incorporates multimodal transportation, which helps mitigate adverse impacts of seasonal events like hurricanes. They demonstrated that the reliable, dynamic model produces less costly supply chain management decisions for disaster events when compared both to a model that minimizes cost assuming normal conditions and to a reliable, static model.

A few studies have examined optimum BBSC facility location decisions under uncertainty. Dal-Mas et al. [116] proposed a MILP model for the BBSC that considers corn and ethanol selling price uncertainty in Northern Italy. Their model has two objectives, first to maximize expected net present value under different scenarios of biomass production cost and biofuel price and to minimize conditional value-at-risk. Marvin et al. [107] proposed a MILP model for BBSC with multiple types of biomass. Their model aims to determine optimal bioenergy plant locations and capacities in the Midwestern U.S. The authors used sensitivity analysis to demonstrate the supply chain robustness to ethanol selling price uncertainty. Cundiff et al. [118] formulated a linear stochastic optimization model with recourse under biomass production uncertainty due to weather conditions.

2.3 Biomass Densification

This section describes the importance of densification to the BBSC, densification types, and studies that incorporate densification into holistic BBSC models.

2.3.1 Background

Low bulk density is a major barrier to widespread adoption of lignocellulosic biomass feedstocks for transportation fuel production, because it causes challenges during biomass harvesting, transporting, and storing [8, 119]. Low-density biomass is susceptible to loss resulting from weather events; handling processes at production fields, SSLs, and the bioenergy plant; and shipping. Low density and dry matter loss create logistical hurdles when moving bulky biomass from the field to a centralized bioenergy plant [120, 121], potentially significantly increasing biofuel cost. Sokhansanj et al. [76] asserted that a large fraction of biomass feedstock costs can be attributed to the handling associated with moving biomass from fields to preprocessing locations or conversion plants.

Biomass densification is proposed to increase BBSC efficiency [2, 8, 9, 121]. This densification could be implemented at the field, SSLs, or local biomass processing depots used exclusively for densifying biomass [120, 122]. The conventional densification process for corn stover and switchgrass is accomplished by baling, pelleting, cubing, briquetting, or pyrolysis. The first four densification types produce solid densified biomass, while pyrolysis produces liquefied densified biomass.

The idea of densification is not new. Biomass is traditionally densified in fields with balers [123]. Baling continues to be an essential step in the BBSC, because bioenergy plants need uniform feedstock with low ash and moisture content. Baling methods are a significant factor affecting total supply chain logistic cost. The baling operation is an indispensable technology that increases biomass supply chain efficiency by producing a standard uniform unit with higher density that is more efficiently handled, transported, and stored than loose biomass [121].

A number of research studies investigated the benefit and feasibility of further densifying baled biomass before transporting it to the bioenergy plant. Hess et al. [2] and Forsberg [121] recommended densification, with the densification units as close to the production fields as possible to simplify handling, storing, and transportation. Upstream densification also reduces GHG emissions by decreasing fossil fuel consumption for biomass transport [4, 12, 13, 14].

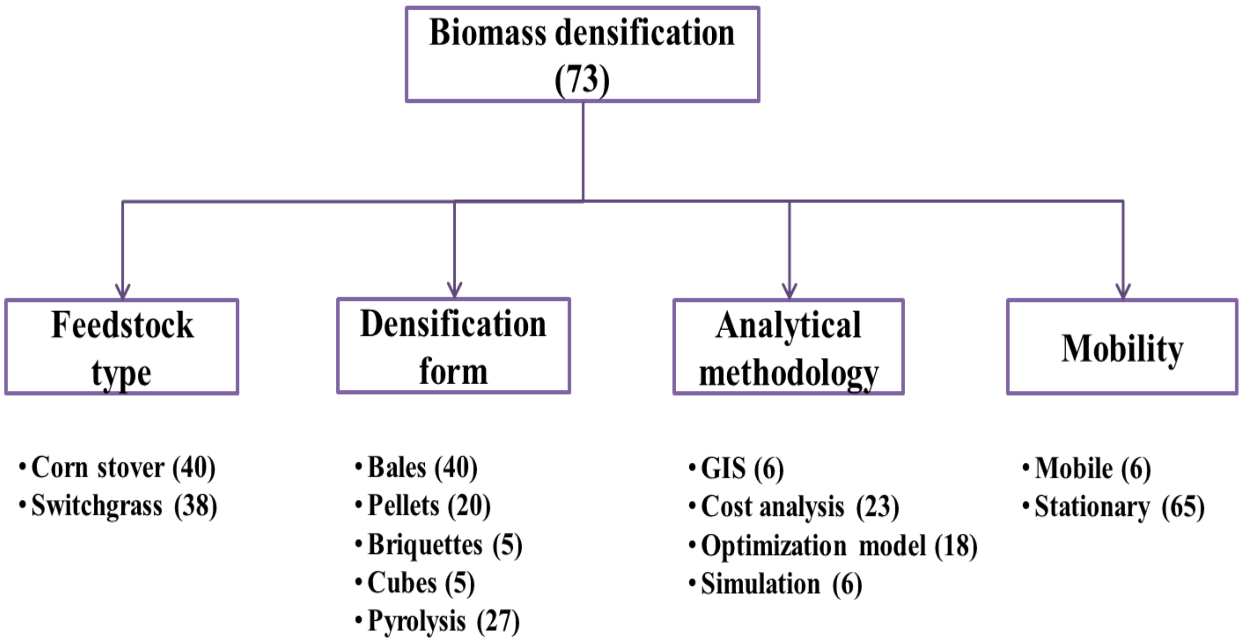


Figure 2.2: Number of papers describing dimensions of BBSC with densification

Most existing literature on densification focuses primarily on understanding densification methods and associated properties of densified biomass. This chapter reviews studies that have used different analytical methodologies to manage densification in the context of biomass feedstock supply chains for ethanol production. Figure 2.2 classifies reviewed densification models according to four criteria: biomass feedstock type, densification form, modeling methods used in the paper, and mobility of the densification technique considered. The figure makes clear that baling is the most-studied densification technique, while cubing and briquetting have received the least attention in literature. Mobility is not commonly addressed in the biomass densification literature, as nearly all studies considered stationary machines. Cost analysis is the most common method, followed closely by optimization models.

Table 2.2 compares ethanol yield for various densification forms. Biomass densification increases ethanol yield per m^3 of transported biomass. The ratio in Table 2.2 shows that pelleted form has an ethanol yield of 4 to 5 times the baled form.

Table 2.2: Comparison of densities and ethanol yield for various types of corn stover densification forms

Densification form	Density (kg/m^3)	Ethanol yield ($gallon/m^3$)[a]	Ethanol yield ratio[b]
Loose	70 [5]	5.69	1/9.29
Chop	71 [5]	5.77	1/9.15
Round bale	144 [124]	11.70	1/4.51
Square bale	156 [119]	12.68	1/4.17
Briquettes	190[125]	15.44	1/3.42
Cubes – regular size	450 [5]	36.56	1/1.45
Cubes – small size	550 [5]	44.69	1/1.19
Pellet	650 [5]	52.81	1

[a] Ethanol yield is calculated by multiplying densification form density (kg/m^3) by ethanol yield (73.71 gallon/ton) and conversion factor 0.0011 (ton/kg)
[b] Ratio of ethanol yield for each densification form to that from pelleted biomass

Table 2.2 summarizes the bulk density and ethanol yield for each primary densification technology. Each densification form has different advantages and disadvantages. For example, bales have low density compared to other densification types, and briquettes need additional preprocessing at the bioenergy plant. Moreover, the high costs required for cubing and pyrolysis densification may outweigh handling and transportation cost reductions. Overall, numerous factors influence the choice of optimal densification techniques in BBSC systems that convert corn stover or switchgrass to ethanol.

2.3.2 Baling

Baling is a common densification method that is usually carried out at production fields. Bale shape and size depends on the baling machine that is used; the most common are round, rectangular, or square. A round baler has lower capital cost than a large rectangular baler. However, square and rectangular baling are preferred over round bales for large scale biomass handling [126]. Round bales are difficult to stack, thereby increasing handling and transportation costs, and the weight of stacking can cause them to deform [127]. Research has found that baling can significantly increase biomass bulk density compared to loose form [5, 12]. Loose biomass without any densification has bulk density ranging from 50 to 130 kg/m3 [5], while the bulk density of bales can be as high as 255 kg/m3 [123].

Sokhansanj and Turhollow [124] estimated the cost of densifying and collecting biomass in round and rectangular baling forms. Increasing biomass bulk density by baling reduces costs and simplifies biomass handling and transportation logistics. Several studies have assessed the impact of different harvesting and baling techniques on the total transportation cost. Three main approaches have been proposed: cost analysis, MILP models, and simulation.

2.3.2.1 Cost analysis

Cost analysis is a technique for determining the most economically attractive biomass baling type in the BBSC by comparing costs or identifying conditions that favor one type of baling over another. Brownell and Liu [3] developed a mathematical model to help managers determine the cost of various switchgrass harvesting methods at different production fields for a predefined bioenergy plant location and three plant capacities: 2,205 ton/day (2,000 tonne/day), 5,512 ton/day (5,000 tonne/day), and 11,023 ton/day(10,000 tonne/day). The study focused on four biomass forms: loose material, round bale, large rectangular bale, and compressed rectangular bale. The primary model objective is to identify the harvesting and handling system combination with the lowest cost for each field, while simultaneously determining the number and locations of SSLs. Results showed that bioenergy plant capacity significantly influences SSL size and location. For the given case study, the authors concluded that increasing biomass density decreased transportation and storage costs, but this was made possible by utilizing expensive densification equipment that increased harvesting cost.

Sultana and Kumar [6] estimated the delivery cost associated with a combination of multiple biomass feedstocks in multiple densification forms. Biomass delivery cost includes all costs incurred in the BBSC, namely harvesting, collection, storage, preprocessing, transportation, and processing at bioenergy plant. They considered three biomass types (wheat straw, corn stover, and forest biomass) and four densification forms (loose, bales/bundles, chopped/chipped, and pellets). They found that pelleted biomass was the lowest-cost delivery option for a bioenergy plant with a capacity greater than 66,138 dry ton/day, due to pellets' high bulk density compared to other forms. Interestingly, delivering a combination of biomass types was less expensive than delivering a single type. They also noted that at longer distances, the transportation cost differences between biomass densification forms are higher than at shorter distances.

2.3.2.2 Mixed integer linear programming

MILP is widely used to manage the BBSC with different baling types by optimizing decisions about biomass types, baling forms, BBSC facility locations, feedstock storage, transportation modes, and processing [17, 18, 19, 20, 21, 22, 23, 24, 25, 97, 101]. A few authors explicitly included baling types as decision variables in their proposed models. In general, studies found that the most efficient and economical baling types depend on field size, climate, transportation distances between fields and bioenergy plant, and the harvesting time window [128, 129].

Judd et al. [10] formulated a MILP model to minimize the cost of a switchgrass-based ethanol supply chain, where costs included biomass transportation, mobile equipment transportation between SSLs, and SSLs establishment. Decision variables included SSL sites, biomass flow between BBSC facilities, and type of handling and transportation systems used at SSLs, under the assumption that bioenergy plant location and capacity are given. Biomass is densified at the production field into round baled form. The authors considered three handling and transportation equipment options for biomass at SSLs; two options used a rack (rear or side-loading rack system), and one option used a densification system to convert baled biomass into briquettes. They considered the possibility of moving handling machines between SSLs (mobile machines). The authors found the side-loading rack handling system has a 21.3% lower total cost compared to the densification system. Densification was advantageous if the densified biomass was transported more than 81 km, and equipment mobility generated savings.

Griffith et al. [89] proposed a MILP model to maximize the net present value of the biomass supply chain, assuming that biomass is densified only into large rectangular bales. The decision variables included bioenergy plant location, biomass quantity harvested from each field, and number of harvesting and baling machines. Model parameters were based on Oklahoma weather conditions, and the bioenergy plant was assumed to process a single biomass, either switchgrass or forage sorghum. The results demonstrated that switchgrass was less expensive to deliver $54.43/ton ($60/tonne) than forage sorghum $67.13/ton ($74/tonne), where delivery cost includes land rent for biomass production, establishment and maintenance, fertilizer, harvest, field storage, and transportation. The authors attributed this to differences in harvest windows and drying time for the two biomasses. Forage sorghum has a five-month harvest window, compared to the nine-month window for switchgrass, and requires twice as much drying time prior to baling. Thus, sorghum requires more harvesting machines and the harvesting cost is $26.17/ton ($28.85/tonne), while that of switchgrass is $14.27/ton ($15.73/tonne).

2.3.2.3 Simulation

Many researchers have used simulation models to evaluate aspects of biomass logistics system performance, including baling operations. The method's capability and flexibility for modeling and evaluation [130] make it an important analytical tool.

Sokhansanj et al. [131] developed a discrete event simulation model called the Integrated Biomass Supply and Logistics (IBSAL) model for the BBSC. The paper describes a case study examining harvesting, wrapping, and stacking operations for square corn stover bales. The model identified the number and capacity of machines needed to meet the predetermined bioenergy plant demand for biomass feedstock. Their work is considered an advancement in BBSC modeling, because they considered daily weather conditions and their effect on dry matter loss and moisture content.

Kumar and Sokhansanj [132] used the previously proposed IBSAL model [131] to determine the most efficient switchgrass supply among five potential densification methods: square baling, round baling, loafing, dry chopping, and wet chopping. The evaluation is based on three criteria: delivered cost (collection and transportation costs), energy consumption, and GHG emissions. Results showed that loaves have the lowest collection and delivery cost to bioenergy plant at $33.6/dry ton ($37/dry tonne) and $12.4/dry ton ($13.67/dry tonne), respectively. However, square baling has the lowest energy consumption and GHG emissions, followed by wet chopping, loafing, dry chopping, and round baling. Sokhansanj et al. [127] likewise found that loafing was a less expensive option for densifying switchgrass compared to rectangular bales and chopping, but this study did not explicitly compare total delivery costs for the three operations.

2.3.3 Pelleting, Briquetting, and Cubing

Biomass baling reduces biomass handling, storage, and transportation costs. However, bales lack desirable qualities. If multiple baling types are used concurrently, their different storage and transportation requirements prohibit a consistent, uniform, smooth biomass supply chain. In addition, high costs for transportation and handling equipment negate some transportation cost savings. Flowable biomass forms, such as pellets, briquettes, and cubes, can be handled and transported with equipment currently used for grain commodities to overcome these challenges [133].

The aforementioned obstacles associated with baled biomass have motivated researchers to recommend densifying biomass to pelleted form [9]. Pelleting is a densification technique that produces biomass with density up to 700 kg/m3 [5, 123] and energy density of 9.8–14.0 GJ/m3 [123, 134], both of which are much greater than those achieved by baling. Pelleting increases bulk density through mechanical and thermal processing [123, 135]. The high temperature generated during pelleting softens lignin, a complex natural polymer in the plant, enabling it to act as a binder to form durable pellets [136, 137]. Pelleted biomass has a uniform cylindrical shape with a diameter of approximately 6 mm and length less than 25 mm [5]. Pelleting makes biomass handling processes more efficient compared to bales [138, 139] and reduces high handling, storage, and transportation costs associated with biomass feedstocks' low bulk density [2, 9, 140].

Another research area examines characteristics and quality of pelleted biomass for ethanol production. Guragain et al. [140] studied the effect of pelleting as a pre-processing step by comparing sugars and ethanol production for pelleted biomass with those for unpelleted biomass.

Their study considers four types of biomass: wheat straw, corn stover, big bluestem, and sorghum stalk. Based on the amount of released sugars, they found no significant difference in ethanol production between pelleted and unpelleted biomass. They also found that pelleted biomass consumes fewer enzymes than unpelleted biomass. However, due to higher mass loss for pelleted biomass during the alkali pretreatment process, overall ethanol yield was not significantly higher than that of unpelleted biomass. Pelleting effects were found to differ among the four biomass types, highlighting the need for customized processes.

Pelleting cost has also received attention in the literature. Mani et al. [141] estimated woody biomass pelleting costs for different pelleting plant capacities. They defined pelleting cost as the sum of operating and capital costs. They found that pelleting cost of plant of capacities 6.61 ton/hr (6 tonne/hr) and 11.02 ton/hr (10 tonne/hr) are \$46.27/dry ton (\$51/dry tonne) and \$36.29/dry ton (\$40/dry tonne), respectively. Sultana and Kumar [6] found that pelleted biomass is an attractive choice as bioenergy plant capacity increases, because the plant must draw biomass from a larger area to meet the capacity. Roni et al. [133] introduced a hub-and-spoke design for large-scale bioenergy production, in which agricultural residues are further densified near production fields to decrease transportation costs. Although the densification form assumed for their model is not specified, they indicate that biomass is converted to a flowable form with physical properties similar to wood chips.

Briquetting and cubing are other biomass densification processes that also produce flowable products, although fewer studies have examined their use in BBSC operations. Briquettes are similar to pellets in shape but with different dimensions (approximately 32 mm in diameter and 25 mm thick). Briquettes have density of 350 kg/m3 and energy density of 6.4 GJ/m3 [123]. Cubes are larger and less dense than pellets, with bulk density ranging from 400 kg/m3 [123] to

450 kg/m3 [5, 12] and energy density from 7.3 GJ/m3 [123] to 7.993 GJ/m3 [5]. Sokhansanj and Turhollow [5] calculated the cost of densifying corn stover by cubing and then compared the transportation and storage cost for cubes with that of bales. The study found that cubing increases corn stover density and reduces associated transportation and storage costs. However, cubes still had higher final delivered costs ($65.38/dry ton, $71.92/dry tonne) than conventional corn stover bales ($54.57/dry ton, $60.15/dry tonne), even though baled biomass requires a grinding operation at the bioenergy plant and cubes may not. The higher cubing equipment and operation costs exceeded the savings in handling and transportation costs. The authors discuss operational changes that could reduce cubing costs.

Thoreson et al. [8] studied various corn stover densification methods, including grinding, baling, briquetting, and pelleting densification operations. The authors also measured the logistical impact of various harvest techniques on large-scale stover production. Results showed that increasing corn stover bulk density from 240 kg/m3 to 640 kg/m3 may reduce equipment requirements and the number of truckloads by as much as 70% compared to loose corn stover.

2.3.4 Pyrolysis

Researchers have classified pyrolysis as a promising densification technique, because it results in the highest density among current technologies. Pyrolysis involves heating biomass to high temperature (400°C–600°C) in the absence of oxygen [142]. Before heating, feedstocks are dried and ground to minimize water content in the densified liquid and to optimize heat transfer rate [143]. The pyrolysis process decomposes biomass feedstock into three main products: liquid bio-oil, solid biochar, and synthesis gas [142].

Bio-oil, an intermediate biofuel product [123], is the highest yield product from the pyrolysis process [142, 144]. Further processing is required to convert it to ethanol and make it suitable for use as a transportation fuel; removing impurities and reducing oxygen content decreases its viscosity and corrosivity [15]. The yield ratio of pyrolysis products depends on factors such as biomass feedstock type and pyrolysis conditions [145]. Fast pyrolysis, which employs a higher heat transfer rate than traditional pyrolysis, produces a higher percentage of bio-oil, potentially reaching 60–75 % of total product weight [142]. Bio-oil yield from traditional pyrolysis may reach up to 60% of total product weight [146].

Handling processes for liquid bio-oil include pumping and tank storage, which are simpler than handling for other densified biomass forms [123]. As a result of bio-oil's high density, transportation between BBSC locations is more likely to be limited by weight restrictions on trucks (36.3 tons on most major U.S. highways) than by the load's volume [12]. Pyrolysis capital costs are greater than those of other densification processes, which may make it unattractive under some conditions [12].

Comparatively few research studies investigate BBSC optimization in systems with biomass pyrolysis. Rogers and Brammer [11] determined the effect of pyrolysis on overall biomass transportation cost for a U.K. supply chain in which the pyrolysis plant produces bio-oil to be used at an electrical power generation plant. They calculated fixed and variable costs for truck movement between production fields and the pyrolysis plant while taking into account different pyrolysis plant capacities. They compared the use of satellite pyrolysis plants versus a central one. Results indicated that a distributed network, in which biomasses are densified into bio-oil at satellite pyrolysis plants located near production fields and then transported to the generation plant, would only be economical if a large proportion of land is used as a feedstock source.

Li et al. [15] compared the total annual cost of two BBSC designs in which bio-oil is produced from corn stover and upgraded at a distributed fast pyrolysis facility before being transported to a central bioenergy plant. The first MILP model considered distributed fast pyrolysis facilities and an existing bioenergy plant in Louisiana. The second model identifies the optimal location in Iowa for a new bioenergy plant instead of utilizing the existing plant. The authors compared the results from the two models for an Iowa study region. The models identified optimal locations and capacities for pyrolysis units and the new bioenergy plant. The second model resulted in lower total annual BBSC cost; transportation cost reductions to the optimal bioenergy plant location offset the new capital investment.

Li et al. [16] proposed an optimization model that captures capacity expansion over time according to the phased goals set by the RFS2 for a BBSC with fast pyrolysis densification. The MILP model was demonstrated for a case study region in Iowa, with corn stover feedstock and a planning horizon from 2014 – 2022. The model maximized net present value while considering facility location and capacity decisions, transportation decisions between BBSC facilities, and demand both in- and out-of-state. The authors found that bioenergy plants tended to be centrally located and that capacity expansion at existing facilities typically occurred before new facilities were built. Fast pyrolysis facility location decisions favored regions with high biomass availability and areas close to bioenergy plants.

2.4 Mobile Densification

The majority of prior research considers BBSC systems with stationary densification units. Using one or more stationary densification facilities makes it possible to realize economies of scale when biomass can be transported to the locations in large quantities. However, stationary densification becomes economically unattractive under some conditions. To improve the BBSC, researchers suggest utilizing mobile densification units that can be moved between BBSC facilities [4, 12, 13, 14]. To our knowledge, the study by Judd et al. [10] is the only one that proposes a prescriptive optimization model for the BBSC that captures mobile densification machines. Researchers have conducted descriptive studies focused primarily on two types of mobile densification: mobile pelleting and mobile pyrolysis.

Large-scale commercial mobile pelleting machines are in early development. The U.S. Department of Energy's Idaho National Laboratory, developed a small, transportable pelleting machine that can be taken to biomass sources and storage locations [147]. This unit was for demonstration only, however. Although some studies describe benefits associated with mobile pelleting machine utilization [148, 149], no study to date has considered optimizing mobile pelleting utilization and movement in the BBSC.

A few research studies have investigated the economic feasibility of incorporating mobile fast pyrolysis units in the BBSC and analyzed their movement between facilities. In this approach, the pyrolysis unit is transported to the production fields or SSLs where low bulk density biomasses in various baling forms are converted into high-density bio-oil.

Badger and Fransham [12] discussed efforts to develop mobile fast pyrolysis machines. The study compared capital and handling costs of bio-oil and green wood chips. Handling system capital costs for the two forms were found to be roughly equivalent, but the bio-oil system required about half as much land area for handling and storage as did the system for green wood chips. Although the authors do not explicitly calculate operating and maintenance costs, they expect these to be lower for bio-oil since the system requires less labor and equipment.

Palma et al. [4] compared the probability of economic benefit when utilizing a mobile pyrolysis plant versus stationary one using a Monte Carlo financial simulation model that incorporates transportation logistics costs and GIS data. The case study region included locations in Illinois and Texas that supply corn stover, as well as an energy sorghum feedstock source in

Nebraska. The pyrolysis unit was stationary or moved monthly, bi-monthly, quarterly, or bi-annually. The results suggested that a stationary pyrolysis plant has the highest net present value, and the mobile pyrolysis plant becomes less economical as plant relocation frequency increases. The authors concluded that the pyrolysis unit's high transportation costs outweigh biomass transportation cost savings. The probability that the mobile pyrolysis unit achieves a positive net present value was less than 16% for all biomass and movement frequency scenarios. However, the stationary system is more likely to be successful. Sensitivity analysis on important input parameters indicated that if the feedstock prices decrease by 75% or oil prices increase by 75%, then the probability of economic success will be greater than 90% for all scenarios. These results are more conservative regarding the benefits of mobile pyrolysis over stationary pyrolysis units than those in [12].

Ha et al. [13] used GIS to determine the best locations and movement for mobile pyrolysis units used to densify corn stover and bioenergy sorghum in the North Central U.S. The mobile pyrolysis units were allowed to move bi-annually. The study suggested that mobile pyrolysis units be placed in regions with highest feedstock production rates and dry weather, a combination that reduced feedstock hauling distances, ensured transport was not affected by wet weather, and supported biomass drying. A related GIS analysis [14] determined mobile pyrolysis machine movement to minimize feedstock transportation distance in the North Central U.S. for corn stover, energy sorghum, and switchgrass. In this study, the authors took into account factors such as transportation networks, seasonality, bioenergy plant location, feedstock availability, and fields' production rates.

2.5 Conclusion

Bioethanol is a promising renewable energy source that reduces fossil fuel dependence while reducing GHG emissions. Biomass densification improves BBSC efficiency by producing a dense biomass that is simpler and less expensive to handle and transport. This chapter presents a broad overview of densification techniques and BBSC models that incorporate densification. We have seen that baling is the most-studied densification technique, and cost analysis using mathematical equations is the most common method for managing BBSC systems. Future research is needed to develop mathematical models that optimize the movement of mobile densification units in the BBSC. Such comprehensive BBSC optimization models should also incorporate uncertainty. Moreover, despite the fact that numerous optimization models have been developed for the BBSC, these are almost exclusively from a centralized perspective. Many studies point out that the U.S. has the potential to meet RFS2 production goals for cellulosic-based biofuel, but achieving this potential may require BBSC models that account for farmers' willingness to harvest crop residues or grow energy crops for the bioenergy plant.

2.6 Relation to Thesis Objectives

This chapter identifies research gaps in the BBSC studies and the opportunities to improve the supply chain to reduce logistics costs. First, the review indicates that mobile pelleting is a promising technology to reduce BBSC logistics costs. However, there is no mathematical optimization model that manages the BBSC considering mobile pelleting units. Second, currently there does not exist a model that explicitly accounts for farmers' objectives in BBSC optimization. To fill this gap, the author, in Chapter 3, focuses on understanding the role of mobile densification in the BBSC by proposing comprehensive BBSC optimization model that integrate mobile densification units. To fill the second gap, the author in Chapter 4 modifies the comprehensive BBSC optimization model proposed in Chapter 3 to integrate farmers' choice.

Chapter 3 - Optimization of Lignocellulosic Biomass-To-Biofuel Supply Chains with Mobile Pelleting

Chapter 3 is based on the paper, "Optimization of Lignocellulosic Biomass-To-Biofuel Supply Chains with Mobile Pelleting," which is currently under revision after first review by a peer-reviewed journal.

3.1 Introduction

Biomass-to-biofuel supply chains (BBSCs) face significant logistical challenges. Among these are the low bulk density of biomass feedstocks. Densification has an important role in minimizing BBSC logistics costs, and its benefits are greatest when biomass is densified close to the supply source. One way to accomplish this is by using mobile densification units, which are capable of traveling to sites close to the supply sources, rather than transporting low bulk density biomass to a fixed densification site. To date, no study has introduced an optimization approach for managing BBSCs with different biomass types and multiple baling forms in conjunction with mobile densification units. This chapter addresses that gap, with the primary focus on BBSCs that convert lignocellulosic biomasses into ethanol.

Different biomass feedstocks can be used to produce ethanol, including corn grain, agricultural residues (e.g., corn stover, wheat straw, rice straw), and dedicated energy crops (e.g., switchgrass, sorghum). Lignocellulosic biomasses (LB), such as switchgrass and corn stover, are considered promising biofuel feedstocks, because they are readily available and relatively inexpensive compared with traditional biofuel feedstocks [103, 150]. However, their low bulk density and high dry matter loss result in high handling and transportation costs [4, 12, 13, 80].

To overcome these obstacles, researchers suggest densifying biomass feedstock before transporting it to the bioenergy plant [3, 5, 6, 7, 8, 12]. Densification methods, such as baling, cubing, pelleting, and pyrolysis, result in different biomass forms and bulk densities. In addition to these traditional methods, in which densification machines operate at fixed locations, mobile densification machines that may be transported between sites are proposed to decrease total BBSC cost [4, 12, 13]. Research shows that mobile pelleting, in particular, holds promise for improved BBSC management [149], but to date there is no mathematical optimization model that addresses this opportunity.

Most BBSC studies focus on a single type and form of biomass. However, one feedstock type may not be sufficient to fully utilize bioenergy plant capacity and fulfill biofuel demands, especially if biomass supply is seasonal [25]. Biomass form (e.g., round bale or rectangular bale) is often determined by production field operators, not by the bioenergy plant, and thus it is more realistic to consider multiple forms. To address these issues, we propose a model that explicitly accounts for different biomass feedstock types and forms. This increases both flexibility and complexity in the BBSC.

Optimizing BBSC operations while accounting for multiple feedstock types, different biomass forms, and mobile densification opportunities is expected to produce economic and environmental benefits. This research is compatible with efforts in the United States and worldwide to produce renewable energy sources that decrease dependency on fossil fuel and reduce greenhouse gas (GHG) emissions. For instance, the current U.S. renewable fuel standard established by the Energy Independence and Security Act of 2007 [31] sets a goal to consume 36 billion gallons of biofuel per year by 2022, of which at least 16 billion gallons per year should be from lignocellulosic biomass.

This chapter's objective is to investigate conditions under which mobile densification is economically attractive. We first summarize related literature (Section 2). Then we introduce a mixed integer linear programming (MILP) model for the BBSC in Section 3 that considers different lignocellulosic biomass types, harvesting (baling forms) at the production fields, and mobile pelleting machines (MPMs) moving between satellite storage locations (SSLs). The proposed MILP model captures both strategic and tactical level decisions. Strategic decisions include the number and locations of SSLs and the number of MPMs. Tactical decisions include biomass flow between BBSC facilities, biomass inventory, MPM movement between SSLs, and the amount of densified biomass. We describe data for a case study in Section 4 and use these data to demonstrate the MILP model in Section 5. We describe the results of sensitivity and scenario analyses in Sections 6 and 7, and we present a breakeven analysis of mobile pelleting costs in Section 8. We conclude in Section 9 with directions for future research.

3.2 Problem Context

The research in this study builds on existing literature that describes methods for managing the BBSC with one or more of the following: strategic and/or tactical level decisions; densification; and mobile densification. We summarize relevant studies and our contributions here.

High BBSC logistics costs motivate researchers to optimize supply chain decisions. Many studies propose MILP models that capture strategic aspects, including bioenergy plant location [17, 19, 20, 21, 95, 96, 97, 98, 99, 106], collection facility location [17, 18, 95, 105], and/or supply field location [99]. Many models also consider tactical and operational decisions, such as the flow of biomass and biofuel between BBSC facilities [17, 18, 19, 20, 21, 95, 96, 97, 98, 99, 103, 105, 106].

Despite the fact that a bioenergy plant may receive biomass in different baling forms, all of the previously mentioned models consider a single biomass feedstock form. The literature also pays much less attention to optimizing densification decisions within the BBSC [3, 4, 12, 13, 15, 103, 106].

There are a number of studies that investigate the effect of biomass densification on BBSC design and management decisions without explicitly employing optimization. Pelleting is one of the most important densification techniques, because it increases biomass bulk density [151, 152, 153, 154, 155, 156], reduces transportation costs [157, 158], and simplifies handling [152, 155].

Notably, research has shown no difference in ethanol production between pelleted and unpelleted biomass [140]; the study considers wheat straw, corn stover, big bluestem, and sorghum stalk biomasses. Several studies demonstrate that supply chain characteristics significantly influence the economic attractiveness of pelleting. For example, Krishnakumar and Ileleji [148] investigate the benefit of pelleting biomass in minimizing BBSC logistical requirements and costs. They compare five combinations of biomass type and form: corn grain, baled corn stover, baled switchgrass, pelleted corn stover, and pelleted switchgrass. The results show that baled corn stover has the lowest transportation cost for a small bioenergy plant, but that pelleted switchgrass has the lowest transportation cost for a large capacity bioenergy plant. In the latter case, biomass needs to be transported from a larger region to fully utilize the bioenergy plant capacity; the transportation cost savings for pelleted biomass outweigh pelleting cost. Mani et al. [141] divide pelleting into three operations, drying, size reduction, and densification, and estimate costs for each operation for different pelleting plant capacities. The authors come to a similar conclusion as [148], finding that pelleting unit costs decrease as pelleting plant capacity increases due to scale economies.

While the preceding papers focus primarily on densification units that operate in fixed locations, there are some studies that investigate the effect of mobile densification units on BBSC design and total cost. The literature focuses mainly on mobile pyrolysis, since pyrolysis produces bio-oil that has the highest energy density compared to other densified biomass forms. Badger and Fransham [12] investigate the benefit of densifying woody biomass into bio-oil using mobile pyrolysis units. The authors indicate that by densifying biomass to bio-oil at a site close to the supplying field, this will increase the distance from supplying field to bioenergy plant for which bio-oil is cost effective. Palma et al. [4] use Monte Carlo financial simulation and GIS to compare the economic feasibility of a stationary pyrolysis unit and a mobile pyrolysis unit. For their study region, the costs of hauling the mobile machine exceed the savings in biomass transportation and storage costs. Ha et al. [14] use GIS to determine locations and routes of mobile pyrolysis units used to densify corn stover, energy sorghum, and switchgrass to bio-oil. The study concludes that pyrolysis units should visit locations with high biomass availability.

In summary, while there are many research studies that apply optimization techniques to BBSC management decisions and a few that consider densification, none optimize the BBSC with mobile densification. In this context, our study makes two primary contributions. First, we propose a mathematical optimization model for the BBSC with mobile densification. The model makes it possible to quantify conditions that make mobile densification an attractive choice, and it is generalizable across regions and input parameter values. Second, we demonstrate the model's applicability for BBSC decision support using data from the state of Kansas.

3.3 Problem Formulation

This section presents a BBSC model with multiple biomass types, multiple baling forms, and mobile pelleting machines. The BBSC is modeled on a time-expanded network. The planning horizon is divided into discrete time periods t =1, …, $|T|$, where T is the set of periods in the planning horizon. Each BBSC facility (production fields, SSLs, and bioenergy plant) is replicated in each time period. Figure 3.1 depicts a small example BBSC with two potential fields, one potential SSL for storing and densifying biomass, and one bioenergy plant. A dashed arc connecting the same facility in different time periods represents the decision to store biomass or biofuel in inventory, while a solid arc connecting different facilities represents a transportation decision. If at least one mobile pelleting machine is stationed at an SSL during any time period, the corresponding facility is shaded.

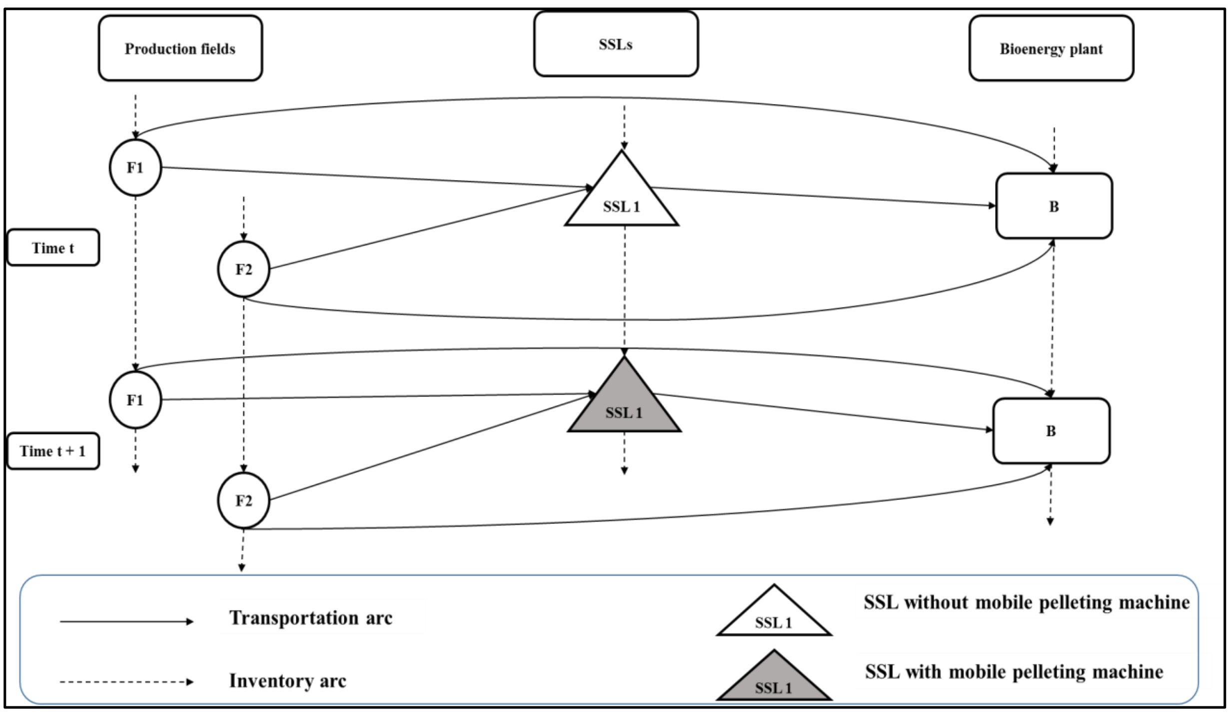


Figure 3.1: Biomass-to-biofuel supply chain network representation

The time- expanded network is represented on a directed graph $G = (L, A)$. Facilities in the node set L include the set of potential production fields L_1, set of potential SSLs L_2, and the prespecified location of the bioenergy plant n. Note that $L = L_1 \cup L_2 \cup$ n and $L_1 \cap L_2 = \emptyset$, implying that SSLs cannot be located at potential production fields. The set A of network arcs includes transportation and inventory arcs. Flows on transportation arcs represent decisions about biomass movement between BBSC facilities. Transportation costs depend on distance and biomass form (round bale, rectangular bale, or pelleted). Flows on inventory arcs represent decisions to store biomass or biofuel at a facility from one time period to the next. Inventory costs depend on storage duration, storing conditions, and biomass form. As shown in the figure, the term BBSC here refers to supply chain operations from the point of harvesting biomass into different densification forms at production fields to the point producing ethanol at the bioenergy plant to satisfy demand; pre-harvest and post-refining operations are excluded.

A MILP is developed to solve the problem. The objective function is to minimize the total BBSC cost for the planning horizon including (1) biomass purchase cost, (2) biomass transportation cost, (3) fixed cost associated with opening SSLs, (4) transportation cost of mobile pelleting machines between SSLs, (5) inventory holding cost of biomass and biofuel, (6) biomass densification cost at SSLs, and (7) biofuel production cost. Decision variables representing the amount of biomass held in inventory, transported, densified, and converted to biofuel are nonnegative and continuous. In addition, binary variables represent decisions to open SSLs and to move mobile pelleting machines. Sets and indices are shown in Table 3.1, while the parameters are represented in Table 3.2. The decision variables are summarized in Table 3.3.

Table 3.1: Sets and indices

Notation	Description
L	Set of all locations in biomass-to-biofuel supply chain, $l \in L$
L_1	Set of biomass production fields, $L_1 \subseteq L$
L_2	Set of all candidate locations for satellite storage, $L_2 \subseteq L$
n	Given location of bioenergy plant, $n \in L$
0	Depot where the MPMs are stationed before being transported to SSL for densifying biomass, $0 \in L$
B	Set of biomass types, $b \in B$
K	Set of biomass forms, $k \in K$, $k = 1$ (rectangular), $k = 2$ (round), $k = 3$ (pelleted)
T	Set of time periods in the planning horizon, $t \in T$
W	Set of mobile pelleting machines, $w \in W$

Table 3.2: Input parameters

Parameter	Description	Unit
A_{lbkt}	Available biomass of type $b \in B$ in form $k \in K$ at production field $l \in L_1$ at time $t \in T$	ton
φ_{bk}	Price of biomass type $b \in B$ in form $k \in K$	\$/ton
H_{klt}	Unit inventory holding cost of biomass in form $k \in K$ at facility $l \in L$ at time $t \in T$	\$/ton
H	Unit inventory holding cost of biofuel	\$/gallon
μ	Unit densification cost (pelleting) of biomass feedstock	\$/ton
$d_{ll'}$	Distance between facility $l \in L$ and facility $l' \in L$, $l' \neq l$	mile
T_k	Unit transportation cost per ton of biomass in form $k \in K$	\$/ton.mile
π	Cost of transporting mobile pelleting machine	\$/mile
S_{lbk}	Storage capacity for biomass type $b \in B$ in form $k \in K$ at facility $l \in L$	ton
S'	Storage capacity for biofuel at bioenergy plant	gallon
P_{bk}	Unit cost of converting biomass feedstock type $b \in B$ in form $k \in K$ to biofuel	\$/ton

D_t	Demand for biofuel at time $t \in T$	gallon
F	Annualized fixed cost of opening bioenergy plant	\$/year
V_l	Annualized fixed cost of opening SSL at location $l \in L_2$	\$/year
θ_{kl}	Dry matter loss rate of biomass in form $k \in K$ during storage at facility $l \in L$	unitless
λ_k	Dry matter loss rate of biomass in form $k \in K$ during transportation	unitless
α_b	Conversion rate of biomass type $b \in B$	unitless
m	Number of mobile pelleting machines available	unitless
q	Mobile pelleting machine capacity	ton/period
C	Bioenergy plant capacity	gallon/period

Table 3.3: Decision variables

Variable	Description	Unit
$Y_{bkll't}$	Amount of biomass type $b \in B$ in form $k \in K$ shipped from facility l to facility l' for $l, l' \in L$ and $l' \neq l$, at time $t \in T$	ton
X_{bklt}	Amount of biomass type $b \in B$ in form $k \in K$ stored at facility $l \in L$ from time period $t \in T$ to the next time period	ton
X'_t	Amount of biofuel stored at bioenergy plant from time period $t \in T$ to the next time period	gallon
E_{bkt}	Amount of biomass type $b \in B$ in form $k \in K$ used to produce biofuel in time period $t \in T$	ton
R_{bklt}	Amount of biomass of type $b \in B$ in form $k \in K$ pelleted at facility $l \in L_2$ in time period $t \in T$	ton
B_t	Biofuel production in time period $t \in T$	gallon
G_l	1 if an SSL is opened at location $l \in L_2$	binary
Z_{wlt}	1 if mobile pelleting machine $w \in W$ is located at facility $l \in (L_2 \cup 0)$ in time period $t \in T$	binary
$U_{wll't}$	1 if mobile pelleting machine $w \in W$ travels from facility $l \in (L_2 \cup 0)$ to facility $l' \in (L_2 \cup 0)$ in time period $t \in T$	binary

The MILP optimization model is presented below.

$$Minimize \sum_{l \in L_1} \sum_{l' \in (L_2 \cup n)} \sum_{b \in B} \sum_{k \in K\setminus\{3\}} \sum_{t \in T} \varphi_{bk} Y_{bkll't} + \sum_{l \in L} \sum_{b \in B} \sum_{k \in K} \sum_{t \in T} H_{klt} X_{bklt} + H \sum_{t \in T} X'_t$$

$$+ \sum_{l \in L_1} \sum_{b \in B} \sum_{k \in K\setminus\{3\}} \sum_{t \in T} \varphi_{bk} \theta_{kl} X_{bklt} + \sum_{l \in L_2} \sum_{b \in B} \sum_{k \in K\setminus\{3\}} \sum_{t \in T} \mu R_{bklt}$$

$$+ \sum_{b \in B} \sum_{k \in K} \sum_{t \in T} P_{bk} E_{bkt} + \sum_{l \in L/n} \sum_{l' \in L:\, l' \neq l} \sum_{b \in B} \sum_{k \in K} \sum_{t \in T} T_k\, d_{ll'} Y_{bkll't}$$

$$+ \sum_{w \in W} \sum_{l \in (L_2 \cup 0)} \sum_{l' \in L_2} \sum_{t \in T} \pi d_{ll'} U_{wll't} + \sum_{l \in L_2} V_l G_l$$

Subject to:

$$B_t + X'_{t-1} \geq D_t \qquad \forall\, t \in T \qquad (1)$$

$$\sum_{l' \in L_2} Y_{bkll't} + Y_{bklnt} + X_{bklt} \leq A_{lbkt} + (1-\theta_{kl}) X_{bkl,t-1}$$
$$\forall\, l \in L_1, b \in B, k \in K\setminus\{3\}, t \in T \qquad (2)$$

$$Y_{bklnt} + X_{bklt} + R_{bklt} = (1-\lambda_k) \sum_{l' \in L_1} Y_{bkl'lt} + (1-\theta_{kl}) X_{bkl,t-1}$$

$$\forall\, l \in L_2, b \in B, k \in K\setminus\{3\}, t \in T \qquad (3)$$

$$Y_{b3lnt} + X_{b3lt} = (1-\theta_{3l})\, X_{b3l,t-1} + \sum_{k \in K\setminus\{3\}} R_{bklt}$$

$$\forall\, l \in L_2, b \in B, t \in T \qquad (4)$$

$$E_{bkt} + X_{bknt} = (1-\lambda_k) \sum_{l' \in (L_1 \cup L_2)} Y_{bkl'nt} + (1-\theta_{kn}) X_{bkn,t-1}$$

$$\forall\, b \in B, k \in K\setminus\{3\}, t \in T \qquad (5)$$

$$E_{b3t} + X_{b3nt} = (1-\lambda_3) \sum_{l' \in L_2} Y_{b3l'nt} + (1-\theta_{3n}) X_{b3n,t-1}$$
$$\forall\, b \in B, t \in T \qquad (6)$$

$$B_t = \sum_{b \in B} \sum_{k \in K} \alpha_b E_{bkt} \qquad \forall\, t \in T \qquad (7)$$

$$X'_t + D_t = X'_{t-1} + B_t \qquad \forall\, t \in T \qquad (8)$$

$$X_{bklt} \le S_{lbk}\, G_l \qquad \forall\; b \in B, k \in K, l \in L_2, t \in T \qquad (9)$$

$$X_{bknt} \le S_{nbk} \qquad \forall\; b \in B, k \in K, t \in T \qquad (10)$$

$$X'_t \le S' \qquad \forall\, t \in T \qquad (11)$$

$$B_t \le C \qquad \forall\, t \in T \qquad (12)$$

$$\sum_{b\in B} \sum_{k\in K\backslash\{3\}} R_{bklt} \le q \sum_{w\in W} Z_{wlt} \qquad \forall\, l \in L_2, t \in T \qquad (13)$$

$$\sum_{l'\in L_1} Y_{bkl'lt} \le S_{lbk} G_l \qquad \forall\, l \in L_2, b \in B, k \in K\backslash\{3\}, t \in T \qquad (14)$$

$$U_{wll't} \ge Z_{wl't} + Z_{wl,t-1} - 1 \qquad \forall\, w \in W, l' \in (L_2 \cup 0), l \in (L_2 \cup 0), t \in T\backslash\{1\} \qquad (15)$$

$$U_{wll't} \le Z_{wl't} \qquad \forall\, w \in W, l \in (L_2 \cup 0), l' \in (L_2 \cup 0), t \in T \qquad (16)$$

$$U_{wll't} \le Z_{wl,t-1} \qquad \forall\, w \in W, l \in (L_2 \cup 0), l' \in (L_2 \cup 0), t \in T\backslash\{1\} \qquad (17)$$

$$\sum_{l\,\in (L_2\cup 0)} U_{w0l1} = 1 \qquad \forall\, w \in W \qquad (18)$$

$$\sum_{l'\,\in L_2} U_{wll't} = \sum_{l'\,\in (L_2\cup 0)} U_{wl'l,t-1} \qquad \forall\, w \in W, l \in L_2, t \in T\backslash\{1\} \qquad (19)$$

$$\sum_{l\,\in (L_2\cup 0)} U_{w0lt} = U_{w00,t-1} \qquad \forall\, w \in W, t \in T\backslash\{1\} \qquad (20)$$

$$\sum_{l\,\in L_2} \sum_{w\,\in W} Z_{wlt} \le m \qquad \forall\, t \in T \qquad (21)$$

$$Z_{wlt} \le G_l \qquad \forall\, w \in W, l \in L_2, t \in T \qquad (22)$$

$$B_t \ge 0 \qquad \forall\, t \in T \qquad (23)$$

$$X'_t \ge 0 \qquad \forall\, t \in T \qquad (24)$$

$$Y_{bkll't} \ge 0 \qquad \forall\, l \in L_1, l' \in L_2, b \in B, k \in K\backslash\{3\}, t \in T \qquad (25)$$

$$Y_{bklnt} \ge 0 \qquad \forall\, l \in (L_1 \cup L_2), b \in B, k \in K\backslash\{3\}, t \in T \qquad (26)$$

$$Y_{b3lnt} \ge 0 \qquad \forall\, l \in L_2, b \in B, t \in T \qquad (27)$$

$$E_{bkt} \quad \geq 0 \qquad \forall\, b \in B, k \in K, t \in T \tag{28}$$

$$X_{bklt} \quad \geq 0 \qquad \forall\, l \in L, b \in B, k \in K\backslash\{3\}, t \in T \tag{29}$$

$$X_{b3lt} \quad \geq 0 \qquad \forall\, l \in (L_2 \cup n), b \in B, t \in T \tag{30}$$

$$R_{bklt} \quad \geq 0 \qquad \forall\, l \in L_2, b \in B, k \in K\backslash\{3\}, t \in T \tag{31}$$

$$G_l \quad \in \{0,1\} \qquad \forall\, l \in L_2 \tag{32}$$

$$Z_{wlt} \quad \in \{0,1\} \qquad \forall\, w \in W, l \in L_2, t \in T \tag{33}$$

$$U_{wll't} \quad \in \{0,1\} \qquad \forall\, w \in W, l \in (L_2 \cup 0), l' \in L_2, t \in T \tag{34}$$

The objective function consists of nine terms. The first term is the biomass purchase cost. The next two terms are the inventory holding cost of biomass at BBSC facilities and of biofuel at the bioenergy plant, respectively. The fourth term accounts for biomass that is purchased but lost in storage at the field. The fifth term is the biomass densification cost. The cost of converting biomass into biofuel is represented in the sixth term. Biomass transportation cost between facilities is reflected in the seventh term. The eighth term is the cost associated with transporting mobile pelleting machines between SSLs. The last term is the fixed cost associated with opening SSLs.

Constraint (1) ensures that the biofuel demand in each planning period is met through that period's production or with inventory carried from the previous period. To guarantee that no more unpelleted biomass is shipped from fields than what is actually available at the time of shipping, constraint (2) is established. Constraints (3) – (8) describe flow balance at time-space locations for biomass and biofuel, where the left-hand side of each equation represents flow out and the right-hand side represents flow into a node. Feedstock flow balance constraints for the unpelleted and pelleted biomass feedstock at SSLs are constraints (3) and (4), respectively; they account for dry matter loss during storage and transportation. Constraints (5) and (6) are the flow balance constraints at the bioenergy plant for the unpelleted and pelleted biomass feedstock, respectively.

Constraint (7) links biofuel production to the corresponding biomass via the conversion rate. Biofuel flow balance at the bioenergy plant is enforced by constraint (8).

Constraints (9) and (10) are capacity constraints on feedstock inventory at the SSLs and at the bioenergy plant, respectively, while constraint (11) enforces biofuel inventory capacity limits at the bioenergy plant. The bioenergy plant's production capacity in each time period is reflected in constraint (12). Similarly, constraint (13) is the densification capacity constraint for the mobile pelleting machines. To prevent shipping biomass to unopened SSLs, constraint (14) is established.

Constraints (15) – (22) concern mobile pelleting machine movement. Constraint (15) ensures that if a mobile pelleting machine moves from SSL l' in period *t*-1 to SSL l in period *t*, then the binary variable $U_{wll't}$ equals 1. Constraints (16) and (17) ensure that a MPM does not travel to a SSL unless it is assigned to visit it. Constraint (18) states that the depot is the starting point for all MPM routes. MPM flow balance is enforced by constraints (19) and (20) for SSLs and depot, respectively; the left-hand side of each equation represents the number of mobile pelleting machines that leave a time-space node and the right-hand side gives the number that arrive. The number of mobile pelleting machines in use in any time period is limited by constraint (21). Constraint (22) requires that mobile pelleting machines are only used at open storage facilities. Constraints (23) – (31) enforce non-negativity, while constraints (32) – (34) define the binary variables.

3.4 Case Study

To demonstrate the applicability of the model, we analyze a case study using data from the state of Kansas. Kansas is a forerunner in the biofuel industry. Currently, there are fourteen ethanol plants in Kansas, and corn grain is the main feedstock [159]. The case study considers two LB types, corn stover and switchgrass, and two baling techniques at production fields, large rectangular bales and large round bales. Baled biomass may be densified at SSLs using one or more of 25 mobile pelleting machines that can move between SSLs. The case study has a one-year planning horizon, where the planning period is one month. Corn stover, the residue left after harvesting corn grain, is available at production fields year-round. Switchgrass is available at production fields only at harvesting windows. Switchgrass cannot be harvested from March to June, but it can be bought when it is available and stored at production fields.

Corn stover availability in the selected study region is determined by considering two factors: (1) the amount of corn stover that can be removed from a given field, and (2) the fraction of corn acres from which any stover will be harvested. Concerning the first factor, if a field is chosen to supply corn stover, best practice leaves some stover in the field to prevent erosion and preserve soil organic material [160, 161, 162]. Milhollin et al. study [162] Suggest harvesting at most 50% of the corn stover. The average gross corn stover yield in Kansas in the last ten years (2008-2017) is 3.948 ton/acre [163]. Thus, using a 50% removal rate, we assume that net corn stover yield from selected fields is 1.974 ton/acre. With respect to the second factor, some farmers are not willing to harvest corn stover from their production fields at all; one study found that 77% of Kansas farmers are willing to do so [28]. In our study, we conservatively assume that no more than 50% of corn acres are potential corn stover sources for the bioenergy plant.

To determine switchgrass availability, we consider farmers' willingness to plant switchgrass and the land that could be devoted to this crop. A survey of Kansas farmers found that 44% are willing to plant switchgrass, and that those who are willing will devote about 5% of their acres to the crop [28]. Based on these results, we assume that 2% of the total crop and pasture land in the study region that is not planted to corn can be planted to switchgrass. The switchgrass yield is assumed to be 7 ton/acre [164].

The case study region is depicted in Figure 3.2, where F_i represents the *i*th potential field, SSL_j represents the *j*th potential SSL, and *B* represents the bioenergy plant location. The case study has 10 production fields, two candidate SSLs, and one bioenergy plant. The production fields in our case study are assumed to be the 10 Kansas counties with the greatest number of acres planted to corn in 2015 [165].

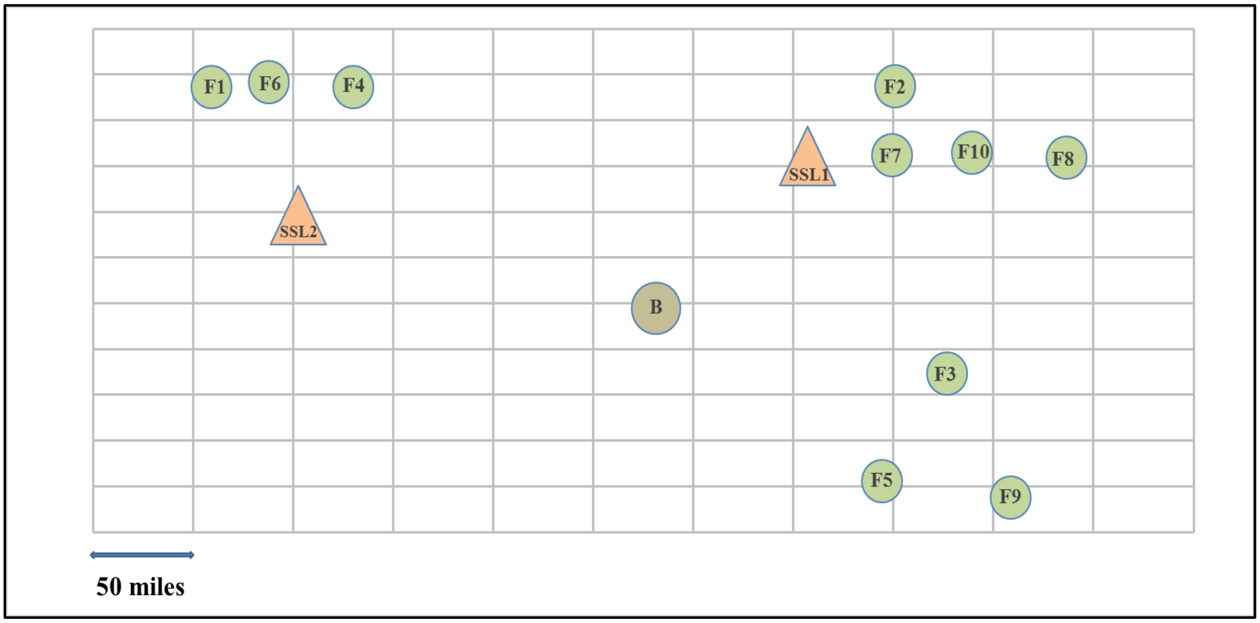


Figure 3.2: Case study geographical layout

In this study, each production field consists of a number of smaller fields. The biomass is baled into large round bales (5 ft × 4 ft) or large rectangular bales (4 ft × 8 ft) depending on the equipment available at production fields. Then, the bales are arranged at the field's edge and stored until they are transported by truck to the SSL or directly to the bioenergy plant. At the SSL, the stored baled biomass may keep its original form or may be densified into pellets before being transported to the bioenergy plant. We assume that trucks are used to transport mobile pelleting machines between SSLs in the BBSC.

There are different techniques for storing biomass at BBSC facilities. For example, bales may be covered with a tarp or uncovered, and they may be kept on wooden pallets, a gravel surface, or on bare ground [166]. Each storage method has different cost and dry matter loss characteristics. We assume that baled biomass is covered with tarps at all locations, that it is stored on bare ground at production fields and SSLs, and that it is stored on gravel at the bioenergy plant. Pelleted biomass is kept in storage bins at SSLs and at the bioenergy plant.

Storage loss represents the amount of dry matter that biomass loses after one month of storage at fields, SSLs, or bioenergy plant locations. Storage loss depends on two factors: storage type and densification form. For simplicity, we assume dry matter loss per month is constant. Dry matter loss during transportation is very small so it is neglected.

Table 3.4 summarizes the parameter estimates used for the case study. A major contribution of this work is the compilation of more than 50 input parameter values. Most parameter estimates used for the case study come from journal papers and United States Department of Agriculture (USDA) publications. However, because mobile pelleting is still under development, the cost of moving mobile pelleting machines ($/mile) is estimated based on values associated with similar processes.

Table 3.4: Values of input parameters

Parameter	Value	Source
Price of rectangular switchgrass ($/ton)	φ_{21}=41.63	[166]
Price of round switchgrass ($/ton)	φ_{22}=49.88	[166]
Price of rectangular corn stover ($/ton)	φ_{11}=70	Assumed based on differences in rectangular and round bale costs in [166]
Price of round corn stover ($/ton)	φ_{12}=80	[167]
Unit inventory holding cost of rectangular biomass at field and SSL ($/ton) (tarp only)	H_{11t}=H_{12t}=4.84	[166]
Unit inventory holding cost of round biomass at field and SSL ($/ton) (tarp only)	H_{21t}=H_{22t}=4.84	[166]
Unit inventory holding cost of pelleted biomass at SSL ($/ton)	H_{32t}=0.08	[141]
Unit inventory holding cost of rectangular biomass at bioenergy plant ($/ton) (tarp and gravel)	H_{13t}=10.75	[166, 168]
Unit inventory holding cost of round biomass at bioenergy plant ($/ton) (tarp and gravel)	H_{23t}=17.78	[166, 168]
Unit inventory holding cost of pelleted biomass at bioenergy plant ($/ton) (steel bins)	H_{33t}=1.1525	[169, 6]
Unit inventory holding cost of biofuel at the bioenergy plant (30% product value) ($/ gallon)	H =0.654	[168]
Conversion rate of corn stover (gallons /ton)	α_1=73.71	[170]
Conversion rate of switchgrass (gallons /ton)	α_2=90	[17]
Bioenergy plant processing capacity (gallons/ month)	C=8,360,000	[168]
Annualized fixed cost of bioenergy plant with capacity level $\boldsymbol{C}$ ($)	F=72,000,000	[171, 168]
Dry matter loss of rectangular biomass at bioenergy plant (tarp and gravel) (per month) (0.31 / 200 days)	θ_{13}=0.0465	[172]
Dry matter loss of round biomass at bioenergy plant (tarp and gravel) (per month) (0.16 / 200 days)	θ_{23}=0.024	[172]

Dry matter loss of rectangular biomass at fields and SSLs (tarp only) (per month) (0.19*2 / 200 days)	θ_{11}=θ_{12}=0.057	Assumed twice the loss for round biomass based on [172]
Dry matter loss of baled biomass at fields and SSLs (tarp only) (per month) (0.19 / 200 days)	θ_{2l}=θ_{22}=0.0285	[172]
Unit transportation cost of rectangular biomass ($/(ton.mile))	T_1=0.263	[166, 168]
Unit transportation cost of round biomass ($/ton. mile)	T_2=0.322	[166, 168]
Unit transportation cost of pelleted biomass ($/(ton. mile))	T_3=0.088	[131, 6]
Processing cost of baled corn stover ($/ton)	P_{1k}=44.30	[17]
Processing cost of baled switchgrass ($/ton)	P_{2k}=50	[168, 95]
Processing cost of pelleted corn stover ($/ton)	P_{13}=32.3	[169]
Processing cost of pelleted switchgrass ($/ton)	P_{23}=38	[169]
Ethanol price ($/gallon)	2.18	[20, 173]
Unit cost of pelleting ($/ton)	μ =48	[149]
Cost of moving mobile pelleting machine ($/mile)	π =1.639	[174]
Annualized fixed cost of opening SSLs ($/year)	V_1,V_2=500,000	Assumed
Bioenergy plant capacity for storing baled biomass (ton)	S_{311},S_{312},S_{321}, S_{321}=5,000	Assumed
Bioenergy plant capacity for storing pelleted biomass (ton)	S_{313},S_{323}=20,000	Assumed
SSL capacity for storing baled biomass (ton)	S_{211},S_{212},S_{221}, S_{222} =100,000	Assumed
SSL capacity for storing pelleted biomass (ton)	S_{213},S_{223}=200,00 0	Assumed

Figure 3.3 shows the amount of biomass of different types and densification forms available at production fields in the case study. Each production field has a different combination

of biomass types and forms. For example, some fields have all four combinations (e.g., Fields 5, 7, 9 and 10), while others have just two (e..g, Fields 1 and 4). During the switchgrass harvesting months (t =1, 2, 7, 8, 9, 10, 11, 12), the total biomass available each month is 249,000 dry tons, of which 200,000 dry tons are corn stover and 49,000 dry tons are switchgrass. In the remaining months, the total biomass availability is 200,000 dry tons per month, consisting only of corn stover.

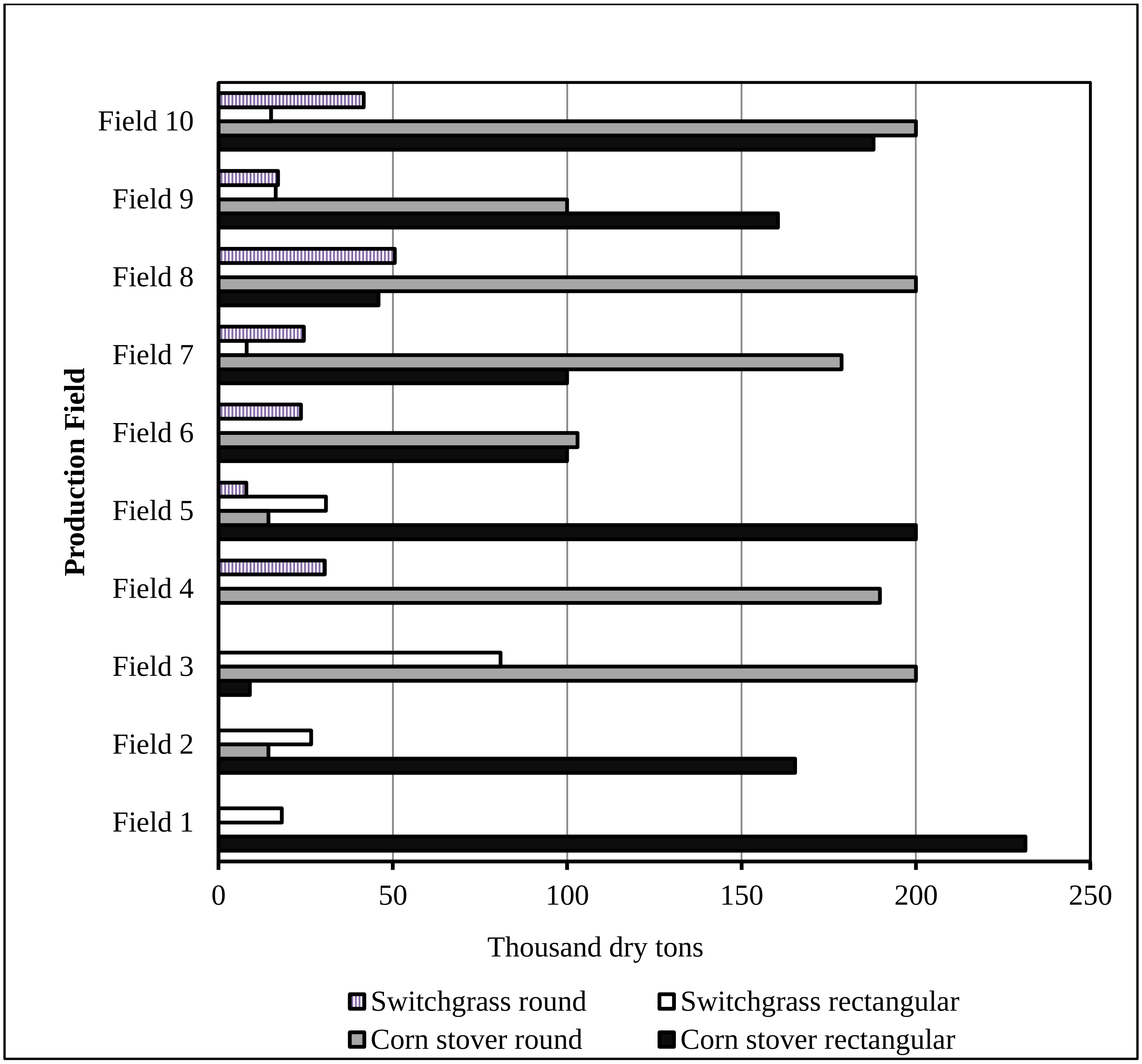


Figure 3.3: Biomass availability at production fields

To estimate the necessary MPM parameters for our model, we depend on [149], who describes technical specifications for a potential mobile pelleting machine. The model requires two parameters, the MPM capacity per month (q) and the pelleting cost per ton (μ). We suppose that if a MPM visits a SSL, it remains there for one planning period (month). Mason [149] estimates the MPM capacity to be 5 ton/hr. We assume that a MPM can operate 12 hrs/day, 20 days/month. Thus, each MPM has a monthly capacity of 1,200 ton/month. Total pelleting cost per ton of biomass is $48/ton and includes fuel, labor, setup, insurance, equipment amortization, and maintenance costs [149]; these cost components are summarized in Table 3.5. Fuel cost per ton is calculated by multiplying fuel consumption (30 gallon/hr, [149]) by fuel price ($3/gallon), then dividing the result by machine capacity (5 ton/hr), yielding $18/ton. Labor cost per ton is calculated under the assumption that a MPM requires two operators each earning $40/hr [149], which gives $16/ton. Mason [149] estimates the machine setup cost and insurance costs to be $1/ton. Equipment amortization cost of $6/ton is computed by dividing the MPM purchase price ($1,800,000) by the number of tons that can be pelleted during its useful life (60,000 hrs, or 300,000 tons) [149]. Finally, Mason [149] estimates maintenance cost of a MPM and the truck used to transport it between SSLs to be $6/ton.

Table 3.5: Pelletizing input parameters [149]

Parameter	Value
Fuel cost ($/ton)	18
Labor cost ($/ton)	16
Setup cost ($/ton)	1
Equipment amortization($/ton)	6
Insurance costs ($/ton)	1
Maintenance cost ($/ton)	6
Total pelleting cost ($/ton)	48

3.5 Results

In this section, we summarize the results produced by the MILP model for the case study region under the base case parameters presented in Section 4, which are representative of current economic conditions and technology capabilities. The model is implemented using IBM ILOG CPLEX Studio and solved using CPLEX 12.6.2 on a desktop computer with a 3.4 GHz processor. The resulting MILP problem includes 3,692 binary variables, 3,850 continuous variables, and 9,540 constraints. The optimal solutions for main case study, sensitivity analysis, and scenario analysis are found in less than 2 minutes.

The optimal solution generated by the MILP model shows that no SSL is opened and MPMs are not utilized. This is due to the high densification cost of baled biomass into pelleted form and the high fixed cost associated with opening a SSL. In summary, utilizing a MPM is not an attractive decision under current economic conditions. Total annual BBSC cost by category is illustrated in Figure 3.4. Feedstock costs paid to production field owners' account for 39.95% of the BBSC cost. Transportation, the second largest cost, accounts for 30.61%, processing for 28.88%, storage for 0.43%, and storage loss for 0.13% of total cost.

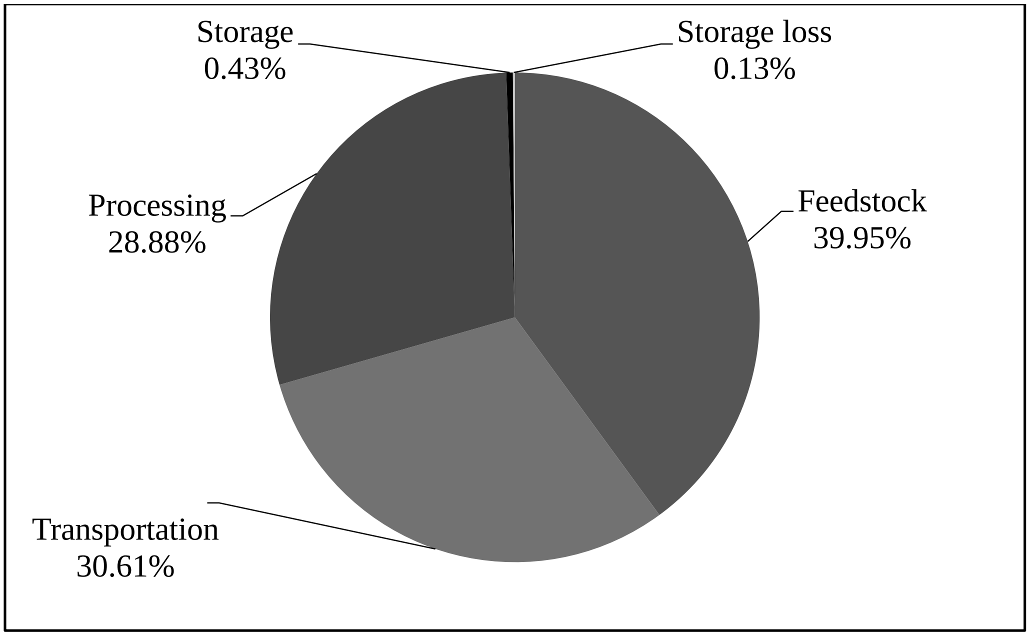


Figure 3.4: Total annual BBSC cost by category

Figure 3.5 shows the dry tons of switchgrass and corn stover that are processed at the bioenergy plant in each month. The bioenergy plant processes switchgrass whenever it is available. Figure 3.6 summarizes the dry tons of different forms of biomass processed at the bioenergy plant in each month, illustrating that the rectangular form is preferred over round biomass. This is due to its lower transportation and storage cost, which outweighs the greater storage loss incurred by rectangular bales.

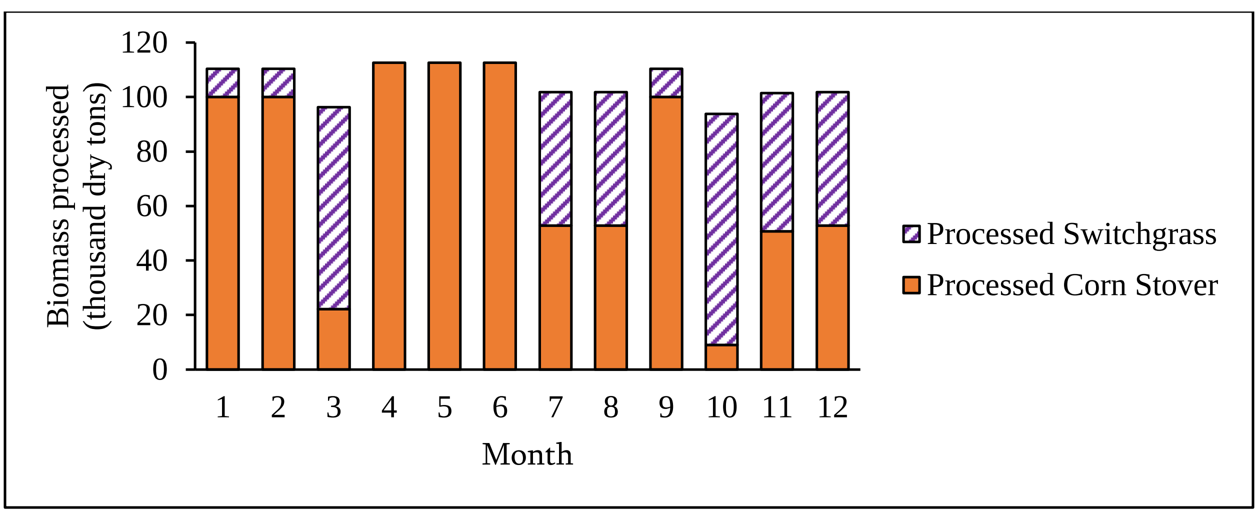


Figure 3.5: Total biomass processed at the bioenergy plant each month, by type

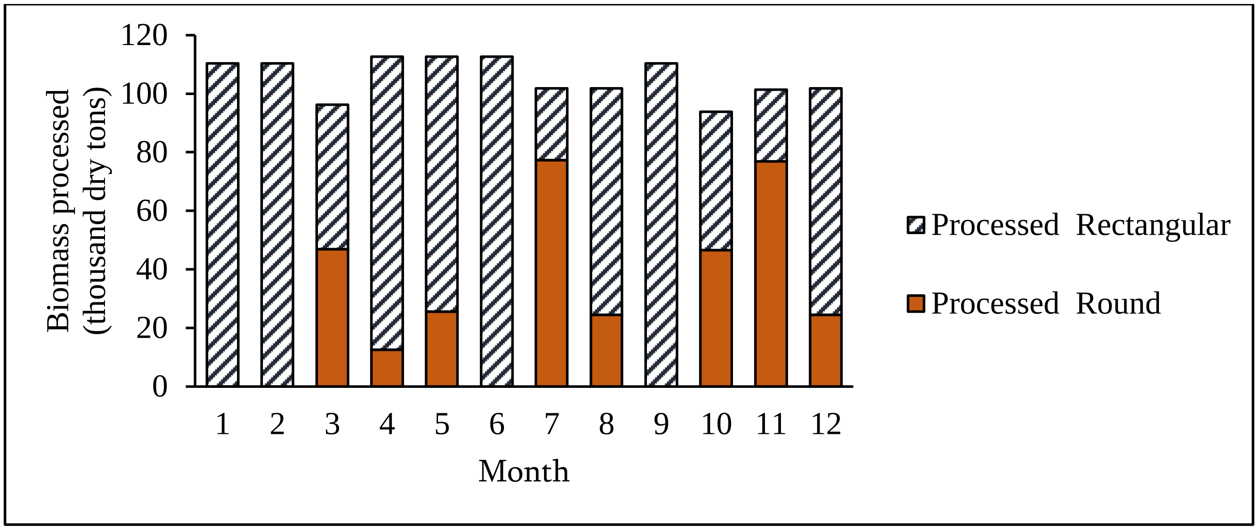


Figure 3.6: Total biomass processed at the bioenergy plant each month, by baling form

For the base case study, densification using MPMs is not an attractive option. There are several potential reasons. First, mobile pelleting is a new technology in an early development stage, leading to high densification cost ($48/ton). This cost is likely to decrease as technology improves. Secondly, it is assumed that biomass densification by MPMs occurs at SSLs; thus, it is necessary to establish a SSL and pay the associated fixed cost. This fixed cost, however, may differ for different locations. Moreover, since the base case is limited to 25 MPMs, the benefits accrued by pelleting limited biomass quantities cannot offset these fixed costs. Finally, all fields in the case study region are within 500 miles of the bioenergy plant. Bioenergy plants that draw biomass from a larger region are more likely to benefit from densification to reduce transportation costs of bulky biomass [12, 6]. In the next sections, we examine the sensitivity of the results to independent and combined changes in these parameters.

3.6 Sensitivity Analysis

Here we describe sensitivity analyses for independent parameter changes and the resulting impact on decisions related to biomass densification. Analyzing sensitivity to individual parameters helps to determine those that are most significant to the choice to pellet. For this reason, independent changes in parameters including densification cost, SSL fixed cost, number of MPMs, and travel distances are considered separately. The sensitivity analyses for densification cost and SSL fixed cost consider decreases in the nominal parameter value from 0% to 100% in 1% increments. We analyze the system with 25, 50, and 75 MPMs. To examine the effect of distances between BBSC facilities, the original distances are increased in 1% increments from 1% to 20%. We adjust the distances between the SSLs and bioenergy plant, and between fields and bioenergy plant, but the distances from fields to SSLs remain the same as in the base case study. When creating the new parameter values, we make sure to satisfy the triangle inequality between any combination of field, SSL, and bioenergy plant. This is necessary to prevent using a SSL as a stop for biomass. This will occur if the total distance from a field to a SSL to the bioenergy plant is less than the distance directly from a field to the bioenergy plant.

Results indicate that mobile pelleting machine utilization is sensitive to independent changes in biomass densification costs, transportation distances, and satellite storage location fixed cost. Figure 3.7 – 3.9 show the sensitivity of the tons of pelleted biomass to parameter changes. There are several findings to note. First, mobile pelleting machines will be utilized if the densification cost is reduced by 15%, 13%, or 11% when there are 25, 50, or 75 MPMs in the BBSC, respectively. Moreover, if SSL fixed cost is reduced by 67%, then MPMs will be utilized a regardless of the number of machines available. Finally, mobile pelleting machines will be utilized if distances are increased by 17%, 13%, or 12% when there are 25, 50, or 75 MPMs in the BBSC, respectively.

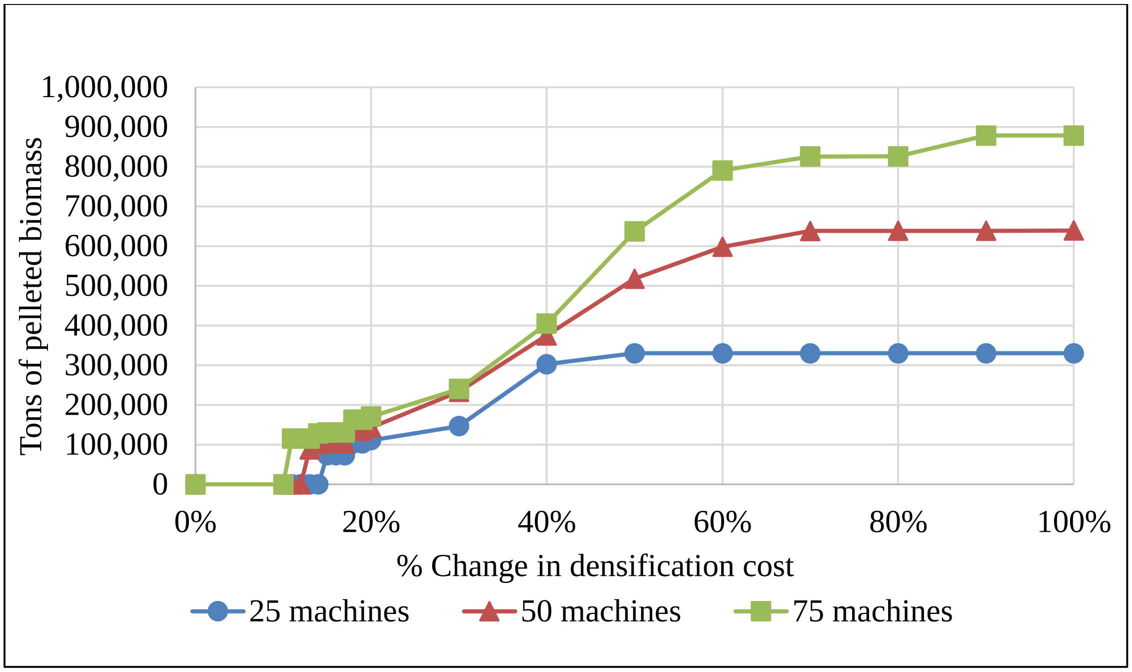


Figure 3.7: Effect of changes in densification cost on pelleted biomass quantity

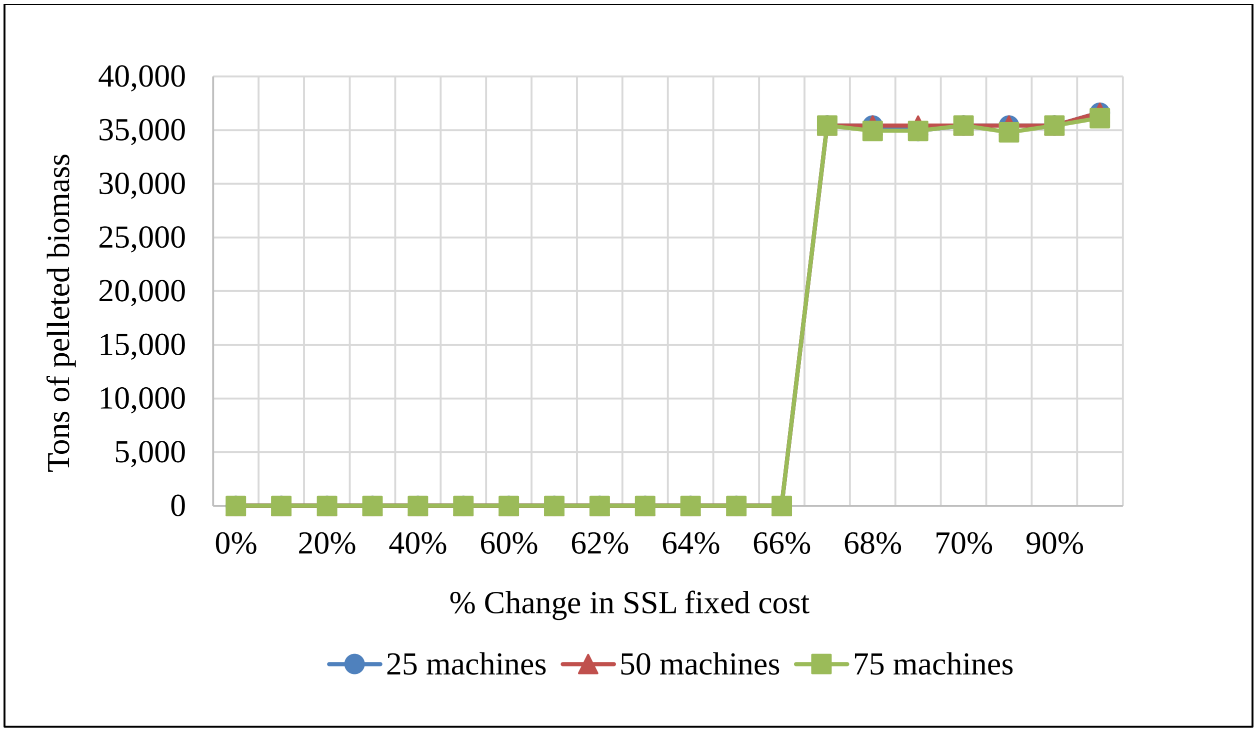


Figure 3.8: Effect of changes in SSL fixed cost on pelleted biomass quantity

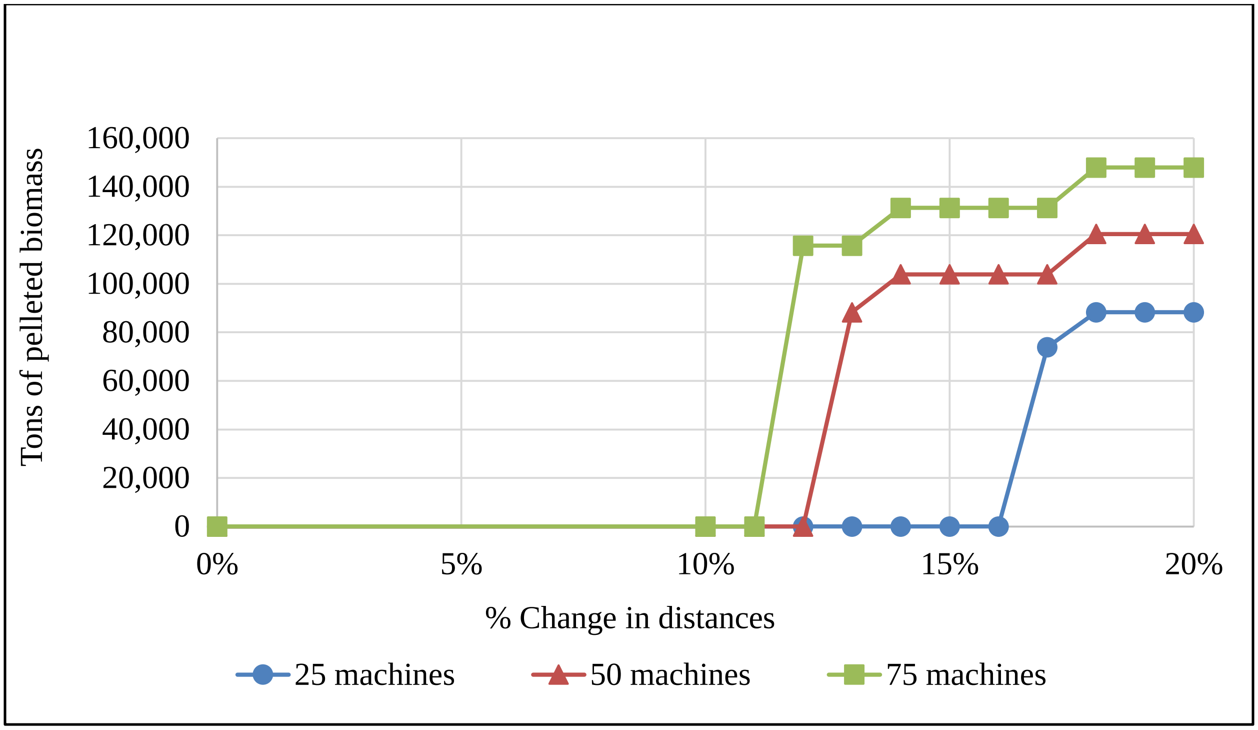


Figure 3.9: Effect of transportation distances between BBSC facilities on amount of pelleted biomass

3.7 Scenario Analysis

After observing the independent parameter impacts, the effect of simultaneous changes in these parameters is examined using scenario analysis to offer insight into conditions under which mobile densification is economically viable. The parameters chosen to construct multiple scenarios are densification cost, SSL fixed cost, and travel distance. Densification cost and SSL fixed cost have three levels: original cost, a decrease of 10%, and a decrease of 20%. Three travel distance levels are also used: original distances, 10% increase, or 20% increase, where the changes are applied to distances between fields and the bioenergy plant, and between SSLs and the bioenergy plant. There are 27 different scenarios, as listed in Table 3.6. The scenario type is represented by three digits, the first digit for densification cost, the second for SSL fixed cost, and the third for travel distances (0 = no change from base case, 1=10% change, 2=20% change). All scenario analyses are conducted for a BBSC with 25 MPMs.

Results from the MILP model show that MPMs are utilized when the distances between facilities are large (20% increase) or the densification cost is low (20% decrease), regardless of other parameter values (S3, S6, S9, S12, S15, S18, S19, S20, S21, S22, S23, S24, S25, S26, S27). Also, reducing biomass densification costs and/or satellite storage location fixed costs decreases the distance threshold for which mobile densification is attractive (S11, S14, S17, S19, S20, S22, S23, S25, S26). If the densification cost and distances between BBSC facilities do not change (original values), then changing SSL fixed cost will not affect the choice to pellet (S1, S4, S7). Also, if the densification cost is reduced by 10% (medium level) without changing the distances, then densification remains unattractive for any value of SSL fixed cost (S10, S13, S16).

Table 3.6: Scenario construction

Scenario number	Scenario type	Densification cost ($/ton)	SSL fixed cost ($)	Traveled distances (% increase)	Tons of pelleted biomass
S1	000	48.0	500,000	0%	0.00
S2	001	48.0	500,000	10%	0.00
S3	002	48.0	500,000	20%	88,306.18
S4	010	48.0	450,000	0%	0.00
S5	011	48.0	450,000	10%	0.00
S6	012	48.0	450,000	20%	88,306.18
S7	020	48.0	400,000	0%	0.00
S8	021	48.0	400,000	10%	0.00
S9	022	48.0	400,000	20%	88,306.18
S10	100	43.2	500,000	0%	0.00
S11	101	43.2	500,000	10%	103,222.22
S12	102	43.2	500,000	20%	176,038.00
S13	110	43.2	450,000	0%	0.00
S14	111	43.2	450,000	10%	103,222.22
S15	112	43.2	450,000	20%	176,038.00
S16	120	43.2	400,000	0%	88,306.18
S17	121	43.2	400,000	10%	103,222.22
S18	122	43.2	400,000	20%	176,038.00
S19	200	38.4	500,000	0%	111,044.00
S20	201	38.4	500,000	10%	146,544.00
S21	202	38.4	500,000	20%	287,408.34
S22	210	38.4	450,000	0%	111,044.00
S23	211	38.4	450,000	10%	146,544.00
S24	212	38.4	450,000	20%	286,764.34
S25	220	38.4	400,000	0%	111,044.00
S26	221	38.4	400,000	10%	146,544.00
S27	222	38.4	400,000	20%	286,764.34

Next, we investigated the impact of the number of MPMs (from 1 to 25) on MPM utilization under each of the 27 scenarios. Figure 3.10 shows scenarios that utilize mobile densification for a different number of machines. Results indicate that by adding more MPMs to the BBSC, the number of scenarios that utilize MPM increases. This is because mobile densification becomes more attractive when additional MPMs are available, since the increased densification capacity offsets the fixed costs associated with establishing SSLs. However, there are five scenarios where densification remains unattractive even if there are enough MPMs to densify all biomass. This occurs for original travel distance and densification cost regardless of SSL fixed cost (S1, S4, S7), when SSL fixed cost is unchanged and densification cost decreases 10% (S2), and when SSL fixed cost is unchanged and transportation distance increases 10% (S10).

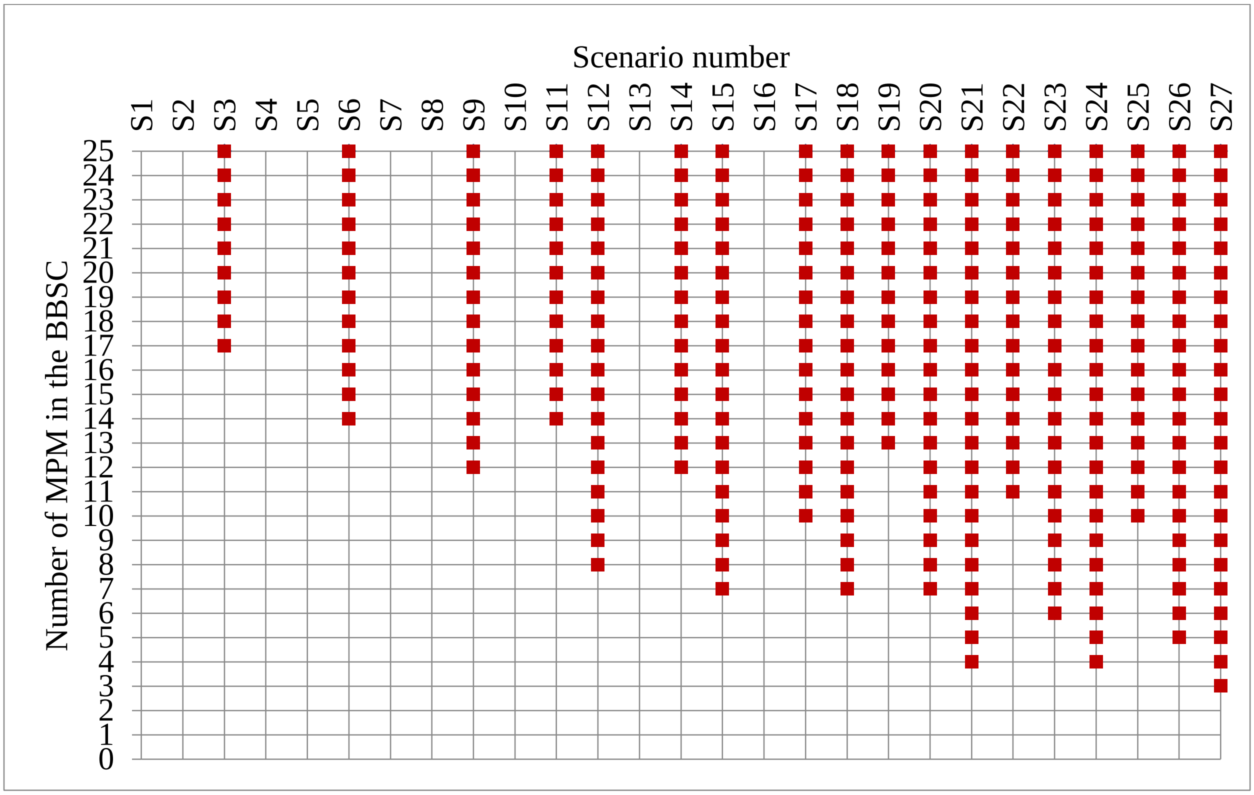


Figure 3.10: Scenarios that utilize mobile densification for different number of MPMs

Finally, we examine the effect of number of MPMs on their mobility. Although densification occurs for some scenarios with as few as three MPMs, the machines do not move from one SSL to another under any scenario unless there are at least 19 machines. Here we compare mobility in each scenario when there are 25, 50, and 75 MPMs, respectively. The number of utilized MPMs and mobility were calculated for each scenario, where mobility is defined as the number of MPM movements between SSLs. Table 3.7 illustrates the results. Note that mobility only occurs when distances between facilities are highest and densification cost is lowest (S21, S24, S27); these are the only scenarios in which two SSLs are opened. For scenarios that utilize MPMs and do not have mobility, once a MPM moves to a SSL, it will remain there until the end of the planning horizon.

Table 3.7: Scenario analysis

Scenario		25 MPM		50 MPM		75 MPM	
Scenario #	Scenario Type	# of machines utilized	Mobility	# of machines utilized	Mobility	# of machines utilized	Mobility
S1	000	0	0	0	0	0	0
S2	001	0	0	0	0	0	0
S3	002	25	0	50	0	75	0
S4	010	0	0	0	0	0	0
S5	011	0	0	0	0	73	0
S6	012	25	0	50	0	75	0
S7	020	0	0	0	0	0	0
S8	021	0	0	0	0	73	0
S9	022	25	0	50	0	73	0
S10	100	0	0	0	0	0	0
S11	101	25	0	50	0	75	0
S12	102	25	0	50	0	75	0
S13	110	0	0	0	0	73	0
S14	111	25	0	50	0	75	0
S15	112	25	0	50	0	75	0
S16	120	0	0	50	0	73	0
S17	121	25	0	50	0	75	0
S18	122	25	0	50	0	75	0
S19	200	25	0	50	0	75	0
S20	201	25	0	50	0	75	0
S21	202	25	128	50	55	75	37
S22	210	25	0	50	0	75	0
S23	211	25	0	50	0	75	0
S24	212	25	123	50	55	75	37
S25	220	25	0	50	0	75	0
S26	221	25	0	50	0	75	0
S27	222	25	125	50	55	75	39

3.8 Breakeven Analysis

The preceding sections compared scenario sets to identify circumstances under which mobile pelleting is economically attractive. Given the input parameters for a particular system, it is also possible to calculate a priori the distance from field to bioenergy plant for which the total cost for pelleted biomass is equivalent to the total cost for baled biomass. Here we introduce an expression for calculating this value, denoted the breakeven distance. It represents the maximum distance that the bioenergy plant is willing to transport biomass from a supplying field without further densification at a SSL. The breakeven distance is calculated for each combination of biomass type and densification form.

Let X_{bk} be the breakeven distance from field to bioenergy plant for biomass type b and densification form k. This distance consists of two components; r is the fraction of the total breakeven distance represented by the distance from field to SSL, and $(1-r)$ is the fraction represented by the distance from SSL to bioenergy plant (see Figure 3.11). Then X_{bk} can be calculated using Equation (35), which captures the total cost incurred by transporting baled biomass directly to the bioenergy plant (left-hand side) and the total cost incurred by transporting and densifying pelleted biomass (right-hand side).

$$\frac{D_t}{\alpha_b}(\varphi_{bk} + P_{bk} + T_k X_{bk}) = \frac{D_t}{\alpha_b}(\varphi_{bk} + P_{b3} + \mu + rT_k X_{bk} + (1-r)T_3 X_{bk}) + V_l. \quad (35)$$

D_t is the demand for biofuel at time t and α_b is the conversion rate of biomass type b. The terms in parentheses on the left represent the baled biomass purchase cost, the baled biomass processing cost at the bioenergy plant, and transportation cost of baled biomass from field to bioenergy plant, respectively. The right-hand side represents the cost incurred by pelleted biomass and consists of six terms: baled biomass purchase cost, pelleted biomass processing cost at the bioenergy plant, densification cost, transportation cost of baled biomass from field to the SSL to be densified, transportation cost of pelleted biomass from SSL to bioenergy plant, and the fixed cost associated with opening a SSL. Equation (35) simplifies to:

$$X_{bk} = \frac{P_{b3} - P_{bk} + \mu + \frac{\alpha_b V_l}{D_t}}{(T_k - T_3)(1 - r)}. \tag{36}$$

Increasing densification cost, SSL fixed cost, or *r* will increase the breakeven distance. High densification cost or SSL fixed cost make densification less attractive at short distances. On the other hand, densification is more attractive the closer the SSL is to the supplying field. Changes in demand also affect breakeven distance, where higher demand results in a smaller breakeven distance.

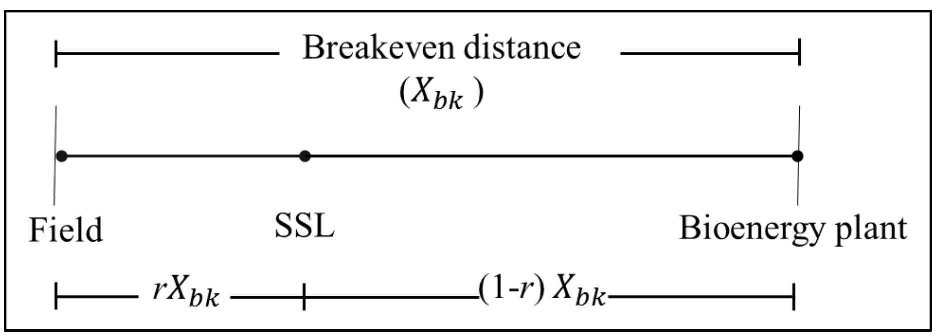


Figure 3.11: Representation of the BBSC facilities

Table 3.8: Cost elements for baled and pelleted biomass

Cost element	Switchgrass/Rectangular	Switchgrass/Round
Purchase cost (\$/ton)	φ_{b21}=41.630	φ_{b22}=49.88
Transportation cost of baled biomass (\$/(mile. ton))	T_1 =0.263	T_2=0.322
Baled biomass cost		
Conversion cost-bale (\$/ton)	P_{21}=50	P_{22}=50
Pelleted biomass cost		
Densification cost (\$/ton)	μ =48	μ =48
SSL fixed cost (\$/month)	V_l=41,666.67	V_l=41,666.67
Transportation cost of pelleted biomass (\$/(mile. ton))	T_3=0.088	T_3=0.088
Conversion cost-pellet (\$/ton)	P_{23}=38	P_{23}=38

Breakeven distance can be calculated for any combination of parameter values. Cost parameters corresponding to our case study are summarized in Table 3.8 for baled and pelleted biomasses. Suppose the monthly demand for ethanol (D_t) is 10,000,000 gallons, and that required biomass can be provided by one large production field. If this production field is planted only with switchgrass, we need a supply of ($\frac{D_t}{\alpha_b}$) =111,111.111 tons to satisfy biofuel demand. The breakeven distance for rectangular switchgrass bales is:

$$X_{21} = \frac{207.857}{1-r}. \tag{37}$$

The breakeven distance for round switchgrass is:

$$X_{22} = \frac{155.795}{1-r}. \tag{38}$$

Figure 3.12 illustrates the relationship between total breakeven distance (X_{bk}) and the ratio (r) between the distance from the field to the SSL and the total distance for switchgrass in rectangular and round forms. The breakeven distance increases as *r* increases, because the SSL is closer to the bioenergy plant than to the production field. This makes densification less attractive. The breakeven distance for round bales is less than that for rectangular bales. This is because the transportation cost of round bales is higher than that of rectangular bales, so converting round bales to pellets becomes economically attractive at smaller distances. Similar observations are true for corn stover biomass.

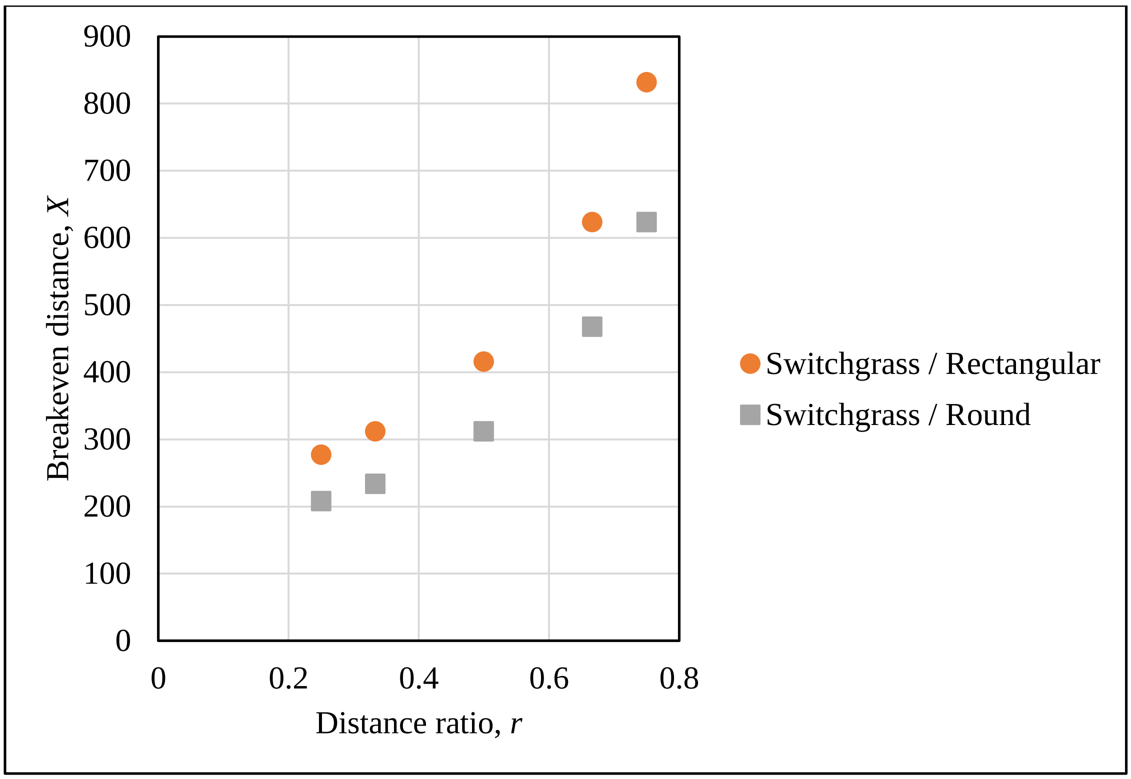


Figure 3.12: Breakeven analysis of the effect of SSL location on the choice to pellet

3.9 Conclusion

This chapter introduces a MILP to optimize BBSC design in settings with multiple types and forms of biomass feedstock and mobile densification units. The method is demonstrated with a case study that reflects current technology and economic characteristics of mobile pelleting. We find that mobile densification is unattractive under these conditions. However, sensitivity analysis shows that mobile pelleting is beneficial with modest changes in densification cost, SSL fixed cost, or travel distances. Increasing the number of available MPMs also makes mobile densification more attractive.

This work provides a foundation for future study of this and related problems. The proposed optimization model can be adapted to manage supply chains for other products in which mobile units are employed to change product characteristics, such as density or form. For example, in addition to mobile pelleting for biomass feedstock used for ethanol production, mobile machines are used to mill olives at individual farm sites [175], to densify biomass for electricity [176], and to convert biomass to bio-oil via pyrolysis [12, 14, 15, 4, 11]. Future research may build on this framework by accounting for uncertainty in system parameters or representing farmers' choices about biomass production explicitly in the model.

Chapter 4 - Optimization of Lignocellulosic Biomass-To-Biofuel Supply Chains Considering Mobile Pelleting and Farmers' Choices

4.1 Introduction

The optimization model proposed in Chapter 3 adds to the state of the art, as there is no research study that proposes an optimization tool to manage the complexities of having different types and forms of biomass, in addition to mobile densification. However, the previous study does not account for farmers' decisions. Farmers play an important role in the BBSC, and ignoring their decision and preference may prevent the bioenergy plant from meeting biofuel demand. One way to account for farmers' decisions is to incorporate the probability that farmers will sell biomass feedstock to the bioenergy plant in the optimization model of the BBSC. This will help accurately estimate biomass supply at field level. To date, no study has proposed an optimization tool to manage the BBSC considering mobile densification and farmers' decisions. To fill this gap, this chapter modifies the comprehensive BBSC optimization model proposed in Chapter 3 integrating farmers' choices.

Most BBSC research studies assume that farmers are willing to sell all available biomass at a specified price. These studies also assume the bioenergy plants pay a fixed biomass price per ton for all farmers, regardless of origin. However, fixed payments for all farmers is not realistic because farmers' preferences differ based on favorability to contract payment or other contract options, conservation and environmental concern, and demographic factors such as age and education [26, 27, 28, 177]. Due to these factors, bioenergy plants may need to pay different prices to receive the same biomass quantity from different farmers. To guarantee sufficient supply for the bioenergy plant and obtain acceptable biomass prices for farmers, contractual arrangements may need to be proposed [26, 28, 177, 178, 179, 180]. Bioenergy plants offer other services in the contract that affect farmers' probability to participate in the BBSC; such as harvesting biomass, transportation services to the bioenergy plant, and nutrient replacement options. Soil nutrient loss can be compensated by using fertilizer, and farmers' probability to provide biomass to bioenergy plants increases if the bioenergy plant will pay for fertilizer [28].

We propose a mixed integer linear programming (MILP) model for the biomass-to-biofuel supply chain that considers densification using MPMs and farmers' choices. This study investigates the most important factors that influence type of contract offered to farmers in different locations and under different weather conditions. Several factors may affect contract payment, such as geographical factors (distance from bioenergy plant and SSLs), farmers' probability to provide biomass to bioenergy plant, and corn stover yield, the latter of which depends both on location and weather.

We organize the paper into five sections. First, we briefly summarize several papers that manage BBSC considering farmers' choices in Section 2. Second, we describe model structure and formulation in Section 3. We describe the case study, including the parameters used in formulating the model to examine corn stover conversion to ethanol in Kansas, in Section 4. We present results in Section 5. We provide conclusions and future research directions in Section 6.

4.2 Problem Context

Most of the research studies in the area of optimizing the BBSC consider traditional densification techniques and account for bioenergy plant objectives. Few research studies account for mobile densification, as summarized in Section 3.2, or farmers' decisions in the BBSC. This section summarizes studies that propose tools to manage the BBSC considering farmers' choices.

Farmers' decisions within the BBSC are difficult to model because there are a lot of factors that affect their choices, such as economic and environmental impacts. The majority of studies that investigate the importance of including farmers' decisions not directly utilize optimization models. Past research has investigated farmers' decision with choice experiments and agent-based simulation models.

The studies that propose economics models do not integrate them with the complete BBSC. Economics models use choice experiments to estimate farmers' probability of selling bioenergy crops to a bioenergy plant. Choice experiments depend on surveys distributed to farmers that investigate farmers' preference for contract attributes to estimate farmers' probability to provide biomasses including corn stover [26, 27, 28], switchgrass [28, 177, 179], and sweet sorghum [28]. The results of Bergtold et al. [27] study are used as an input to our optimization model in order to have an accurate estimate of supply at each field. Bergtold et al. [27] investigate farmers' probability to provide corn stover to a bioenergy plant under contract in Kansas. They utilize choice experiments to determine the probability that a farmer is willing to supply biomass feedstock considering different contract options: the net return and the other three contract attributes (contract length, biomass refinery harvest option, and a nutrient replacement option). Results indicate that eastern and central districts of Kansas have a higher probability of participating in the BBSC compared to the western part of Kansas. Under preferable contract conditions, farmers in the western part of Kansas are less likely to participate in the BBSC.

Agent-based simulation is another tool that has been employed to model farmers' behavior and their interaction with other farmers in their neighborhood [29, 30]. Agent-based simulation has been utilized to investigate farmers' choices of irrigation plan [181], crop choice [182], and participation in the BBSC [30, 183].

Two interesting studies propose agent-based simulation to estimate farmers' willingness to supplying biomass to the bioenergy plant [30, 183]. Huang et al. [30] propose an agent-based simulation model that considers farmers' decision making in growing row crops (corn) versus dedicated energy crops (switchgrass). Farmers decide the number of acres dedicated for row crop and the number of acres farmers will rent out to the bioenergy plant. The model considers farmers' economic and environmental preferences, environmental impact of soil erosion, and neighborhood influence. Their model is demonstrated for a case study region in Iowa. The model finds that Iowa is able to supply 14.2% of the RSF2 goal by 2022. Huang and Hu [183] incorporate similar decision part of farmers as [62]. However, they add interactions with the bioenergy plant and omit the impact of neighboring farmers on farmers' decisions. In their model, farmers' decisions are profit driven; they do not consider other factors such as an environmental impact on soil erosion. After a bioenergy plant observes farmers' decision they adjust their contract pricing accordingly to increase their profit for the next year. Their model is demonstrated for a case study in the state of Iowa. Results indicate that a constant land renting price strategy yield higher profit for the bioenergy plant than a flexible renting price strategy.

This study adds to the state of the art in two ways. First, we propose an optimization model that simultaneously considers different densification forms, the complexities of having mobile densification units, and farmers' probability to provide crop residue (corn stover) to the bioenergy plant. This contribution builds on the unique model introduced in Albashabsheh and Heier Stamm study [184]. Second, we implement a case study based on the state of Kansas that demonstrates the model.

4.3 Problem Description and Formulation

This section presents the MILP model for the BBSC, in which we consider biomass densification using MPMs and farmers' choices. The objective of the proposed model is to minimize BBSC total cost. The BBSC consists of potential biomass suppliers, potential SSLs, and a bioenergy plant. We consider ethanol produced from corn stover from irrigated and non-irrigated land types. For the same supplying field, each land type has a different yield (ton/acre) and production cost ($/ton). It is important to consider both land types to gain insight about preferred biomass supply under different conditions, because they have different biomass production costs and yield characteristics.

Decisions in the optimization model are chosen to minimize the cost to the bioenergy plant. The associated costs are feedstock cost, biomass and biofuel storage costs, densification cost, processing cost, biomass transportation cost, MPM transportation cost, and annualized fixed cost of SSLs and bioenergy plant. Our model considers strategic and tactical level decisions. The strategic level decisions include determining the bioenergy plant capacity and the number and location of SSLs. Tactical level decisions include determining biomass quantity purchased from each potential supply location, net return offered to each supply location, biomass transported between BBSC facilities, biomass stored at different BBSC facilities, biofuel stored at bioenergy plant, biomass densified, and MPM movement between SSLs.

In practice, farmers decide, for a given contract, whether or not they will provide biomass. This decision depends on multiple factors, such as environmental aspect and profit, and farmers' preferences differ. We consider four attributes for each contract: (1) the average annual expected net return ($/acre) from biomass after production costs, (2) contract length, (3) whether or not the bioenergy plant harvests the biomass, and (4) whether or not the bioenergy plant pays for the nutrient loss.

We include the influence of farmers' choices by considering farmers' probability to provide biomass to the bioenergy plant under different contract options. We assume farmers are rational and they seek to increase the payment they receive from the bioenergy plant. This means that farmers' probability to sell biomass to the bioenergy plant increases by increasing contract payment if other contract attributes are fixed. We assume farmers' probability to provide biomass to the bioenergy plant is affected by contract attributes they receive from the bioenergy plant.

In this model, farmers' decisions are modeled by modifying the supply that is available for the bioenergy plant to purchase. This modified supply is an input to the optimization model. Although each farmer makes his/her own decision, we model the cumulative result of these decisions at the county level. We assume that the available supply under a given contract is equal to the total biomass in the county multiplied by the probability that farmers in the county accept the contract.

Table 4.1 lists model sets and indices, while Table 4.2 shows model parameters. Table 4.3 presents model decision variables.

Table 4.1: Sets and indices

Notation	Description
L	Set of all locations in biomass-to-biofuel supply chain, $l \in L$
L_1	Set of counties, $L_1 \subseteq L$
L_2	Set of all candidate locations for satellite storage, $L_2 \subseteq L$
L_3	Set of all candidate locations for bioenergy plant, $L_3 \subseteq L$
0	Depot where the MPMs are stationed before being transported to SSL for densifying biomass, $0 \in L$
Y	Set of years of the contract, y $\in Y$
u	Set of land types, $u \in U$, u =1 (irrigated), u = 2 (non-irrigated)
K	Set of biomass forms, $k \in K$, k = 1 (round), k = 2 (pelleted)
T	Set of time periods in the planning horizon, $t \in T$
W	Set of mobile pelleting machines, $w \in W$
C	Set of contracts, $c \in C$
E	Set of bioenergy plant capacity level, $e \in E$

Table 4.2: Parameters

Parameter	Description	Unit
S_{lct}^{u}	Corn stover available in county $l \in L_1$ from land type $u \in U$ under contract $c \in C$ at time $t \in T$	ton
η_{lcy}^{u}	Contract payment under contract $c \in C$ at county $l \in L_1$ for land type $u \in U$ at year of contract $y \in Y$	\$/ton
N	The cost of nutrient replacement per dry ton of corn stover removed	\$/ton
A_{ly}^{u}	The cost of harvesting corn stover at county $l \in L_1$ of land type $u \in U$ at year $y \in Y$	\$/ton
H_{klt}	Unit inventory holding cost of corn stover in form $k \in K$ at facility $l \in L$ at time $t \in T$	\$/ton
H	Unit inventory holding cost of biofuel	\$/gallon
μ	Unit densification cost (pelleting) of corn stover feedstock	\$/ton
$d_{ll'}$	Distance between facility $l \in L$ and facility $l' \in L$, $l' \neq l$	mile
T_k	Unit transportation cost per ton of corn stover in form $k \in K$	\$/ton.mile
π	Cost of transporting mobile pelleting machine	\$/mile
S_{kl}	Storage capacity for corn stover in form $k \in K$ at facility $l \in L$	ton
S_l'	Storage capacity for biofuel at bioenergy plant $l \in L_3$	gallon
P_k	Unit cost of converting corn stover in form $k \in K$ to biofuel	\$/ton
D_t	Demand for biofuel at time $t \in T$	gallon
F_{le}	Annualized fixed cost associated with opening bioenergy plant of capacity level $e \in E$ at location $l \in L_3$	\$/year
V_l	Annualized fixed cost associated with opening SSL at location $l \in L_2$	\$/year
θ_{kl}	Dry matter loss rate of corn stover in form $k \in K$ during storage at facility $l \in L$	unitless
λ_k	Dry matter loss rate of corn stover in form $k \in K$ during transportation	unitless
α	Conversion rate of corn stover	unitless
m	Number of mobile pelleting machines available	unitless

q	Mobile pelleting machine capacity	ton/period
Ω_e	Bioenergy plant capacity under capacity level $e \in E$	gallon/period

Table 4.3: Decision variables

Variable	Description	Unit
Q^u_{lcy}	Amount of corn stover purchased from county $l \in L_1$ from land type $u \in U$ under $y \in Y$ year of contract c	ton
β_{lt}	Demand in time period $t \in T$ statisfied by bioenergy plant $l \in L_3$	ton
$Y_{kll't}$	Amount of corn stover in form k shipped from facility l to facility l', $l' \neq l$, at time $t \in T$	ton
X_{klt}	Amount of corn stover in form k stored at facility $l \in L$ from time period $t \in T$ to the next time period	ton
X'_{lt}	Amount of biofuel stored at bioenergy plant $l \in L_3$ from time period $t \in T$ to the next time period	gallon
E_{klt}	Amount of corn stover in form k used to produce biofuel in time period $t \in T$ at bioenergy plant at $l \in L_3$	ton
R_{lt}	Amount of baled corn stover pelleted at facility $l \in L_2$ in time period $t \in T$	ton
B_{lt}	Biofuel production at bioenergy plant $l \in L_3$ in time period $t \in T$	gallon
g^u_{lc}	1 if the bioenergy plant decide to offer contract $c \in C$ for county $l \in L_1$ land type $u \in U$	binary
G_l	1 if an SSL is opened at location $l \in L_2$	binary
M_{le}	1 if an bioenergy plant of capacity level $e \in E$ is opened at location $l \in L_3$	binary
Z_{wlt}	1 if mobile pelleting machine w is located at facility $l \in (L_2 \cup 0)$ in time period $t \in T$	binary
$U_{wll't}$	1 if mobile pelleting machine w travels from facility $l \in (L_2 \cup 0)$ to facility $l' \in (L_2 \cup 0)$ in time period $t \in T$	binary

The MILP optimization model is presented below.

$$Minimize \sum_{l \in L_1} \sum_{u \in U} \sum_{y \in Y} \sum_{c \in C} (\eta^u_{lcy} Q^u_{lcy} + A^u_{ly} Q^u_{lcy} + N Q^u_{lcy}) + \sum_{l \in L} \sum_{k \in K} \sum_{t \in T} H_{klt} X_{klt}$$
$$+ H \sum_{l \in L_3} \sum_{t \in T} X'_{lt} + \sum_{l \in L_2} \sum_{k \in K \backslash \{2\}} \sum_{t \in T} \mu R_{klt} + \sum_{l \in L_3} \sum_{k \in K} \sum_{t \in T} P_k E_{klt}$$
$$+ \sum_{l \in L \backslash \{L_3\}} \sum_{l' \in L: l' \neq l} \sum_{k \in K} \sum_{t \in T} T_k d_{ll'} Y_{kll't} + \sum_{w \in W} \sum_{l \in (L_2 \cup 0)} \sum_{l' \in L_2} \sum_{t \in T} \pi d_{ll'} U_{wll't}$$
$$+ \sum_{l \in L_2} |Y| V_l G_l + \sum_{l \in L_3} \sum_{e \in E} |Y| F_{le} M_{le}$$

Subject to:

$Q^u_{lcy} \leq \sum_{t \in T: 12y-11 \leq t \leq 12y} S^u_{lct} \; g^u_{lc}$ $\quad \forall \, l \in L_1, u \in U, y \in Y, c \in C$ (1)

$\sum_{c \in C} g^u_{lc} \leq 1$ $\quad \forall \, l \in L_1, u \in U$ (2)

$\sum_{l' \in (L_2 \cup L_3)} Y_{kll't} + X_{kl,t} = \sum_{u \in U} \sum_{c \in C} Q^u_{lcy} + (1 - \theta_{kl}) X_{kl,t-1}$

$\forall l \in L_1, k = 1, y \in Y, t \in T: t = 12y - 11$

(3)

$\sum_{l' \in (L_2 \cup L_3)} Y_{kll't} + X_{kl,t} = (1 - \theta_{kl}) X_{kl,t-1}$ $\quad \forall l \in L_1, k = 1, y \in Y, t \in T: 12y - 10 \leq t \leq 12y$ (4)

$\sum_{l' \in L_3} Y_{kll't} + X_{klt} + R_{klt} = (1 - \lambda_k) \sum_{l' \in L_1} Y_{kl'lt} + (1 - \theta_{kl}) X_{kl,t-1}$

$\forall \, l \in L_2, k = 1, t \in T$ (5)

$\sum_{l' \in L_3} Y_{kll't} + X_{klt} = \sum_{k \in K \backslash \{2\}} R_{klt} + (1 - \theta_{kl}) X_{kl,t-1}$

$\forall \, l \in L_2, k = 2, t \in T$ (6)

$E_{klt} + X_{klt} = (1 - \lambda_k) \sum_{l' \in (L_1 \cup L_2)} Y_{kl'lt} + (1 - \theta_{kn}) X_{kl,t-1}$

$\forall \, l \in L_3, k \in K, t \in T$ (7)

$X'_{lt} + \beta_{lt} = X'_{l,t-1} + B_{lt}$ $\quad \forall \, l \in L_3, t \in T$ (8)

$B_{lt} = \sum_{k \in K} \alpha E_{klt}$ $\quad \forall \, l \in L_3, t \in T$ (9)

$\sum_{l \in L_3} (B_{lt} + X_{l,t-1}) \geq D_t$ $\quad \forall \, t \in T$ (10)

$\sum_{l \in L_3} \beta_{lt} = D_t$ $\quad \forall \, t \in T$ (11)

$X_{klt} \leq S_{kl} G_l$ $\quad \forall \, k \in K, l \in L_2, t \in T$ (12)

$X_{klt} \leq S_{kl} M_{le}$ $\quad \forall \, k \in K, l \in L_3, e \in E, t \in T$ (13)

$X'_{lt} \leq S'_l M_{le}$ $\quad \forall \, l \in L_3, e \in E, t \in T$ (14)

$B_{lt} \leq \sum_{e \in E} \Omega_e M_{le}$ $\quad \forall \, l \in L_3, t \in T$ (15)

$\sum_{k\in K\setminus\{2\}} R_{klt} \leq q \sum_{w\in W} Z_{wlt}$ $\quad \forall\, l \in L_2, t \in T$ (16)

$\sum_{e\in E} M_{le} \leq 1$ $\quad \forall\, l \in L_3$ (17)

$\sum_{l'\in L_1} Y_{kl'lt} \leq S_{kl} G_l$ $\quad \forall\, l \in L_2, k = 1, t \in T$ (18)

$U_{wll't} \geq Z_{wl't} + Z_{wl,t-1} - 1$ $\quad \forall\, w \in W, l' \in (L_2 \cup 0), l \in (L_2 \cup 0), t \in T\setminus\{1\}$ (19)

$U_{wll't} \leq Z_{wl't}$ $\quad \forall\, w \in W, l \in (L_2 \cup 0), l' \in (L_2 \cup 0), t \in T$ (20)

$U_{wll't} \leq Z_{wl,t-1}$ $\quad \forall\, w \in W, l \in (L_2 \cup 0), l' \in (L_2 \cup 0), t \in T\setminus\{1\}$ (21)

$\sum_{l\in(L_2\cup 0)} U_{w0l1} = 1$ $\quad \forall\, w \in W$ (22)

$\sum_{l'\in L_2} U_{wll't} = \sum_{l'\in(L_2\cup 0)} U_{wl'l,t-1}$ $\quad \forall\, w \in W, l \in L_2, t \in T\setminus\{1\}$ (23)

$\sum_{l\in(L_2\cup 0)} U_{w0lt} = U_{w00,t-1}$ $\quad \forall\, w \in W, t \in T\setminus\{1\}$ (24)

$\sum_{l\in L_2} \sum_{w\in W} Z_{wlt} \leq m$ $\quad \forall\, t \in T$ (25)

$Z_{wlt} \leq G_l$ $\quad \forall\, w \in W, l \in L_2, t \in T$ (26)

$B_{lt} \geq 0$ $\quad \forall\, l \in L_3, t \in T$ (27)

$Y_{kll't} \geq 0$ $\quad \forall\, l \in L_1, l' \in (L_2 \cup L_3), k = 1, t \in T$ (28)

$Y_{kll't} \geq 0$ $\quad \forall\, l \in L_2, l' \in L_3, k \in K, t \in T$ (29)

$E_{klt} \geq 0$ $\quad \forall\, k \in K, l' \in L_3, t \in T$ (30)

$\beta_{lt} \geq 0$ $\quad \forall\, l \in L_3, t \in T$ (31)

$X_{klt} \geq 0$ $\quad \forall\, l \in L, k \in K, t \in T$ (32)

$X'_{lt} \geq 0$ $\quad \forall\, l \in L_3, t \in T$ (33)

$R_{lt} \geq 0$ $\quad \forall\, l \in L_2, t \in T$ (34)

$Q^u_{lcy} \geq 0$ $\quad \forall\, l \in L_1, c \in C, y \in Y, u \in U$ (35)

$G_l \in \{0,1\}$ $\quad \forall\, l \in L_2$ (36)

$M_{le} \in \{0,1\}$ $\quad \forall\, l \in L_3, e \in E$ (37)

$Z_{wlt} \in \{0,1\}$ $\quad \forall\, w \in W, l \in L_2, t \in T$ (38)

$U_{wll't} \in \{0,1\}$ $\quad \forall\, w \in W, l \in (L_2 \cup 0), l' \in L_2, t \in T$ (39)

$g^u_{lc} \in \{0,1\}$ $\quad \forall\, c \in C, l \in L_1, u \in U$ (40)

The objective function aims to minimize the total BBSC cost over the entire contract period. The first three terms represent the corn stover contract payment, corn stover harvesting cost, and nutrient replacement cost, respectively. Inventory holding cost for corn stover at all BBSC locations is given by the fourth term, and the fifth term captures inventory holding cost for biofuel at the bioenergy plant. Densification cost for baled corn stover is represented in the sixth term. The seventh term is the cost to convert corn stover to biofuel. Costs for transporting corn stover between BBSC facilities and MPMs between SSLs are reflected in the eighth and ninth terms, respectively. The last two terms capture fixed annual operating costs for SSLs and bioenergy plants, respectively.

Corn stover is purchased in only one month of each year of the contract. Constraint (1) guarantees that the amount of corn stover bought from each county in each year does not exceed the corn stover supply at the county under each contract option. Constraint (2) ensures that at most one contract option is offered for each land type in each county.

Constraints (3)-(8) are flow balance constraints for baled corn stover, pelleted corn stover, and biofuel at each time period. Constraint (3) ensures flow balance for baled corn stover at each county in months where corn stover may be purchased, while Constraint (4) ensures balance in all other time periods. Constraints (5) and (6) are the flow balance constraints at SSLs for baled and pelleted corn stover, respectively. Constraint (7) is the flow balance constraint for baled and pelleted corn stover at bioenergy plants, while Constraint (8) ensures flow balance for biofuel at bioenergy plants. To link between the amount of corn stover processed at each bioenergy plant and the biofuel production, constraint (9) is established.

Constraint (10) requires that biofuel demand is met in each time period. Constraint (11) links the biofuel demand that is satisfied by each bioenergy plant to the total biofuel demand.

Constraints (12)-(18) relate to system capacities. Constraints (12) and (13) are storage capacity constraints for corn stover at SSLs and bioenergy plants, respectively. Constraint (14) is the biofuel storage capacity constraint at bioenergy plants. Constraints (15) and (16) are production capacity constraints for bioenergy plants and MPM machines, respectively. Constraint (17) requires that at most one capacity level is chosen for each bioenergy plant. Constraint (18) prevents shipping corn stover to unopened SSLs.

Constraints (19)-(22) consider mobile pelleting machine movement between SSLs. Based on constraint (19), if the mobile pelleting machine is stationed at SSL l in period t-1 and then at SSL l' in period t, then the binary variable $U_{wll't}$ equals 1. Constraints (20) and (21) link between the two binary variables $U_{wll't}$ and Z_{wlt}. To ensure that each MPM initially is stationed at the depot and may move from there to a SSL to densify biomass, constraint (22) is established. MPM flow balance at SSLs and the depot is ensured by constraints (23) and (24), respectively. These constraints require that the number of MPMs arriving a time-space node (SSLs or depot) equals the number of MPMs that depart that node. Constraint (25) imposes the limit on the maximum number of MPMs utilized, and constraint (26) requires that MPMs can only densify biomass at open SSLs. Constraints (27)-(35) are non-negativity constraints, and constraints (36)-(40) define the binary variables.

4.4 Case Study

We conduct a case study in the state of Kansas to demonstrate model applicability and corresponding analysis. The study considers ethanol produced from corn stover because Kansas ranks eighth in ethanol production out of all states in the United States [159]. The model is solved for three contract periods 2006−2007, 2008−2009, and 2012−2013. These periods are chosen based on average biomass yield, where 2006−2007 is an average period, 2008−2009 is a surplus period, and 2012−2013 is a drought period. Figure 4.1 shows the drought map for Kansas for all contract years. We consider two densification forms of corn stover: large round bales and pellets obtained from mobile pelleting machines. Mobile pelleting machines begin at the depot and then move to SSLs as needed. The case study planning horizon is two years and the planning period is one month. Previous literature states that corn stover must be harvested a few days to a few weeks after the corn grain is harvested [17, 185]. Corn stover typically is harvested into round bales and stored in open fields. The following subsections summarize parameter estimates collected for the case study as gathered from journal papers and government data services such as the United States Department of Agriculture (USDA). Table 4.4 summarizes the parameter estimates used for the case study.

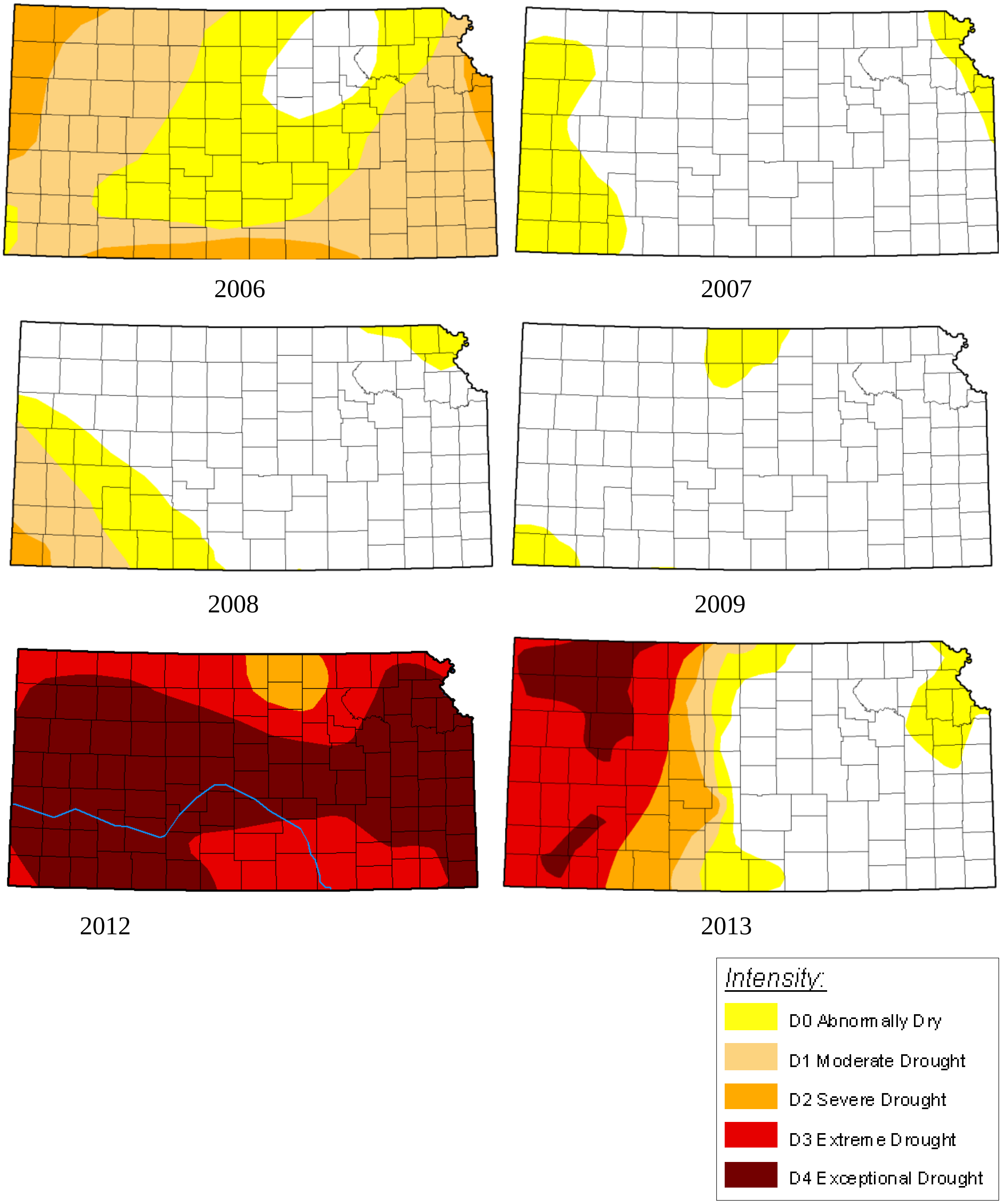


Figure 4.1: U.S. Drought Monitor (USDM) [186] drought map for Kansas for August of each contract year.

Table 4.4: Values of input parameters

Parameter	Value	Source
Unit inventory holding cost of baled corn stover at field and SSL ($/ton) (tarp only)	H_{11t}=H_{12t}=4.84	[166]
Unit inventory holding cost of pelleted corn stover at SSL ($/ton)	H_{22t}=0.08	[141]
Unit inventory holding cost of baled corn stover at bioenergy plant ($/ton) (tarp and gravel)	H_{13t}=17.78	[166, 168]
Unit inventory holding cost of pelleted corn stover at bioenergy plant ($/ton) (steel bins)	H_{23t}=1.1525	[169, 6]
Unit inventory holding cost of biofuel at the bioenergy plant (30% product value) ($/gallon)	H =0.654	[168]
Conversion rate of corn stover (gallons/ton)	α=73.71	[170]
Bioenergy plant processing capacity under different capacity levels (gallons/ month)	Ω_1=4,180,000 Ω_2=8,360,000	[168]
Annualized fixed cost of bioenergy plant under different capacity levels ($/year)	F_{l1}=39,000,000 F_{l2}=72,000,000	[168]
Dry matter loss of baled corn stover at bioenergy plant (tarp and gravel) (per month) (0.16/200 days)	θ_{13}=0.024	[172]
Dry matter loss of baled corn stover at fields and SSLs (tarp only) (per month) (0.19/200 days)	θ_{11}=θ_{12}=0.0285	[172]
Unit transportation cost of round biomass ($/ton.mile)	T_1=0.322	[166, 168]
Unit transportation cost of pelleted biomass ($/(ton.mile))	T_2=0.088	[131, 6]
Processing cost of baled corn stover ($/ton)	P_1=44.30	[17]
Processing cost of pelleted corn stover ($/ton)	P_2=32.3	[169]
Unit cost of pelleting ($/ton)	μ =48	[149]
Cost of moving mobile pelleting machine ($/mile)	π =1.639	[174]
Annualized fixed cost of opening SSLs ($/year)	V_l =500,000	Assumed
Bioenergy plant capacity for storing baled biomass (ton)	S_{13}=50,000	Assumed
Bioenergy plant capacity for storing pelleted biomass (ton)	S_{23}=100,000	Assumed
SSL capacity for storing baled biomass (ton)	S_{12}=100,000	Assumed

SSL capacity for storing pelleted biomass (ton)	S_{12}=200,000	Assumed

4.4.1 Geography

We assume that all 105 counties in Kansas could be potential suppliers of corn stover, but only six counties are considered potential SSLs: Butler, Finney, Jewell, Marshall, Pratt, and Thomas. The SSL counties are selected based on nearness to highways and to counties with high corn availability. The maximum distance between any Kansas county and the closest potential SSL is less than 162 miles. One bioenergy plant in Reno County is chosen based on its proximity to counties with high biomass availability, highways, and railroad network infrastructure. BNSF Railway, the Kansas and Oklahoma Railroad, and the Union Pacific Railroad all pass through the county, thereby simplifying biofuel shipping from the bioenergy plant to distributors or blending facilities. Distances between counties are calculated using Google's Distance Matrix API [187] and the latitude and longitude coordinates of counties' population-weighted centroid, where centroids are determined by the 2010 US Census [188]. Google's Distance Matrix API produces the shortest distance between any two points, so resulting distances satisfy the triangle inequality. Distances within a county are not considered. Figure 4.2 shows facility locations for the case study.

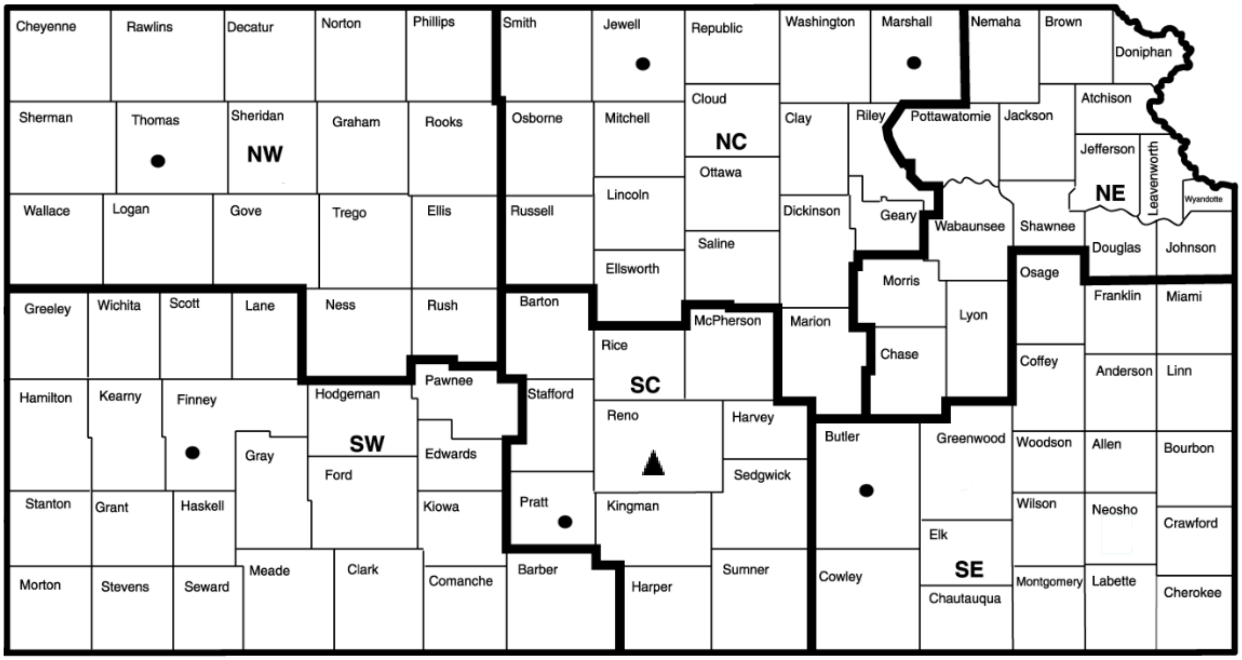


Figure 4.2: Case study facility locations in Kansas counties. The triangle represents the bioenergy plant; circles represent potential SSLs. Heavy solid lines divide districts [189]; NE is northeast, SE is southeast, NC is north central, SC is south central, SE is southeast, SW is southwest.

4.4.2 Potential Corn Stover Supply

County-specific biomass supply calculations considering farmers’ choices are conducted according to methods proposed in a study by Bergtold et al. [27] using harvested corn acreage and corn stover yield. Table 4.5 describes the parameters required to calculate corn stover supply.

Table 4.5: Parameters required to calculate corn stover supply

Parameter	Description	Unit
a_l^u	Total harvested corn acreage in county $l \in L_1$ of land type $u \in U$	acre
y_l^u	Corn grain yield in county $l \in L_1$ of land type $u \in U$	bu/acre
$h({y_l}^u)$	Harvesting index for corn grain yield of ${y_l}^u$	unitless
gs_l^u	Gross yield of corn stover in county $l \in L_1$ of land type $u \in U$	lbs/ acre
ns_l^u	Net corn stover yield in county $l \in L_1$ of land type $u \in U$	ton/ acre
ps_l^u	Total potential amount of corn stover to be harvested in county $l \in L_1$ of land type $u \in U$	ton
c	Level of return	$/ton
ρ_{lc}	Probability of adoption for county $l \in L_1$ under $c \in C$ level of net return	unitless

The USDA's National Agricultural Statistic Service (NASS) [165] provides data for the total harvested corn acreage (a_l^u) and corn grain yield (y_l^u) for irrigated and non-irrigated land in Kansas. However, data for harvested acreage and corn grain yield are not reported by NASS for some counties and years because doing so would reveal individually-identifying information. Appendix A details the method used to impute the missing data, including the procedure to estimate harvested corn acreage and yield at the county level for missing data.

Corn stover yield is estimated using harvest index, which is a function of corn grain yield (bushels per acre) [161]. Harvest index ($h(y_l^u)$) is

$$h(y_l^u) = \begin{cases} 0.45 & if\ y_l^u < 112.5 \\ 0.475 & if\ 112.5 \le y_l^u < 137.5 \\ 0.5 & if\ 137.5 \le y_l^u < 162.5 \\ 0.525 & if\ y_l^u \ge 162.5 \end{cases}$$

$$\forall\, l \in L_1, u \in U. \tag{41}$$

This study considers counties that implement conservation or reduced tillage production systems, meaning that farmers retain a percentage of corn stover on the soil surface to prevent soil erosion and preserve soil organic material. They are considered because they have higher corn stover availability to be harvested compared to conventional tillage system [190]. To account for reduced tillage, the literature suggests an adjustment factor of 0.905 for moderate change in corn stover yield [27, 161]; thus, corn stover yield will be multiplied by 0.905. Equation (3) calculates the estimated gross yield of pounds of corn stover per acre (gs_l^u) for land type u in county l as

$$gs_l^u = \left(\frac{1-h(y_l^u)}{h(y_l^u)}\right) {y_l}^u \times 0.905 \times 56 \qquad \forall\, l \in L_1, u \in U, \tag{42}$$

where 56 is the number of pounds per bushel [27, 161].

This research adopts previous recommendations that farmers keep approximately 1430 lbs per acre of corn stover on the soil surface [161, 191]. Anand et al. [160] recommend adjustments to account for winter decay (88% residue retention) and no-till coulter usage (85% retention). Therefore, net yield of corn stover in tons per acre (ns_l^u) can be calculated using the following formula:

$$ns_l^u = \left(gs_l^u - \frac{\frac{1430}{0.88}}{0.85}\right)\left(\frac{1}{2000}\right) \qquad \forall\, l \in L_1, u \in U. \tag{43}$$

The total potential amount of corn stover available for harvesting in each county equals the net corn stover yield multiplied by the number of acres available and percentage of land that undergoes conservation or reduced tillage practices. In Kansas, approximately 56% of corn-cultivated land undergoes conservation practices and approximately 19% of land designated for corn cultivation experiences reduced tillage [27]. Total potential corn stover supply (ps_l^u) is calculated using the following formula:

$$ps_l^u = ns_l^u \times [a_l^u \times (0.56 + 0.19)] \qquad \forall\, l \in L_1, u \in U. \tag{44}$$

Figure 4.3 and 4.4 display potential corn stover supply for irrigated and non-irrigated land in Kansas counties for the years considered in the case study.

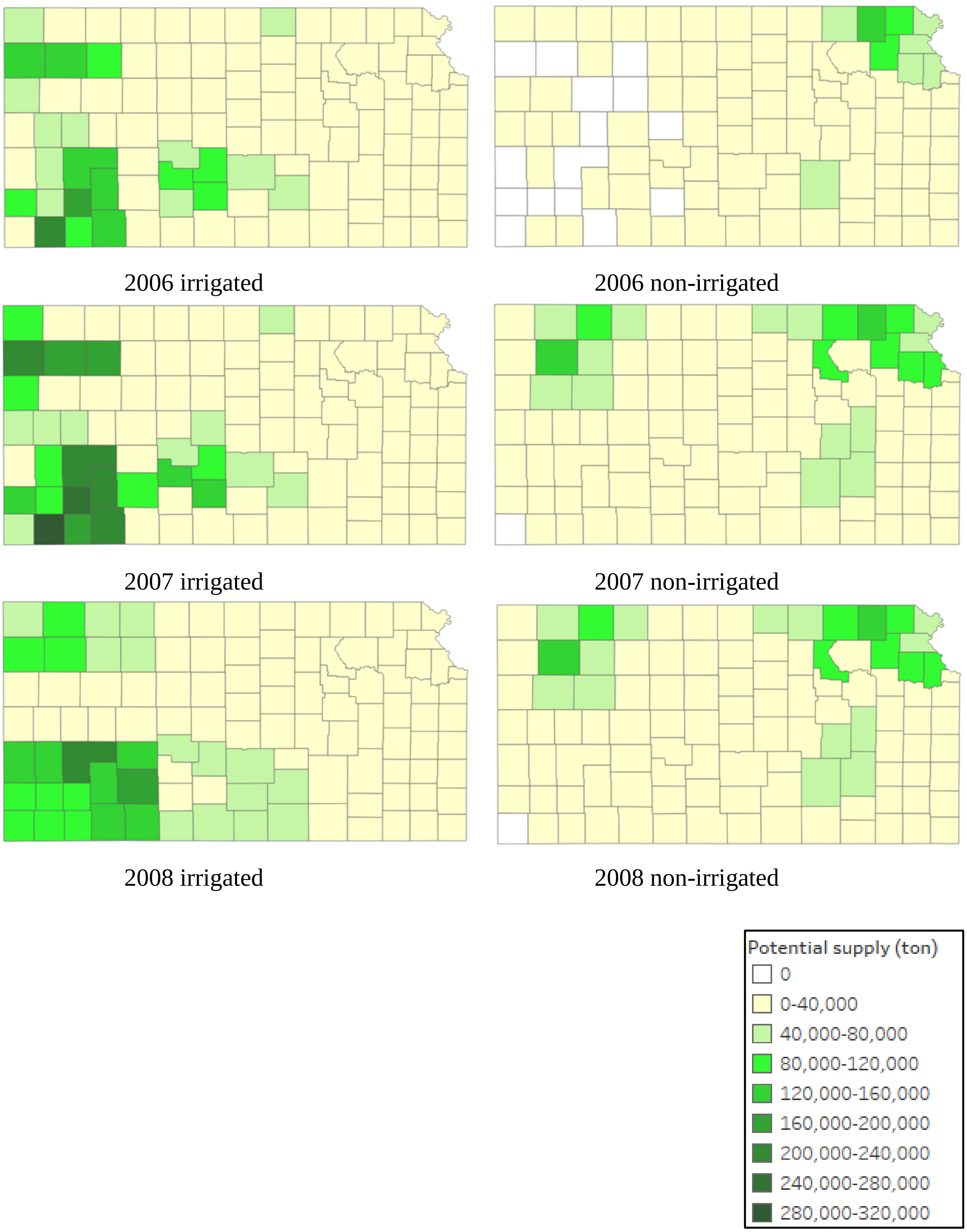


Figure 4.3: Potential supply of corn stover ($\boldsymbol{ps_l^u}$, in dry ton) in 2006, 2007, and 2008 for irrigated land (left map) and non-irrigated land (right map).

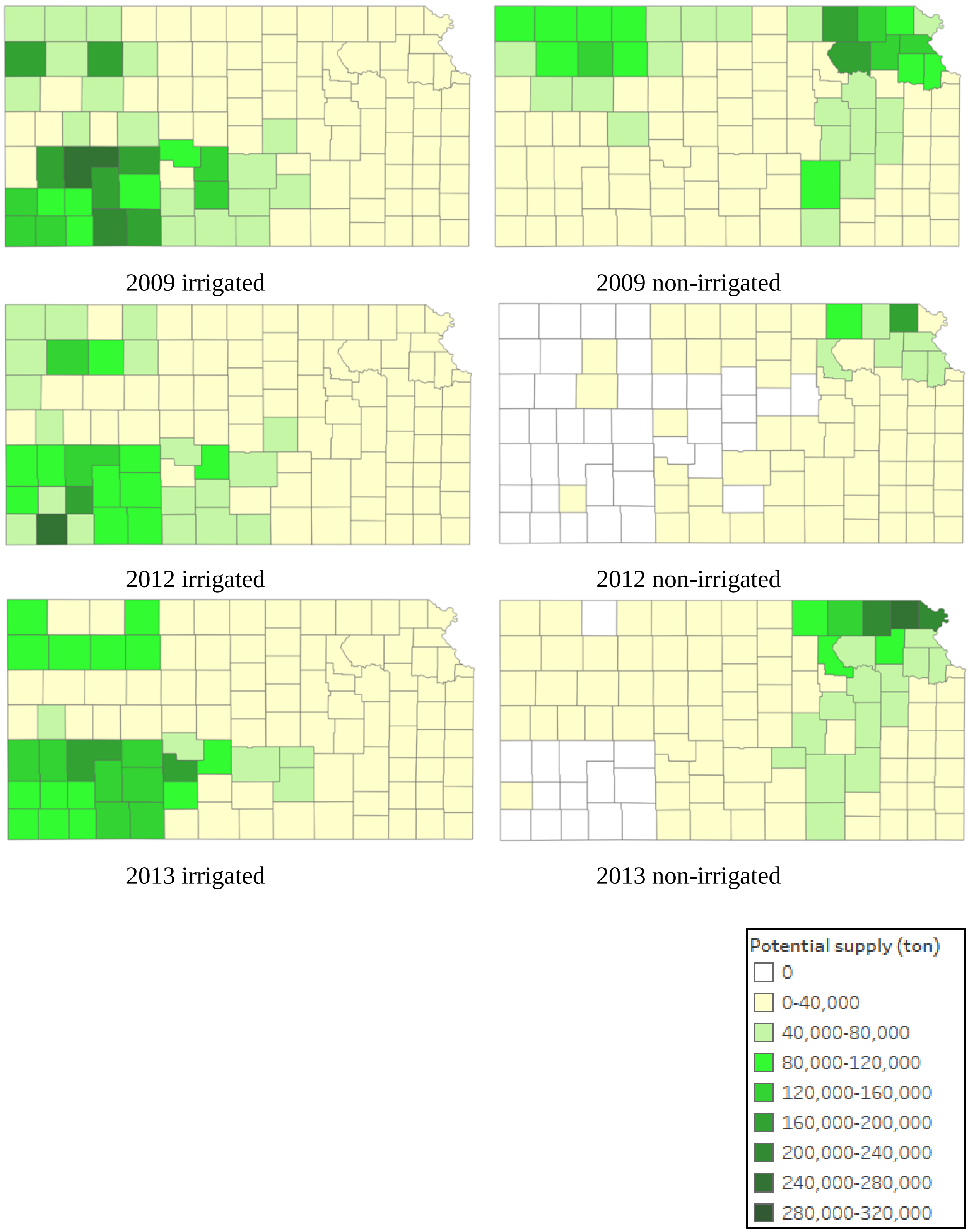


Figure 4.4: Potential supply of corn stover ($\boldsymbol{ps_l^u}$, in dry ton) in 2009, 2012, and 2013 for irrigated land (left map) and non-irrigated land (right map).

4.4.3 Contract Payment to Farmers

Although many studies have proposed optimization models to manage the BBSC under various design options, they have not considered farmers' probability to supply crop residues or grow energy crops for bioenergy processing. Therefore, contractual arrangements between farmers and bioenergy plants are one solution to guarantee sufficient biomass supply [27]. Bergtold et al. [27] investigated farmers' choices and their probability to provide biomass to bioenergy plants by considering four contractual attributes: (1) average annual expected net return from biomass, (2) contract length, (3) whether or not the bioenergy plant harvests the biomass, and (4) whether or not the bioenergy plant pays for nutrient loss incurred as a result of removing biomass. Net return is defined as the payment received by the farmer after accounting for corn stover production cost in \$/acre [27].

This research defines contract types based on net return, in which all contracts have length two years, the bioenergy plant always pays for harvesting and nutrient replacement, and net return varies from \$0/acre to \$75/acre; thus, there are 76 contract types. The contract payment is given in \$/ton (η_{lc}^{u}) after paying harvesting and nutrient replacement expenses and is calculated using the following formula:

$$\eta_{lc}^{u} = \frac{n_c}{ns_l^u} \qquad \forall l \in L_1, u \in U, c \in C, \qquad (45)$$

where n_c is the net return received under contract type c (\$/acre) and $ns_l{}^u$ is the net corn stover yield (ton/acre).

4.4.4 Farmers' Choices

Total potential corn stover supply refers to the total amount of corn stover available for harvesting, assuming farmers provide bioenergy plant with 100% of available corn stover. The potential supply does not, however, account for farmers' choices and their probability to sell biomass to bioenergy plant, or lack thereof. Therefore, in order to account for a realistic supply, this study utilizes research conducted in Kansas to determine the probability that a farmer is willing to supply corn stover under various contractual options [27]. The predicted supply of corn stover from the county (S_{lc}^{u}) can be calculated using the following equation:

$$S_{lc}^{u} = \rho_{lc} \times ns_{l}^{u} \qquad \forall\, l \in L_1, u \in U, c \in C \tag{46}$$

Where the predicted supply of corn stover (S_{lc}^{u}) equals the probability that a farmer sells biomass to the bioenergy plant (ρ_{lc}) multiplied by potential corn stover supply (ns_{l}^{u}) [27]. Predicted supply (S_{lc}^{u}) represents the maximum amount able to be purchased from the county depending on farmers' choices. The predicted supply of corn stover at each county (S_{lc}^{u}) is an input parameter for the optimization model.

4.4.5 Biomass Storage

After harvesting, biomass must be stored within supplying counties, SSLs, or bioenergy plants until it is needed. This study assumes that round corn stover is stored on bare ground and covered with a tarp within the county and SSL, while corn stover at the bioenergy plant is stored on gravel and covered with a tarp; pelleted corn stover is stored in storage bins.

Dry matter loss represents the fraction of biomass lost during biomass storage or transportation. Factors such as densification form, storage conditions, and environment affect dry matter loss. This study assumes that corn stover loss is most closely related to densification form and storage method. Dry matter loss is estimated per month, with the assumption that it is fixed.

4.4.6 Biomass Pelleting

Most parameter estimates used for the case study came from journal papers and USDA publications. However, because mobile pelleting is still under development, the cost of moving mobile pelleting machines ($/mile) is estimated based on values from similar processes. For this case study, 25 mobile pelleting machines are assumed to be available. Albashabsheh and Heier Stamm [184] estimate the densification cost to be $48/ton with mobile pelleting based on a previous technical study that determined MPM cost elements [149].

4.5 Results

The proposed optimization model is solved using IBM ILOG CPLEX version 12.6 on a desktop computer with a 3.4 GHz processor. The resulting MILP problem includes 49,568 binary variables, 52,990 continuous variables, and 133,811 constraints. We examine the BBSC design for three contract periods in Kansas: 2006−2007, 2008−2009, and 2012−2013. Solutions are reached in 5.012 hrs, 1.736 hrs, and 7.656 hrs for contract periods 2006−2007, 2008−2009, and 2012−2013, respectively. In each instance, SSLs are established in Finney and Marshall counties. The bioenergy plant in Reno County has a high capacity level of 8,360,000 gallons per month. We summarize results of the optimization model for Kansas in the following subsections.

4.5.1 Cost Distribution

Optimal cost breakdown for various contract periods is presented in Figure 4.5. Results show that feedstock cost, fixed cost, and processing cost are the primary components of total BBSC cost for all contract periods, as demonstrated in other studies [17, 192]. Logistics cost for contract periods 2006−2007, 2008−2009, and 2012−2013 are 25.75%, 24.98%, and 25.73%, respectively. This is in line with Idaho National Laboratory recommendation that logistics cost should not exceed 25% of the total biofuel production cost.

Corn stover feedstock cost includes harvesting, nutrient replacement, and contract payment expenses. As shown in Figure 4.5, feedstock cost for contract period 2008−2009 is lower than other contract periods. Feedstock cost is lower when yield is higher, because harvesting cost

($/acre) and net return ($/acre) are divided by corn stover yield (ton/acre) to calculate corresponding components of feedstock cost in $/ton. On average, corn stover yield is higher for contract period 2008−2009 than other contract periods.

Fixed cost is the cost incurred for opening SSLs and the bioenergy plant. Fixed costs are identical for all contract periods because all contract periods have identical facility location decisions (SSL number and locations and bioenergy plant capacity).

Densification cost is the summation of costs incurred for densifying baled biomass to pelleted form and MPM transportation. Densification costs for contract periods 2006−2007 and 2012−2013 are similar because the amount of corn stover densified to pelleted form is identical (i.e., 450,00 tons of biomass densified to pelleted form); however, MPM transportation costs differ slightly, totaling $20,368.51 and $19,761.51 for contract periods 2006−2007 and 2012−2013, respectively. Densification cost for contract period 2008−2009 is lower than other contract periods because the amount of densified biomass and MPM transportation cost are lower. The amount of densified biomass is 420,263.48 tons and the MPM transportation cost is $12,041.80 for contract period 2008−2009.

Transportation cost, which is the corn stover transportation cost between BBSC facilities, is lower for contract period 2008−2009 than other contract years. In this surplus period with high yield, the bioenergy plant is surrounded by counties with high supply, consequently decreasing transportation cost associated with transporting biomass from faraway counties.

Finally, storage cost and processing cost are higher for contract year 2008−2009, because the amount of baled biomass that is stored and processed biomass is higher than in other contract periods. As mentioned, the amount of pelleted biomass in surplus period 2008−2009 is lower than other contract periods, thereby increasing storage and processing costs because those costs are higher for bales compared to pellets.

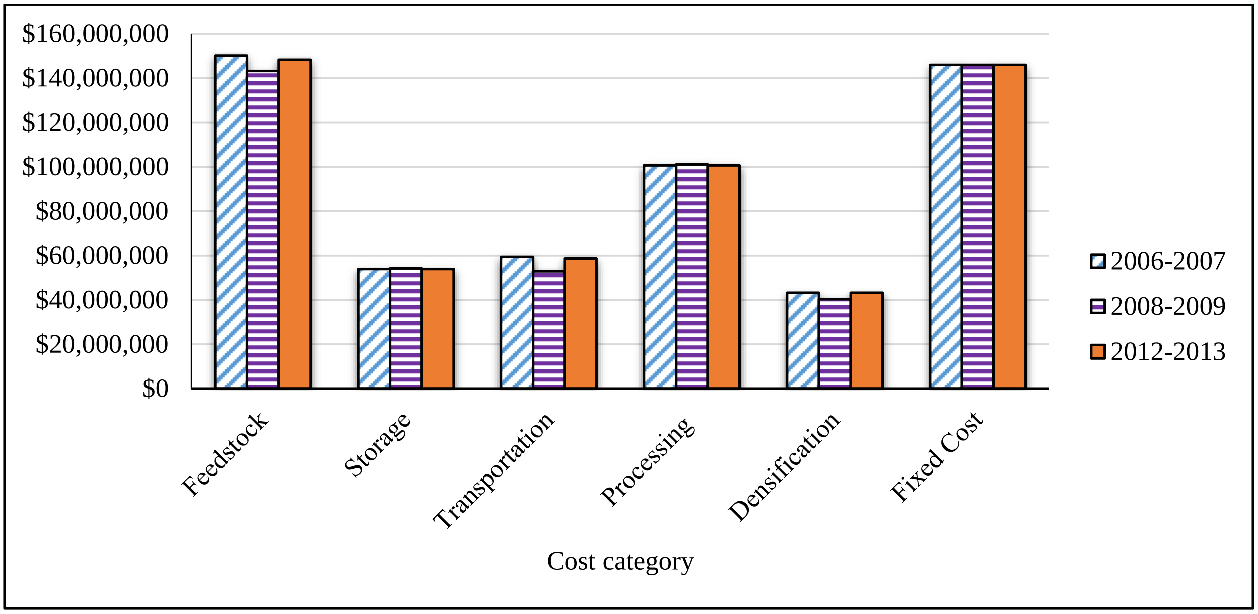


Figure 4.5: Total annual BBSC cost by category.

4.5.2 Amount Purchased

This section captures differences across Kansas districts in amount of corn stover purchased. Figures 4.6 and 4.7 display the amount of corn stover purchased in contract years for irrigated (left maps) and non-irrigated (right maps) land types. The triangles represent the bioenergy plant, and the circles denote open SSLs.

The figures show a few counties in which the bioenergy plant buys a large amount of biomass and many counties in which the bioenergy plant buys a minimal amount of biomass. The optimal solutions indicate that most purchased biomass is from counties close to the bioenergy plant in Reno County and SSLs in Finney and Marshall counties. As a result, the average amount of biomass purchased from south central, southwest, and northeast districts of Kansas are higher than the amount of biomass purchased from other districts. The amount purchased from the northwest district is lowest among all districts and years for all land types. This district has low corn grain yield and is far from the bioenergy plant and SSLs; farmers there also are less willing to sell biomass to bioenergy plant compared to farmers in other districts especially eastern districts.

For all contract periods, the amount of biomass purchased from irrigated land is higher than the amount purchased from non-irrigated land, because irrigated land has higher biomass yield (ton/acre), resulting in lower harvesting cost ($/ton) and contract payment expenses ($/ton) compared to non-irrigated land. Most of the biomass purchased from non-irrigated land in all contract years is from the eastern (northeast and southeast) and central (north central and south central) districts. These Kansas districts have a higher yield, lower transportation costs, and lower contract payment expenses compared to other districts.

The proportion of biomass purchased from irrigated land is highest in 2012, an extreme drought year according to the U.S. Drought Monitor (USDM) [186], when most counties had very low or zero corn grain yield on non-irrigated land. Low yields result in very high contract payments for biomass purchased from non-irrigated land. Since the bioenergy plant must meet demand, most biomass is purchased from irrigated land. Consequently, the proportion of biomass purchased from irrigated land is lowest for the surplus year in 2008.

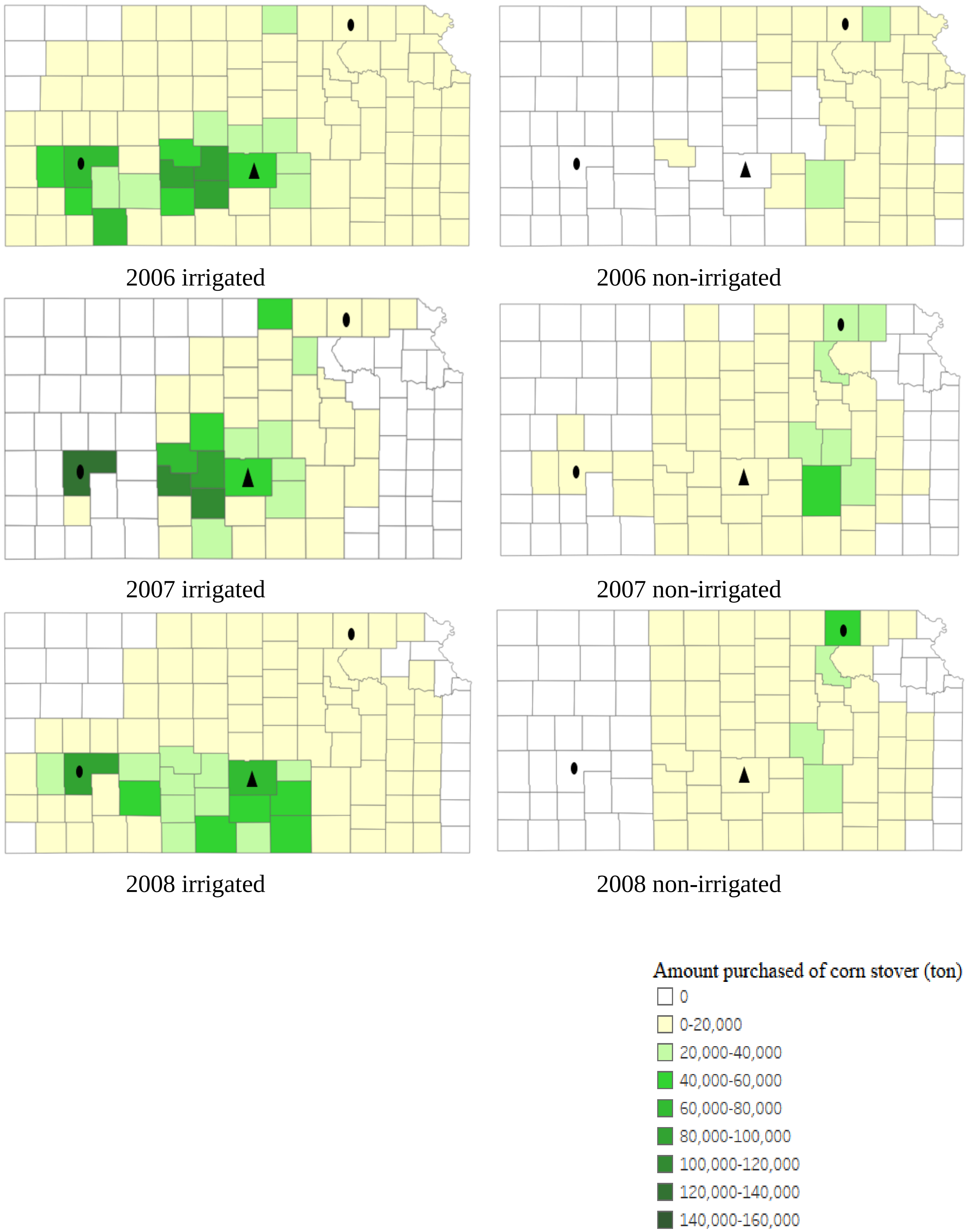


Figure 4.6: Amount of purchased corn stover ($\boldsymbol{Q^{u}_{lcy}}$, in dry ton) in 2006, 2007, and 2008 for irrigated land (left map) and non-irrigated land (right map). Triangles represent the bioenergy plant; circles represent open SSLs.

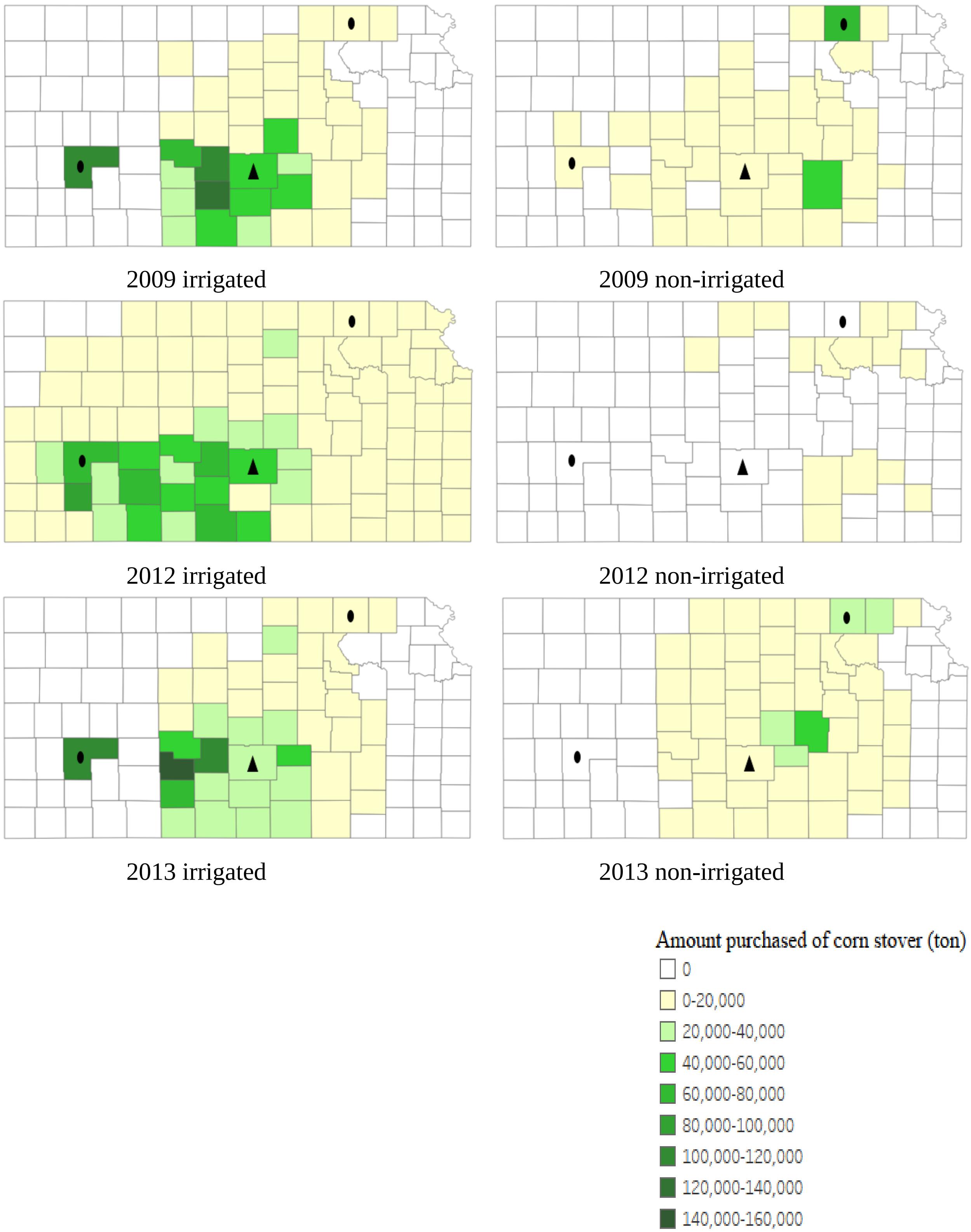


Figure 4.7: Amount of purchased corn stover ($\boldsymbol{Q^{u}_{lcy}}$, in dry ton) in 2009, 2012, and 2013 for irrigated land (left map) and non-irrigated land (right map). Triangles represent the bioenergy plant; circles represent open SSLs.

4.5.3 Densification and Mobility Decisions

This section investigates decisions related to densification. Among the six potential SSLs, two SSLs are open in Finney and Marshall counties for the three contract periods. For all contract periods, the amount of corn stover densified in Finney County, which is located in the southwest district, is approximately twice the amount densified in Marshall County, which is located in the northeast district, because the southwest district of Kansas has high biomass availability compared to the northeast district.

Densification not only helps reduce storage, processing, and transportation costs, it also helps reduce dry matter loss cost, resulting in increased amounts of densified biomass during drought periods when biomass cost increases and high-value biomass is preserved. Figures 4.8–4.10 show the amount of corn stover densified at SSLs each month and MPM mobility.

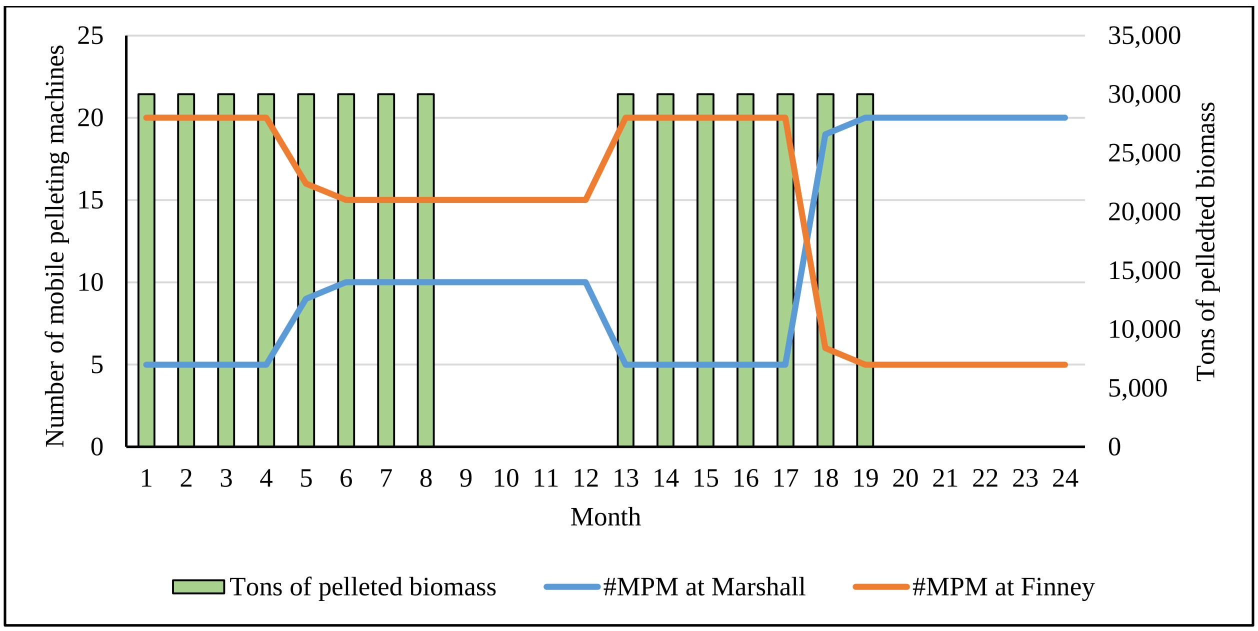


Figure 4.8: Total biomass pelleted at SSLs each month and MPM mobility for contract period 2006–2007.

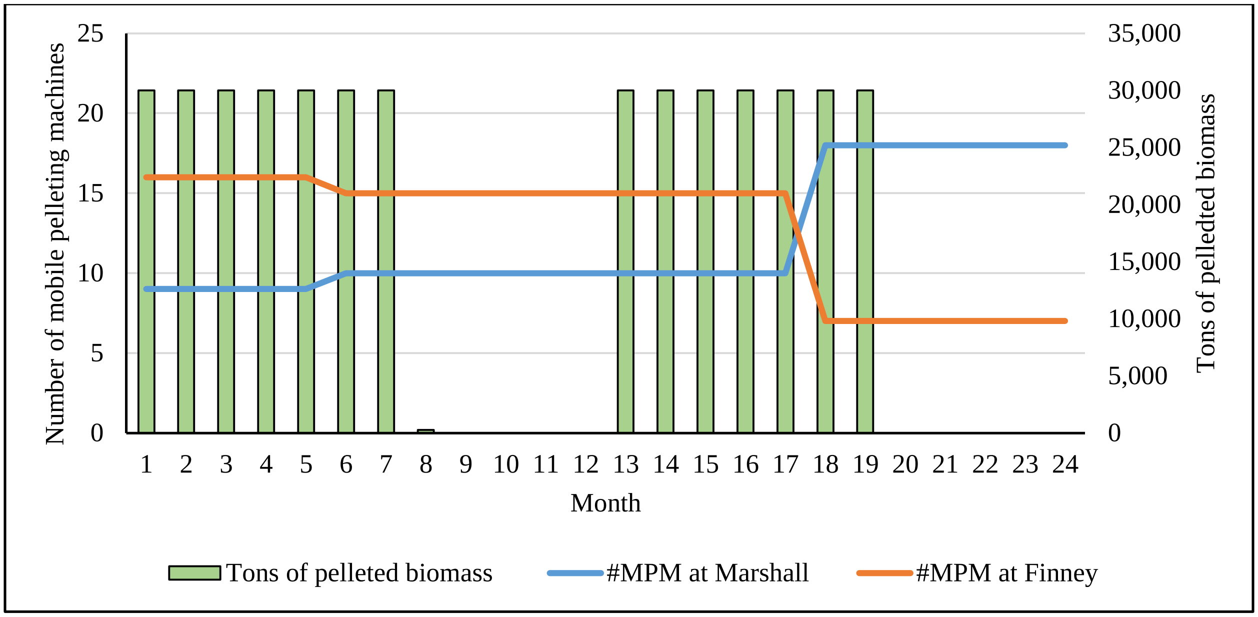


Figure 4.9: Total biomass pelleted at SSLs each month and MPM mobility for contract period 2008–2009.

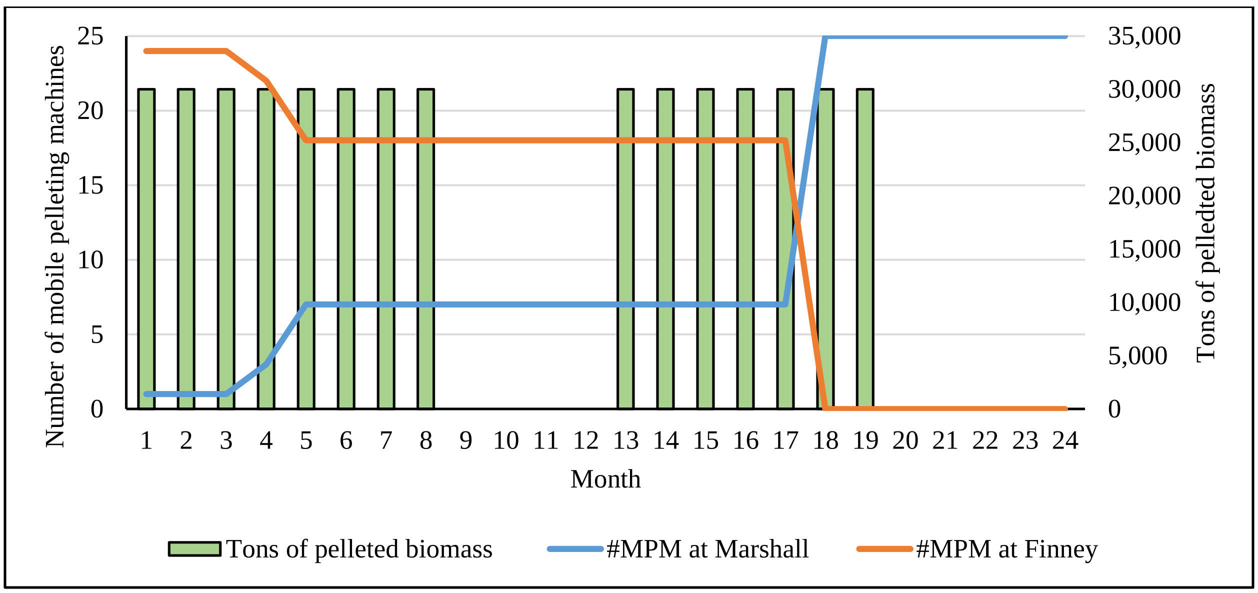


Figure 4.10: Total biomass pelleted at SSLs each month and MPM mobility for contract period 2012–2013.

All 25 MPMs move from depot to SSLs to begin densifying biomass in the first month, and MPMs operate at capacity in most months. However, the results show no densification in the final months of each contract year because densification cost cannot be offset by saving in transportation, storage, and dry matter loss costs. Biomass densified later in the contract year must be purchased during the first month (month 1 or month 13) of the contract year and then stored as bale at field or SSL until it is densified. However, this process incurs densification costs in addition to high dry matter loss and storage costs that cannot be recovered.

The amount of corn stover densified in contract period 2008–2009 is lower than the amount densified in other contract periods, because this is a surplus contract period with high yield and low net return. This contract period has sufficient biomass in counties near the bioenergy plant in Reno County; therefore, less biomass must be transported from distant counties, thereby decreasing the attractiveness of densification. Densification is appealing for years with low yield and high contract payment per ton, because it reduces dry matter loss expenses during the drought years in which biomass costs are high.

MPM mobility is low for contract period 2008–2009 because sufficient biomass is present in counties close to SSLs (i.e., Finney and Marshall counties). Biomass is densified from fewer counties with a significant supply, causing MPMs to remain a long time period at one SSL to densify biomass from a county with a high contract payment before moving to another SSL, consequently decreasing the frequency of MPM movement.

Biomass is stored in supplying counties until it needs to be densified at an SSL or processed at the bioenergy plant. Biomass is transported to an SSL at the time of densification because county-based storage cost and dry matter loss for biomass are the same as those at the SSLs. Counties do not have a storage limit, but SSLs are subject to storage capacities.

An SSL is used to densify biomass and store pellets; biomass is then shipped as needed to at the bioenergy plant. Biomass is densified at the SSL within the early month of contract years and then stored as pellet at the SSL due to comparatively lower SSL storage costs compared to storage costs at the bioenergy plant. The fraction of total pelleting capacity utilized is 62.50%, 58.36%, and 62.50% for contract periods 2006–2007, 2008–2009, and 2012–2013, respectively.

Pelleted biomass is processed into biofuel only after the baled biomass has been completely processed. Processing priority is given to baled biomass because dry matter loss and storage cost of baled biomass are higher than for pelleted biomass.

4.5.4 Contract Payment to Farmers

Figures 4.11 and 4.12 illustrate contract payments ($/ton) counties receive for each contract year; contract payments for irrigated (left maps) and non-irrigated (right maps) lands are shown.

Contract payments for counties near the bioenergy plant in Reno County and SSLs in Finney and Marshall counties are higher than other counties. The bioenergy plant offers high contract payments to increase the probability that farmers provide corn stover to the bioenergy plant. Transportation cost savings exceed the increase in contract payments.

For both land types, the bioenergy plant pays low contract payments ($/ton) to supplying counties in the northwest district of Kansas; these counties are far from open SSLs and the bioenergy plant, they have low yield (ton/acre), and they contain farmers who have low probability to sell biomass to bioenergy plant. (The probability to harvest corn stover (ρ_{cl}) in western Kansas is low).

Supplying counties in the eastern district of Kansas (northeast and southeast) receive lower contract payments ($/ton) in general, but these payments are higher for counties near the SSL in Marshall County. The eastern portion of the state has high yield (ton/acre) and high probability of farmer collaboration with the bioenergy plant.

The bioenergy plant offers high contract payments to many counties with irrigated land in 2012, which is an extreme drought year when yields are low, requiring increased purchase from other counties and increased costs to obtain the required supply. The bioenergy plant does not offer a contract for non-irrigated land unless overwhelming demand must be satisfied.

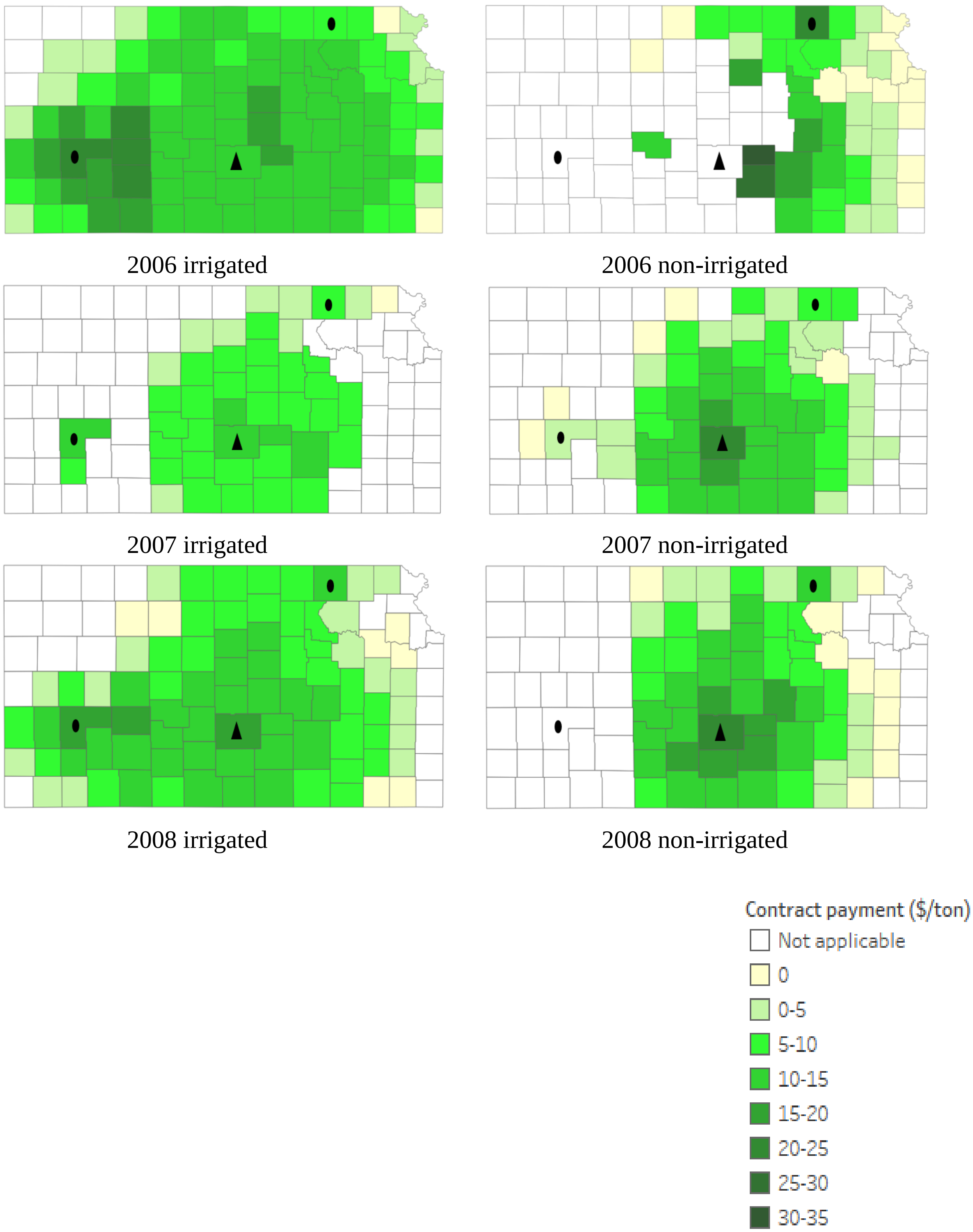


Figure 4.11: Contract payment (η^{u}_{lcy}, in $/ dry ton) in 2006, 2007, and 2008 for irrigated land (left map) and non-irrigated land (right map). Triangles represent the bioenergy plant; circles represent open SSLs.

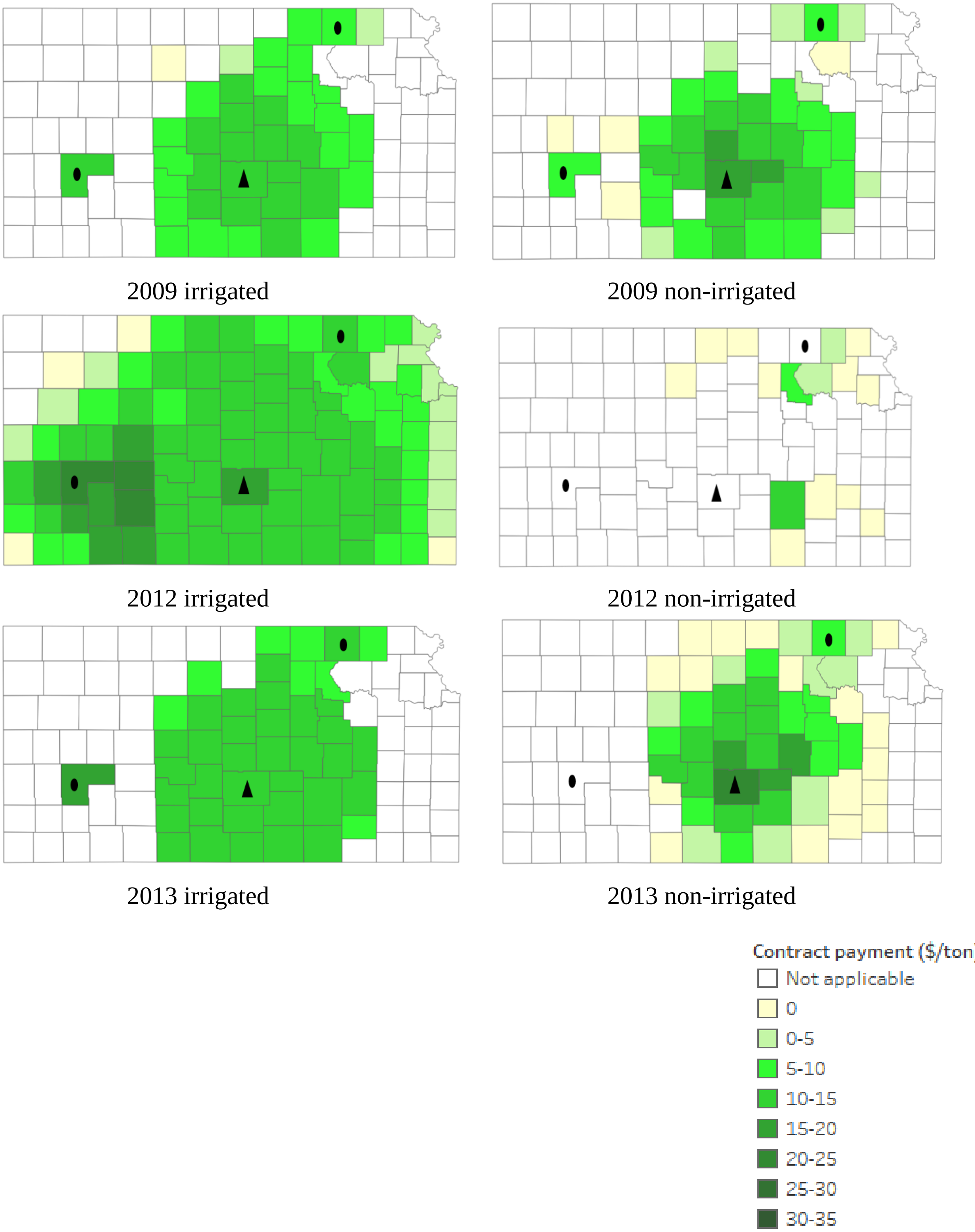


Figure 4.12: Contract payment (η^{u}_{lcy}, in $/ dry ton) in 2009, 2012, and 2013 for irrigated land (left map) and non-irrigated land (right map). Triangles represent the bioenergy plant; circles represent open SSLs.

4.5.5 Net Return

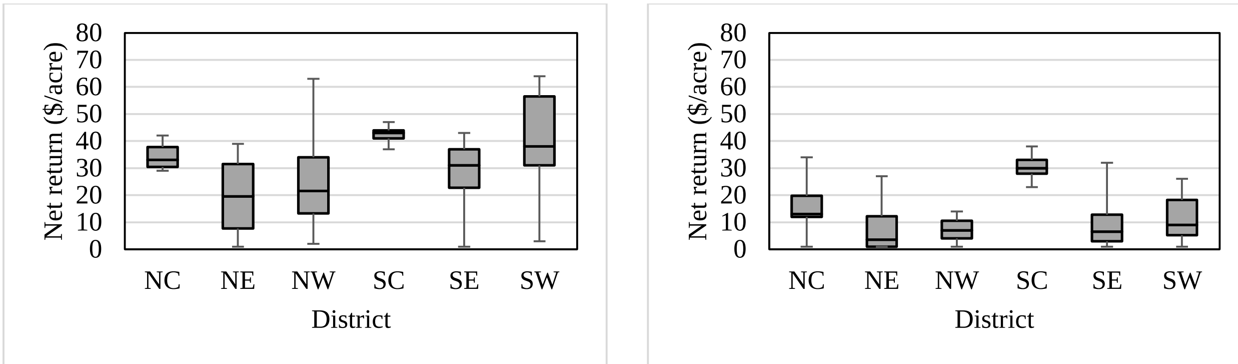
Figure 4.13 shows box-and-whiskers plots of net return for Kansas districts to summarize lower and upper quartiles and median. The box plots indicate variability in net return between and within districts. In general, two factors cause variability in net return: variability in yield within and between districts, and differences in transportation distance between counties that collaborate with the bioenergy plant.

The box plots show that the net return for non-irrigated land is lower than the net return of irrigated land because irrigated land has higher yield. Irrigated land receives higher net return per acre per contract payment ($/ton) because net return ($/acre) equals net corn stover yield multiplied by contract payment ($/ton).

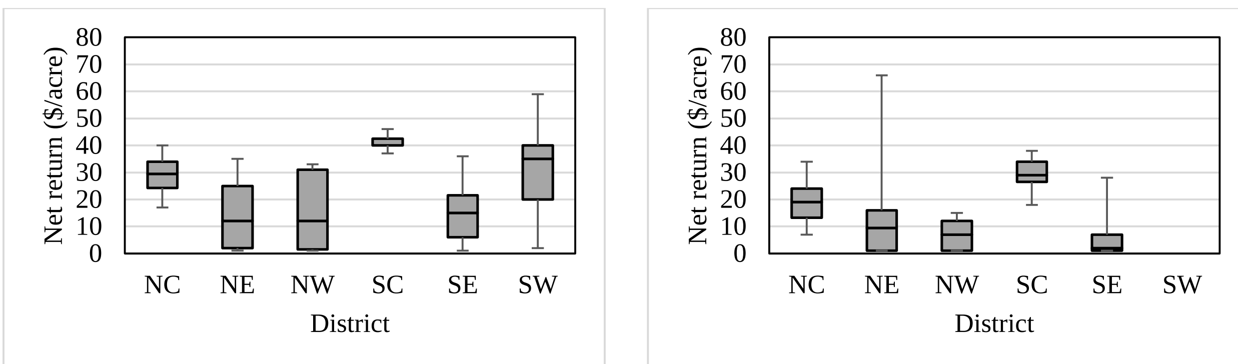
Overall, counties in the south central district of Kansas have high net return and there is low variation in net return between counties in south central district due to proximity to the bioenergy plant in Reno County. The bioenergy plant offers high net returns to increase supply from this district.

Counties in the southwest district of Kansas also receive high net return because an SSL is in Finney County. However, this district has high variability in net return within the district because net return received depends on distance between the county and SSL or bioenergy plant.

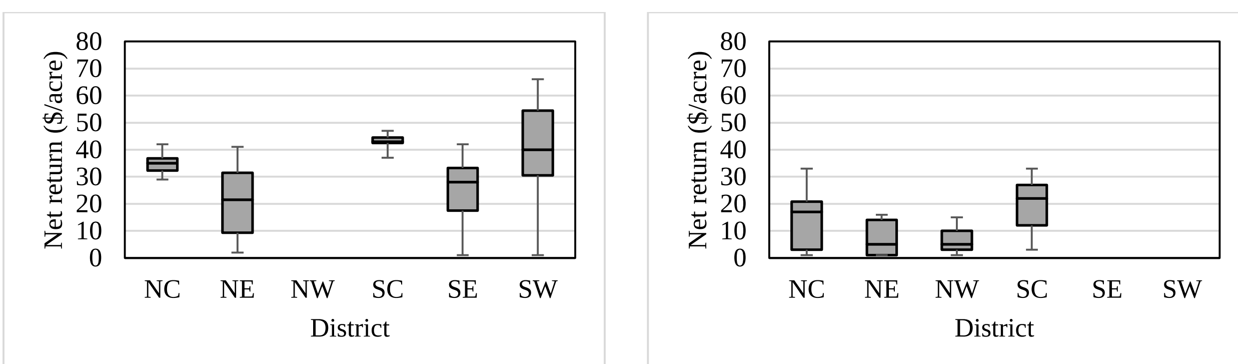
On average, counties in the northwest district of Kansas receive the lowest net return. Because these counties are undesirably far from the bioenergy plant and SSLs and have low yield, the bioenergy plant offers low net return contracts. Conversely, however, the north central district has low variability within the district and fairly high net return because variability in net yield for these counties is low. Irrigated counties in the northwest, southwest, and northeast districts have the highest variability due to variability in net yield.



(a) 2006–2007



(b) 2008–2009



(c) 2012–2013

Figure 4.13: Boxplots representing net return ($\boldsymbol{n_c}$, $/acre) for Kansas districts.

4.6 Conclusion

This chapter presents a MILP model to guide BBSC management decisions while considering mobile densification and farmers' probability to supply biomass to the bioenergy plant. A case study based on the state of Kansas is conducted to illustrate the usage of the model and type of analysis can be drawn from results. We observe from the case study that the most important factors that influence type of contract offered to each supplier and optimal BBSC design are: biomass yield, farmers' willingness to sell biomass to the bioenergy plant, and distances between supplier and SSLs and bioenergy plant. The optimization results indicate that densification is carried out at earlier months in each contract year to avoid high logistic costs associated with storing baled biomass (storage cost and dry matter loss cost during storage) until being densified. Moreover, irrigated land type receive high net return contract compared to non-irrigated land. This is because irrigated land has a higher net yield (ton/acre) which decreases harvesting cost and contract payment per ton of biomass.

The model we propose is promising as it reflects BBSC reality and complexity. However, it is designed for one biomass feedstock (corn stover). A possible future extension is to update the model to account for multiple lignocellulosic feedstocks simultaneously, such as switchgrass and energy sorghum. This can be accomplished by updating supply to consider different types of biomass feedstocks and their associated harvesting seasons. The model should consider the farmers' probability to provide different type of biomass to the bioenergy plant under different contract options.

Chapter 5 - Conclusion

Biomass-to-biofuel supply chains involve logistical challenges that differ from those of other supply chains. This is because biomass feedstocks have special characteristics that add complexity to the optimization problem. First, biomass has low bulk density which increases the logistic costs and decision alternatives associated with handling, transporting, and storing biomass. Second, biomass supply is affected by farmers’ choices. Farmers’ choices and their probability to supply biomass to the bioenergy plant affect the expected biomass availability at supplying sources. To manage previously mentioned complexities, the author created optimization models that consider mobile densification and farmers' choices.

In the first part of this dissertation, an extensive overview of densification techniques and BBSC optimization models that account for biomass densification is presented. The author discusses models that manage BBSC with densification processes. Based on the review, mobile densification is proposed as a technique to reduce logistics costs in the BBSC. However, there does not exist an optimization model to manage the BBSC with mobile densification.

In the second part of this dissertation, an optimization model is developed to design the BBSC with mobile densification. The proposed method helps the BBSC manager to overcome the complexities of having different types and forms of biomass and the opportunity to densify bales at SSLs using MPMs, since the model identifies the best densification form for all locations at the BBSC facilities. This research promotes using a quantitative decision-making approach to identify conditions under which mobile densification is necessary and economically feasible.

The author integrates farmers’ probability to supply biomass to the bioenergy plant under different contract options in the third part of the dissertation. The methodology accurately estimates biomass supply under different contract options. This part helps to build the foundation to consider all BBSC stakeholder objectives, instead of just considering bioenergy plant objectives. The proposed optimization model can help to motivate ethanol production from lignocellulosic biomass, and to satisfy farmers' conditions and requirements.

Despite the advances presented in this dissertation, the proposed models have some limitations that should be addressed in future research. The model proposed in Chapter 4 does not consider the external market for crop residue. For example, during drought years farmers' probability to sell biomass to bioenergy plant may decrease, because the farmer may receive high payment for selling the biomass as livestock feed. Second, the author did not investigate the effect of considering farmers' choices on the BBSC. Future research should compare the results of a model that accounts for farmers' choices with one that does not. The model proposed in Chapter 4 can be modified by omitting farmers' choices and their probability to participate in the supply chain. To investigate the consequences of omitting farmers' choices, differences in biomass purchased for each county should be calculated to determine amount of unmet demand.

The proposed model in Chapter 3 can be easily updated to manage any supply chain that involves a product that changes its properties at a middle stage using a mobile machine before being delivered to the final customer. One example is the olive oil supply chain, where olives are milled using mobile machines at individual farm sites before transport to factories [175]. Also, this model is beneficial for meat supply chain. Instead of transporting livestock hundreds of miles to butcheries, there is a new technology that exists called mobile slaughter unit [193]. These units slaughter and inspect animals at warehouses or fields before transporting them to butcheries. This technology is promising for small-volume producers as it avoids transporting live animals large distances, reduces logistics costs, and reduces capital investment. The research proposed in Chapter 3 can be applied for meat supply chain where animals can be transported directly to butchery or to the closest warehouse to be slaughtered using mobile slaughter unit before transport to butchery.

In practice, bioenergy plants consider may different type of biomass feedstock in their supply chain as hedging strategy to mitigate the effect of biomass supply disruption. The optimization model in Chapter 4 can be adjusted to consider different type of biomass feedstock. The model should consider farmers' probability to sell different types of biomass feedstock under different contract option. This is likely to increase computational requirements of the model. One way to reduce computation time is to decompose the model and solve it in two stages. The first stage is modeled as integer model to determine strategic level decisions such as bioenergy plant capacity, SSLs location, and type of contract offered for each county need. Then the second stage is linear programming model that determine operational decisions related to amount of biomass purchased, stored, and transported over time across the time horizon.

For future research the optimization model proposed in Chapter 4 can be adapted to the long-term planning for the bioenergy plant considering different contract cycles for each supplier. Once the contract ends, the farmer may choose to begin another collaboration with the bioenergy plant. The planning horizon can be divided into different contract cycle of same length. Future research may build stochastic MILP model for this problem that consider the probability that famer will renew or participate in the BBSC chain at each contract cycle.

The research proposed in Chapter 4 helps to illustrate the optimal design of the BBSC for an average, surplus, and drought contract periods. Future research should investigate the effect of yield uncertainty on the BBSC. One way to do that is by using scenario-based stochastic optimization methodology. This can be done by building different scenarios for biomass yield such as low, medium, high, with the probability distribution of yield determined using historical data of biomass yield from USDA. To minimize computational time needed, if the decisions are at the county level, counties can be grouped, where all counties within the same group have same yield distribution.

The research proposed in this dissertation proposes optimization models to dynamically locate mobile machines that move between supply chain facilities in different time periods to produce a different forms of material that have lower logistic costs. To the best of our knowledge, this is the first dynamic study that simultaneously copes with mobile facilities, stakeholders' choices, and losses on transportation and inventory arcs. The proposed models assumes supply is dynamic; however final product demand is the same for all time periods. For future research, this work can be extended by considering a more realistic situation by having dynamic demand. Another direction for future research is considering a multi-objective optimization model such as economic and environmental objectives. For the area of BBSC, the decision maker may have economic considerations that are evaluated by calculating total cost of the BBSC, and /or environmental goals that are evaluated by the effect on soil or greenhouse gas emissions.

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Appendix A - Procedures for Imputing Missing Data

In order to protect farmers' privacy for farm yield and planted acreage, NASS requires a specific number of surveys be completed before publishing harvested acreage or yield by county. NASS requires having at least 30 survey responses from an individual county, or at least 3 survey responses from producers who own at least 25% of county acreage for the crop [194]. If these requirements are not met, then counties in the same district that do not have data of the number of acres harvested or corn grain yield share one number and are referred to as "Other combined counties." In total, the models in Chapter 4 require 2520 values (acres harvested and corn grain yield for 105 counties, 2 land types, and 6 years); of these, 1674 are imputed using the methods described here.

A.1 Missing harvested acreage and yield for individual counties

The total number of harvested acres in combined counties can be divided in proportion to the area of each county using the following formula:

Harvested acreage =

$$\frac{\text{Area of the county} \times \text{total number of acres harvested in the combined counties}}{\text{Total area of the combined counties}}$$

Corn yield of a county that does not meet NASS requirement for individual county reporting is assumed to equal the value given for all unreported counties in the same district and referred to as "Other combined counties."

A.2 Missing harvested acreage and yield for entire district

This part of the appendix illustrates estimation methodology for harvested acreage and corn grain yield if NASS has no data for an entire district. In that case, 17 years of historical data (2000–2016) regarding the total number of harvested acres in the district are used in the following steps to impute harvested acreage in the district:

1. Find the total number of harvested acres in the district for years 2000 to 2016.

2. Calculate the percentage of harvested acres of type u to the total harvested acres in the district using

Percentage of harvested acres of type u =

$$\frac{\text{Number of acres harvested in the district for land of type } u}{\text{Total number of acres harvested in the district for both land types}}$$

3. Calculate the average percentage of harvested acres of type u from the historical data:

Average percentage of harvested acres of type u =

$$\frac{\text{Sum of percentage of harvested acres of type } u}{\text{Number of years considered with reported acreage}}$$

4. Calculate the number of harvested acres in the district using the following formula:

Number of harvested acres in the district =

$$Average\ percentage\ of\ harvested\ acres\ of\ type\ u\ at\ year\ y$$
$$\times\ Total\ number\ of\ acres\ harvested\ in\ the\ district\ for\ both\ land\ types\ at\ year\ y$$

5. Calculate the harvested corn acreage in counties in the same district using the following formula:

$$\text{Harvested acreage in the county}$$
$$= \frac{\text{Area of the county} \times \text{Number of harvested acres in the district}}{\text{Total area of the district}}$$

Corn yield of a county with no available information for the entire district for one year equal

County's average over other years where the data are available