OPTIMIZATION APPROACHES FOR THE ECONOMIC AND ENVIRONMENTAL ANALYSIS OF BIOMASS, BIOFUEL, AND FOOD PRODUCTION

A Dissertation by

Halil Ibrahim Cobuloglu

Master of Science, Bogazici University, 2012

Bachelor of Science, Istanbul Technical University, 2008

Submitted to the Department of Industrial and Manufacturing Engineering
and the faculty of the Graduate School of
Wichita State University
in partial fulfillment of
the requirements for the degree of
Doctor of Philosophy

May 2015

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The following faculty members have examined the final copy of this dissertation for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Doctor of Philosophy with a major in Industrial Engineering.

_____
İ. Esra Büyüktahtakın, Committee Chair

_____
Janet Twomey, Committee Member

_____
Pingfeng Wang, Committee Member

_____
Krishna Krishnan, Committee Member

_____
Hamid Lankarani, Committee Member

Accepted for the College of Engineering

_____
Royce Bowden, Dean

Accepted for the Graduate School

_____
Abu Masud, Interim Dean

DEDICATION

To my dear parents, my sisters, and my brothers

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my supervisor, Dr. İ. Esra Büyüktahtakın. I am thankful for her motivation in making everything excellent. It has been an honor for me to be her first PhD student. I am also thankful for her continuous support, guidance, and funding that have carried my PhD studies to an outstanding level.

I am grateful for all my friends from various countries and the time they have shared with me. Their friendship is as important to me as obtaining my PhD degree. I also appreciate my friends Emmanuel des-Bordes and Eyyub Kibis at the Optimization Laboratory at Wichita State University. Our interaction helped me to advance my personal and professional skills to the highest level. I also thank my friend Eyup Calik for his support.

In addition, I want to express my appreciation to Dr. Twomey, Dr. Yildirim, and Dr. Wang for being great examples of professional life. I am also thankful to Dr. Krishnan and Dr. Lankarani for being on my committee and for their valuable comments on my research in order to bring it to the highest quality.

This research is supported by the National Science Foundation under grant no. EPS-0903806 and the state of Kansas through the Kansas Board of Regents.

ABSTRACT

This dissertation examines optimization approaches to biomass and food production (BFP) at the farm level. The goal of this study is to analyze the environmental and economic effects of utilizing different crop types under various management scenarios. In this study, first we provide a unique optimization approach of quantifying and formulating the economic and environmental benefits of switchgrass production at the farm level. In particular, we propose a multi-objective mixed-integer programming (MIP) model that maximizes the revenue from harvested switchgrass biomass and the economic value obtained from positive environmental impacts of switchgrass yield during the planning horizon. Second, we investigate the economic and environmental tradeoffs between biofuel and food production from switchgrass and corn. This model maximizes the total profit of farmers while ensuring a sustainable food supply. Then, we develop a stochastic multi-criteria decision-making tool for decision makers (DMs) and farmers to select the most sustainable crop type in biomass production. In this method, literature and expert opinions are utilized in order to build up the evaluation criteria with respect to economic, environmental, and social aspects. Finally, we expand the optimization of food and biomass production with a stochastic modelling approach. We perform a decomposition algorithm in order to increase solution speed and solution quality of the stochastic model. The developed mathematical models provide optimal decisions regarding land allocation to food and energy crops; time, amount, and location of seeding, harvesting, and transportation; and budget allocations to farm operations. We apply the proposed methods to various cases in order to evaluate BFP in Kansas.

TABLE OF CONTENTS

TABLE OF CONTENTS (continued)

Chapter Page

TABLE OF CONTENTS (continued)

Chapter Page

TABLE OF CONTENTS (continued)

Chapter Page

LIST OF TABLES

LIST OF TABLES (continued)

LIST OF FIGURES

LIST OF FIGURES (continued)

LIST OF FIGURES (continued)

LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
BFP	Biomass and Food Production
CO_2	Carbon Dioxide
CPU	Central Procession Unit
CRP	Conservation Reserve Program
DM	Decision Maker
GHG	Greenhouse Gas
GIS	Geographic Information System
ha	Hectare
K	Potassium
LL	Lower Limit
LLSM	Logarithmic Least Squares Method
MB	Master Benefit
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MILP	Mixed-Integer Linear Programming
MIP	Mixed-Integer Programming
ML	Most Likely
MOM	Method of Moments
MP	Master Problem

LIST OF ABBREVIATIONS (continued)

Mt	Million Tonnes
M$	Million Dollars
N	Nitrogen
P	Phosphorus
PB	Primal Benefit
PLS	Pure Live Seed
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
QP	Quadratic Programming
RFS2	Renewable Fuel Standards
SAHP	Stochastic Analytic Hierarchy Process
SOC	Soil Organic Carbon
SP	Subproblem
TB	Sales of Switchgrass Biomass
TC	Savings from Net Carbon Emission Reduction
TCE	Total Carbon Emissions
TCS	Total Carbon Sequestration
TEV	Total Economic Value
TNP	Total Nitrogen Pollution
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TR	Total Revenue
TS	Economic Value of Soil Erosion Prevention

LIST OF ABBREVIATIONS (continued)

TSE	Total Soil Erosion Prevention
UL	Upper Limit
USDA	United Stated Department of Agriculture
VIKOR	Multi-Criteria Optimization and Compromise Solution
VSS	Value of the Stochastic Solution

CHAPTER 1

INTRODUCTION

1.1 Background

Renewable energy sources have gained importance due to concerns about the future of scarce energy sources such as fossil fuels along with the pressure of adverse environmental impacts of traditional fuels. Biofuel, an alternative to conventional energy sources, is considered a type of sustainable energy that can replace oil. In order to produce biofuel, biomass is processed in biorefineries. In general, biomass refers to all types of plants and materials from plants, including forestry, agricultural resources such as food and cellulosic crops, or even animal waste. Bioenergy is a general form of biomass-based energy used for purposes such as electricity and heating. Therefore, biofuel is a subsection of bioenergy and refers to energy as fuel derived from biomass [1].

Biomass is a sustainable energy source with an immense amount of supply potential. It is also environmentally friendly due to its benefits, such as prevention of soil erosion and reduction of CO_2 emissions. Considering low supply reliability and damages on the natural life of fossil-based sources, biofuel and bioenergy have turned into popular alternatives. Among the mentioned sources of biomass, lignocellulosic biomass is used to produce second-generation biofuel, whereas first-generation biofuel depends primarily on food commodities. Production of first-generation biofuel plants has already gone commercial, negatively impacting soil quality because these plants require large quantities of chemicals and fertilizers. On the other hand, lignocellulosic materials are typically cheaper. In addition, second-generation biofuels are proposed because of concerns relative to food shortage that may occur as a result of using food

crops in energy production. However, technology is not developed enough to efficiently convert lignocellulosic biomass into biofuel. Therefore, investment in the biofuel industry raises the issue of profitability. In order to increase profitability, many studies focus on the conversion technology that will increase the output and decrease the cost of biofuel production from lignocellulosic biomass [2]. However, in order to make investment in the biofuel industry economically feasible, efficiency issues regarding biomass production and biofuel supply chains need to be considered.

In this dissertation, we present a set of decision models for biomass production at the farm level. The overall goal of this study is to provide efficient management strategies to farmers and decision makers (DMs) in order to maximize the total economic and environmental benefits from biomass production. We consider different crop types in the applications of the models to compare and analyze trade-offs among the economic and environmental outcomes.

In this chapter, in order to define possible contribution areas and the research gap, we review studies about biomass production and biofuel supply chain, particularly for lignocellulosic (energy) crops. In section 1.2, we explain our approach and the categorization of reviewed papers. Here we provide a list of studies along with models used and related areas. In section 1.3, we present papers in various areas that have deterministic models, while in section 1.4, we review the probabilistic models in the biomass production and biofuel supply chain. In section 1.5, we discuss the motivation and objectives relative to the main findings in the literature review. In section 1.6, we provide a summary. Finally, section 1.7 explains the overall organization of the dissertation.

1.2 Overview of Literature Review

A number of studies deal with biomass production at the farm level and supply chain of biofuels. Research conducted in the biofuel and biomass area changes from deep analyses to strategic decisions at the managerial level. In order to systematically cover the literature, we have classified studies according two main perspectives—modeling and research area—as shown in Figure 1.1. Based on the literature review, modeling studies are classified into two groups—deterministic and probabilistic. Probabilistic models are comprised of three categories, while deterministic models encompass two categories. There are also three different categories comprise the research area: production, supply chain, and environment.

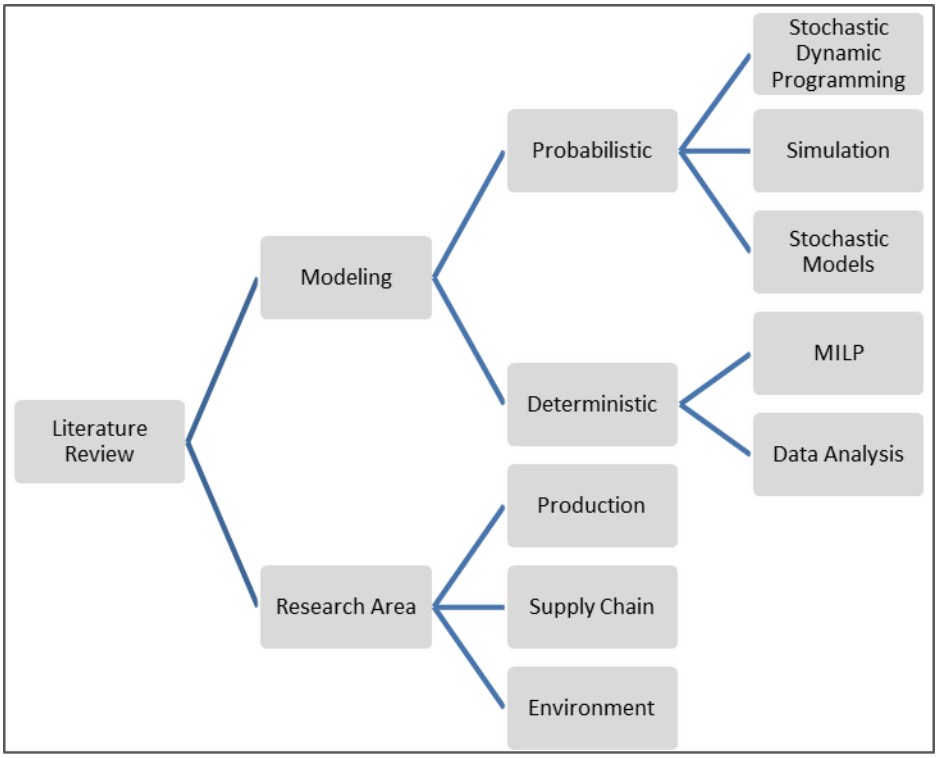

Figure 1.1 Classification of papers in this review.

Before introducing the studies covered in this study, we need to draw attention to the literature review of petroleum-based fuels and biofuels [3], which focuses on the supply chain

and decision levels such as strategic, operational, and tactical. However, we have a different review approach in this paper. First, we primarily focus on the biofuel supply chain, particularly from lignocellulosic biomass. Our review also involves studies of biomass production at the farm level. Second, we categorize articles based on the considered research area: production, supply chain, or environment. Our purpose in this paper is to expand knowledge by classifying papers in the literature relative to cellulosic biomass and the biofuel supply chain. By doing so, we aim to discover those areas where there is a lack of investigation and a need for further attention from researchers.

Here we have reviewed a total of 33 studies, which, as mentioned previously, are classified according to modeling used and the research area in which they are applied. We primarily include studies dealing with energy crops and their production. The reviewed articles are listed in Table 1.1.

1.3 Deterministic Models

Deterministic models used for biomass production and a biofuel supply chain generally utilize optimization models, particularly mixed-integer linear programming (MILP). There are also various data analysis studies such as estimation, data collection, and field experiments. Studies that propose a deterministic model for lignocellulosic biomass and biofuel supply chain are reviewed based on the areas they investigate.

TABLE 1.1 CLASSIFICATION OF STUDIES COVERED IN THIS REVIEW

Paper (Year)	Modeling					Research Area		
	Deterministic		Probabilistic			Production	Supply Chain	Environment
	MILP	Data Analysis	Stochastic Dynamic Programming	Simulation	Stochastic Models			
Thomason et al. [4] (2004)		X				X		
Sokhansanj et al. [5] (2009)		X				X		
van Dam et al. [6] (2009)		X				X		
Duffy and Nanhou [7] (2002)		X				X		
Duffy [8] (2008)		X				X		
Elbersen et al. [9] (2005)		X				X		
Haque and Epplin [10] (2010)	X					X		
Papapostolou et al. [11] (2011)	X						X	
Freire et al. [12] (2004)	X						X	X
Kim et al. [13] (2010)	X						X	
You and Wang [14] (2011)	X						X	X
An et al. [15] (2011)	X						X	
Wetterland et al. [16] (2012)	X						X	X
Love et al. [17] (2011)		X						X
Holguin et al. [18] (2010)		X						X
Ceotto [19] (2009)		X						X
van Dam et al. [20] (2009)		X						X
Roth et al. [21] (2005)		X						X
Murray et al. [22] (2003)		X						X
Clancy et al. [23] (2012)				X		X		
Osmani and Zhang [24] (2014)					X		X	
Sharma et al. [25] (2013)				X	X		X	
You [26] (2013)					X		X	
Awudu and Zhang [27] (2013)					X		X	
Xie et al. [28] (2014)	X						X	
Dal-Mas et al. [29] (2011)			X				X	
Sokhansanj et al. [30] (2006)			X			X	X	
Khanna et al. [31] (2011)			X	X		X	X	
Zhang et al. [32] (2012)				X			X	
Mobini et al. [33] (2011)				X			X	X
Cobuloglu and Büyüktahtakın [34] (2014)	X					X	X	X
Akgul et al. [35] (2012)	X						X	
Zhang et al. [36] (2012)	X					X	X	

1.3.1 Studies on Biomass Production

Increasing the biomass yield amount from a given area is generally a primary concern in many agriculture studies. Research regarding the biomass production from cellulosic crops has various perspectives. Some studies conduct experiments in order to analyze the effects of fertilization, harvesting time, and frequency on yield amount. One of these is performed by Thomason et al. [4] to determine the response of switchgrass to the application of different amounts of nitrogen (N) as fertilizer and to various harvesting frequencies. They develop scenarios and conduct field experiments in central Oklahoma. Their findings indicate that, in order to maximize the harvested amount, multiple harvesting in a year should be done. They claim that the amount of N does not affect the yield amount. On the other hand, multiple harvesting shows side effects such as a decrease in the life cycle of switchgrass, which reduces the total yield. Several data collection studies clearly define the cost of various farm operations. One of these studies conducted by Sokhansanj et al. [5] defines the cost of production, yield per hectare (ha), energy input cost, machinery, and transportation cost of switchgrass. It also provides costs with respect to changing the amount of switchgrass yield per hectare. Similarly, but more comprehensively, van Dam et al. [6] discuss a large-scale cost estimation and economic analysis study for Argentina based on switchgrass and soybeans production. Supply chain options and production locations are evaluated under different scenarios according to the estimated cost and yield rates. Duffy and Nanhou [7] develop different scenarios with various seeding seasons, cultivation land, and machinery types to estimate the cost of switchgrass production per hectare in the state of Iowa. They make some assumptions to determine those values and indicate that the major factors affecting the cost are yield and land charge. The goal

of their study is to be able to show the profitability of producing switchgrass. Another study to estimate the cost is performed by Duffy [8]. This particular study also includes the storage and transportation cost estimation in addition to switchgrass production cost. A study conducted in Europe by Elbersen et al. [9] on the potential yield of perennial grasses analyzes and estimates the yield amount of switchgrass and Miscanthus.

Different than the mentioned studies in terms of methodology, Haque and Epplin [10] minimize the cost of switchgrass production by using the MILP model. They also include the transportation cost of the biomass to the refinery by evaluating the optimal harvesting strategies of production amount, fertilization N, and transportation modes.

1.3.2 Studies on Supply Chain

A considerable number of studies in the literature cover the biofuel supply chain. In one, Papapostolou et al. [11] propose a mathematical model for a supply chain of biofuels that integrates both economic and technical parameters. Performance of the supply chain, which includes suppliers, storage facilities, transporters, and a number of retailers, is affected by those parameters. MILP is used to formulate the problem, which includes only major operational constraints to have a solvable problem model. The authors do not consider cellulosic biomass in their study. On the other hand, Freire et al. [12] propose a mathematical model that considers both economic and environmental consequences of biofuel production. They use a life-cycle assessment framework and partial equilibrium microeconomic model while establishing a multi-criteria linear optimization model. In this study, they consider dedicated energy crops such as sugar beets, wheat, and rapeseed. The model is applied to a biofuel production case study in France. Similar to that research, Kim et al. [13] investigate the value

chain, starting from biomass sources, such as forestry, and ending at the final markets. Locations of biomass, conversion sites, logistics locations, the amount of products that should be transported, capacities, and technologies that are used in those facilities are decided according to the proposed MILP model. The objective function of the model is to maximize overall profit by submitting the cost from revenues.

In addition to the previously mentioned studies, life cycle assessment is investigated as a core subject of biofuel supply chain in research by You and Wang [14]. They propose an MILP model by considering environmental impacts of the supply chain such as greenhouse gas (GHG) emissions along with the economic impacts. However, they do not primarily consider energy crops as the biomass source. A multi-objective multi-period MILP model that minimizes the cost is proposed. This model defines the locations and number of transportation facilities, amounts to be transported, technology in the facilities, and inventory amount. Figure 1.2 presents the scope of that research, which is also the scope of this literature review.

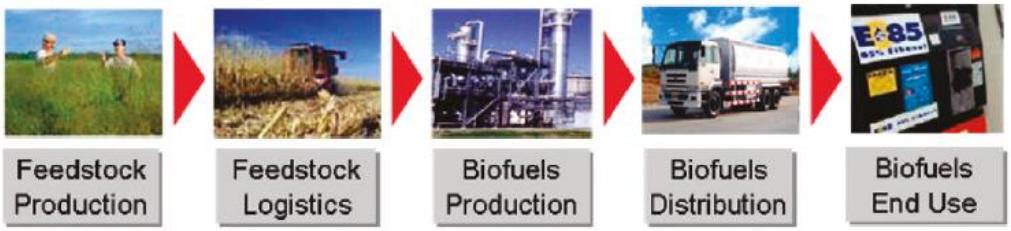

Figure 1.2 Flow of Biofuel Supply Chain from Feedstock Production to Biofuels End User [14].

There are also supply chain studies that maximize profit, such as the work of An et al. [15]. They claim that their model is the first one dealing with all steps involved in the two-directional biofuel supply chain. Using a time-staged deterministic model, their model determines the storage amount of the biomass, technology used, and warehouse locations. On

the other hand, Wetterlund et al. [16] minimize the cost of the entire supply chain system from production plant to fossil fuel transportation. They involve lignocellulosic crops in their study and consider carbon dioxide (CO_2) emitted during transportation.

1.3.3 Environmental Studies

In the literature, various studies are related to the environmental effects of producing second-generation crops. While most of them investigate the effects of producing and harvesting practices on biological diversity, very few deal with hazards to wildlife and human life. One of the recent studies dealing with the risks to human health and wildlife associated with bioenergy crop production on a large scale is done by Love et al. [17]. They investigate the threshold toxicity levels of fertilizers on the health of a bluegill fish species and also humans by using a soil and water assessment tool. Another study by Holquin et al. [18] determine the effects of switchgrass-based biomass crop production on insect diversity in South Carolina. After three years of data collection and sampling, abundant species in various regions and at various times of the year are identified. They indicate that biodiversity is adversely affected if high-density fertilization is implemented on the field. Ceotto [19] finds that when there is grazing, a variety of species increases in the long term. He also analyzes the negative effects of biomass production on grassland. Van Dam et al. [20] convey a large-scale study for environmental effects of switchgrass- and soybean-based bioenergy production. They consider environmental effects such as reduction in GHG emissions, change in carbon stock, soil erosion, and water quality. They present the results of each sustainability principle analyzed according to changing scenarios.

Two similar studies focus on the effects of farm operations on animal population, particularly the change in grassland bird population. In one, Roth et al. [21] investigate the bird diversity and population with respect to harvesting times and methods. They collect data for five years in Iowa for different harvesting scenarios to analyze their effects on bird population. They suggest shifting the harvesting area as a harvest management to support different kinds of bird species. In the other study, Murray et al. [22] explore the effects of converting marginal lands to switchgrass-based biomass production fields. The abundance of bird species increases in Iowa, based on their estimation using a geographic information system (GIS).

1.4 Probabilistic Models

This section includes all studies that utilize probabilistic models for biomass production and the biofuel supply chain. Uncertainty, such as the yield amount and price fluctuations involved in biomass and biofuels, has also been studied by many researchers. For example, Clancy et al. [23] investigate the financial risk associated with biomass production. In order to calculate the net returns of biomass crops such as Miscanthus, they propose a stochastic budgeting model. They determine that Miscanthus is less risky than willow to produce in Europe. Osmani and Zhang [24] maximize the profit of lignocellulosic biofuel supply chain by proposing a two-stage stochastic optimization model. They also simultaneously minimize carbon emissions. It is shown that financial and environmental benefits decrease as uncertainty increases. Sharma et al. [25] develop a stochastic integer optimization model in order to maximize the net return of the technological investments. They also utilize Monte Carlo simulation to quantify the return of investment. You [26] also proposes a stochastic MILP in order to minimize the annualized cost of the supply chain while deciding the network design.

Biomass seasonality and demand uncertainty are considered during decision making. The proposed models are applied to two case studies in the state of Illinois. Similarly, in order to maximize profit, Awudu and Zhang [27] propose a stochastic linear programming model utilizing the Benders decomposition technique and applying the model in North Dakota. Another study by Xie et al. [28] proposes a mixed-integer programming model in order to minimize the lignocellulosic biofuel supply chain. Feedstock supply is considered as the uncertain parameter in the model development. Tactical decisions along with strategic decisions, such as location of the facility, are optimized.

Dynamic programming studies have also been done in the biofuel supply chain area. Dal-Mas et al. [29] propose a dynamic MILP model to minimize the financial risks of investment. Price of the biomass source, which is corn, and selling price of the biofuel are considered in the model development. They demonstrate the model's applicability of with a case study in Italy. Sokhansanj et al. [30] propose a dynamic programming model for operational-level decisions for biomass supply and logistics. Their model includes dry matter loss and weather conditions, which affect moisture content. A case study on corn stover is presented for applying the model. In addition to dynamic programming, some researchers use simulation to analyze the biofuel supply chain. Khanna et al. [31] incorporate a simulation model with a dynamic, nonlinear mathematical program in order to design the biofuel supply network. They allocate two land types for the production of cellulosic crops such as wheat straw, switchgrass, Miscanthus, and corn stover under various cost scenarios. Zhang et al. [32] develop a simulation model as a management tool in the biofuel supply chain. They decide on facility location, inventory, and logistics design while considering GHG emissions as a performance criterion. They also include

harvesting, transportation, and storage in their simulation model. In a similar manner, Mobini et al. [33] develop a simulation model for the forest-based biomass. They define the cost of logistics by also analyzing the CO_2 emitted during the supply chain. However, in this model, biomass is used for power generation instead of biofuel production.

1.5 Motivation and Objectives

In this chapter, we review articles in the literature regarding second-generation bioenergy and biofuel crops. Our paper classifies the studies done so far in terms of research areas, such as production, supply chain, and environment. At the same time, we cluster the articles in terms of the modeling, including deterministic and probabilistic models. In addition, we identify future areas that require further investigation. This literature review may help researchers by providing them with a general overview of the studies conducted in biomass and biofuel supply chains of energy crops.

A histogram with respect to the integration of modeling and the research area is displayed in Figure 1.3.

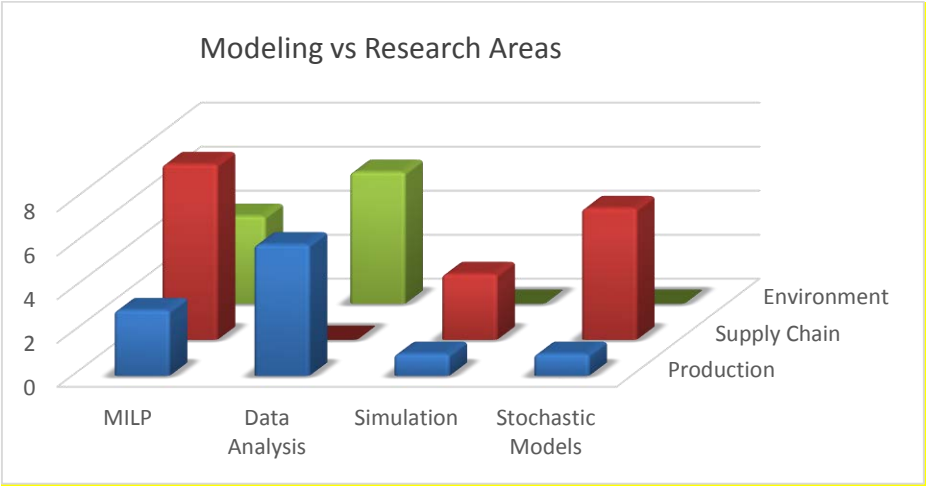

Figure 1.3 Deployment of reviewed studies.

It helps to determine the missing combination of methods and areas to be investigated in the future. As shown, the majority of studies focus on the supply chain and MILP models. There are also a considerable number of studies regarding data analysis in the fields of environmental studies and biomass production. However, few simulation and probabilistic models are developed in order to analyze the environmental effects of biomass and the biofuel supply chain.

We have seen that studies on biomass production focus on the cost of production operations at the farm level. Many researchers conduct field experiments or make data calculations in order to define values of the parameters such as yield amount, transportation cost, fertilization requirement, and production cost. Studies on the supply chain of biofuels generally utilize MILP models to design the network and make optimum decisions. Some of them also consider environmental effects of the biofuel supply chain. On the other hand, most studies on environmental analysis depend on data analysis, particularly field experiments. Environmental aspects are included in some MILP models. However, there is a need for studies that particularly optimize environmental outcomes. For example, we have not encountered any studies in our literature review that determine the effects of fertilization on the environment. When we review stochastic models, we observe that the majority of studies focuses on the supply chain of biofuel. There is also a need for studies that will combine the environmental analysis with stochastic models. Similarly, very few of the reviewed studies solve problems with respect to biomass production using stochastic models.

1.6 Summary of Chapters

Biofuel production from second-generation feedstock has become critical due to environmental concerns and the need for sustainable energy supply. Biofuels derived from cellulosic (energy) crops offer positive environmental impacts, such as enriching degraded soils through carbon sequestration and soil erosion prevention. The second chapter of this dissertation provides a unique optimization approach of quantifying and formulating the economic and environmental benefits of switchgrass production at the farm level. In particular, we propose a multi-objective mixed-integer programming model, which maximizes the revenue from harvested switchgrass biomass and the economic value obtained from the positive environmental impacts of switchgrass yield during a ten-year planning horizon. Environmental impacts include soil erosion prevention, sustainability of bird populations, carbon sequestration, and carbon emissions, while economic impacts are analyzed under various budget, yield, and sustainability scenarios. The proposed model is then applied to a case study in the state of Kansas. Results show that given current market prices, switchgrass cultivation on grassland and cropland is highly profitable. The model results also suggest that if utilized by the government, Conservation Reserve Program (CRP) incentives could make marginal land more favorable over cropland. We perform a sensitivity analysis to address uncertainty in the budget, yield, and utilization of cropland, and present insights into the economic and environmental impacts of switchgrass production. This model can also be extended to biomass production from any other types of energy crops to identify the most efficient production planning strategies under various management scenarios.

Biofuel production from food crops also leads to debates about the increase in food prices and security of the food supply. Therefore, in the third chapter of this dissertation, we develop a multi-objective mixed-integer optimization model to investigate the trade-offs and competition between biofuel and food production using switchgrass and corn. This model maximizes total economic and environmental benefits, and provides optimal decisions regarding land allocations to food and energy crops, seeding time, harvesting time and amount, and budget allocations to farm operations. A piecewise linear lower approximation is developed to linearize the nonlinear revenue curve of corn grain sales. Spatio-temporal environmental impacts such as soil erosion prevention, carbon sequestration and emissions, and nitrogen pollution are included in the model, which simultaneously satisfies the security of the food supply and biodiversity of bird populations. Important insights are obtained by applying the model in Kansas and performing a sensitivity analysis. These results indicate that switchgrass is more profitable than corn in cropland, while it requires CRP incentives for production on marginal land unless priority is given to the environment. Results also imply that corn is not as environmentally friendly as switchgrass on cropland because the loss from soil erosion and N pollution is greater than any savings via carbon sequestration when corn is produced. In order to ensure food security, our study advises managers and policy makers to provide CRP incentives or to adjust the sustainability factor, which restricts cropland availability for biofuel production. Our spatio-temporal optimization model can also be adapted to different regions with alternative energy and food crops under various management scenarios.

Selection of the best biomass crop type is another critical choice for decision makers since each crop type has various environmental, economic, and social impacts. The conflicting

criteria involved in the selection of optimal crop type for biofuel production leads to a multi-criteria decision analysis (MCDA) problem. Therefore, in the fourth chapter of this dissertation, we determine criteria for DMs and farmers to select the most sustainable biomass crop for biofuel production. In this method, literature and expert views are utilized to obtain selection criteria and build up the evaluation model. We propose a stochastic analytic hierarchy process (SAHP) method in the establishment of the MCDA and identify weights of the determined criteria. The most important criteria for biomass crop selection are identified as economic, environmental, and social, with 0.59, 0.26, and 0.15 weights, respectively. We demonstrate the application of the proposed model with a set of available biomass alternatives in Kansas. Our model favors energy crops and choses switchgrass as the most sustainable biomass crop among other alternatives for ethanol production. The sensitivity analysis indicates that the score of wheat crop increases because the economic factor is weighted heavily in decision making. Our analysis also shows that switchgrass becomes more favorable than other alternatives as environmental factors are emphasized in biomass crop selection.

The multi-variable biomass and food production (BFP) problem that is faced by farmers and co-operations is further complicated by uncertainties in crop yield and prices. In the fifth chapter of this dissertation, we present a two-stage stochastic mixed-integer programming (MIP) model that maximizes the economic and environmental benefits of food and biofuel production. The uncertain parameters of yield amount and price level are calculated using real data. The economic aspects include revenue obtained from sales as well as costs related to seeding, production, harvesting, and transportation operations at the farm level. The environmental effects include GHG emissions, carbon sequestration, soil erosion, and N leakage

to water. The first-stage variables define binary decisions for allocating various land types to food and energy crops, while second-stage variables are operational decisions related to harvesting, budget allocation, and amounts of different yield types. We customize the Benders decomposition algorithm for solving this stochastic MIP problem. The computational efficiency of the proposed model is demonstrated with its application on a real case study by considering switchgrass and corn production in the state of Kansas. We measure the solution quality and speed of the decomposition method over stochastic and deterministic models. Results indicate the significance of using the stochastic yield-level information in an optimization model. The proposed stochastic MIP model provides important strategies and insights into biofuel and food production decision making under uncertainty.

1.7 Main Organization of PhD Dissertation

This PhD dissertation is organized by chapters corresponding to published journal papers. Four topic areas correspond to Chapters 2 to 5. Chapter 2 provides an optimization model for economic and environmental analysis of switchgrass-based biomass production. Chapter 3 analyzes the land-use competition between food and biofuel competition based on a mathematical model. Chapter 4 presents a stochastic multi-criteria decision analysis model for the biomass crop selection problem. Chapter 5 proposes the two-stage stochastic programming approach for solving the food and biofuel production problem. Chapter 6 concludes the dissertation and provides the opportunities for future work.

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CHAPTER 2

A MIXED-INTEGER OPTIMIZATION MODEL FOR THE ECONOMIC AND ENVIRONMENTAL ANALYSIS OF BIOMASS PRODUCTION

2.1 Introduction

Growing energy demand and related environmental concerns have motivated researchers to find alternative ways of energy production. The long-term inadequacy of fossil fuels and high greenhouse gas emissions require the use of sustainable and environmentally friendly energy sources. Biofuel is promoted as one of the most important substitutes for fossil-fuel-based energy, among other renewable energy sources [1], [2].

Biofuel is currently used in transportation and can be derived from various biomass resources, including food crops such as corn, wheat, soybeans, and sugarcane, as well as lignocellulosic biomass feedstock, known as energy crops [3]. However, biofuel production from food crops generates debate about security of the food supply and soil acidification as a result of their high fertilization needs. These potential negative impacts motivate researchers to enhance biofuel production from non-food crops (second-generation energy crops) that have low carbon emissions and low fertilization requirements. Consequently, the updated Renewable Fuel Standards (RFS2) in 2007 requires the annual use of 136 hm^3 of biofuels in 2022, while at least 60 hm^3 of this amount must be from second-generation energy crops [2]. Switchgrass (*Panicum virgatum*), a perennial warm-season grass native to North America, is one of the favorable lignocellulosic biomass types because of its environmental benefits, such as soil erosion prevention, low-fertilization requirement, reduction in GHG emissions, tolerance to

drought and variable soil conditions, and improvement of soil productivity via carbon sequestration, in addition to its high energy yield [4].

Biofuel production from switchgrass biomass includes a number of sequential activities, such as land selection and preparation, seeding and fertilization for establishment, harvesting, biomass transportation, and conversion to ethanol in a biofuel production facility, as shown in Figure 2.1. Numerous decision alternatives with many trade-offs arise during this process. For example, the selection of land type for switchgrass cultivation impacts production cost and harvested biomass. Although cropland has a higher biomass yield, the rental cost of these lands is also high. Moreover, seeding time affects the seeding method to be used, thus resulting in various establishment cost scenarios. In addition, seeding, fertilization, and harvesting decisions are made based on a limited budget. Since biofuel production includes some conflicting trade-offs, as stated previously, and is a complex decision-making process by nature, compact decision support systems need to be established. In this paper, we propose an optimization model, which should provide maximum economic value from switchgrass-based biofuel production while accounting for environmental as well as economic constraints.

Figure 2.1 Operation types included in biofuel production from switchgrass.

In the literature, a significant number of studies focus on supply chain optimization for biofuel production, whereas very few studies explicitly include an analysis of switchgrass-based biomass production at the farm level in a mathematical model. Eksioglu et al. [5] develop a

mixed-integer linear programming model for the design and management of a biomass-to-biorefinery supply chain. Decision variables include the number, size, and location of biorefineries, with a constraint on the availability of the lignocellulosic biomass. The model is then applied to a case study in the state of Mississippi. Parker et al. [6] consider the effects of policy and technology changes via an analysis of the MILP model for the biofuel supply. They maximize the total profit of the feedstock supplier and fuel producer while determining optimal locations, technology types, and sizes of biorefineries. They also combine a geographic information system with the proposed model. Papapostolou et al. [7] develop an MILP model for a biofuel supply chain that exports important raw materials and biofuels while considering both technical and economic parameters. Similarly, An et al. [8] present a model to design a lignocellulosic biofuel supply chain system with a case study based on a region in central Texas. Their model also determines the technology type to be used for conversion in facilities and examines switchgrass as feedstock, assuming that there is always an available biomass supply. Čuček et al. [9] consider environmental and economic footprints while developing a multi-criteria optimization model of a regional biomass energy supply chain. Akgul et al. [10] propose an economic optimization model for an advanced biofuel supply chain in the United Kingdom. Their MILP model considers sustainability factors related to food supply and land use, while including strategic decisions such as locating biorefineries, biofuel production rate, and total supply chain cost. Zhang et al. [11] present an MILP model that minimizes the cost of a switchgrass-based ethanol supply chain. They consider switchgrass cultivation only on marginal land and different harvesting methods, in order to define biorefinery capacity and locations, biofuel production volume, and the amount transported to the demand points.

Other than optimization models, simulation methodology has also been employed in some studies, such as that of Zhang et al. [12]. They propose a simulation model of a biomass supply chain for biofuel production by minimizing the cost of feedstock, energy consumption, and GHG emissions associated with harvesting and transportation activities. Ebadian et al. [13] integrate simulation with an optimization model to analyze an agricultural biomass supply chain for cellulosic ethanol production focusing on storage systems. They employ an MILP optimization model to find the number of storage facilities, farms to contract, their locations, and the assignment of farms to storage facilities. In addition, they present a simulation model in order to make more operational decisions such as storage capacity, daily working hours, required equipment, and logistic costs.

The biofuel supply chain has been extensively examined in the literature as stated above, and many of these efforts have identified and quantified all interrelated parameters. However, we have not found any study providing an optimization model and a detailed analysis of switchgrass production at the farm level. In addition, although environmental impacts of biomass production such as soil erosion, bird population, carbon sequestration, carbon emissions, and sustainability of the food supply have been investigated in various papers (see, e.g., [14], [15]), these important features of biomass production have not been formulated simultaneously in an optimization model in order to be analyzed in a decision framework. Therefore, research is needed to incorporate these important environmental impacts into a mathematical decision model.

In this chapter, we formulate a multi-objective MILP model that considers the positive environmental impacts of switchgrass biomass production and maximizes the economic value

obtained from switchgrass-based biomass during its entire life cycle. The model incorporates the economic impacts of switchgrass-based biomass production such as the cost of establishment, production, harvesting, and transportation, and determines the optimal distribution of budget among operations and years, the allocation of land, seeding time, and harvesting amount and time of biomass to be used for ethanol production in a biorefinery.

In addition, the proposed mathematical model contributes to the state of the art by considering the following aspects:

- To our knowledge, none of the reviewed literature considers the seeding scenario, including seeding season and seeding method. Each seeding scenario has a different cost and leads to various yield amounts. The proposed model determines the best seeding scenario including seeding season and seeding method in order to produce the maximum amount of yield given a limited budget.
- Again, to the best of our knowledge, none of the previous work considers the environmental contributions of switchgrass in a biomass production optimization model. As stated by Hartman et al. [16], switchgrass cultivation can be considered on degraded and marginal lands that are in a conservation reserve program since switchgrass can restore soil quality by increasing its organic carbon content. In addition, having a very strong root system, switchgrass prevents soil erosion significantly, which in turn provides savings from reduced loss of fertile soil. The proposed model incorporates switchgrass production on productive as well as degraded land and analyzes its positive impacts on soil-erosion prevention.

- This study also fills the gap of investigating and controlling the effect of harvesting patterns on grassland bird populations. It has been shown that rotational harvesting is required in order to provide a nesting area to birds during winter ([16], [17]). Our model handles the sustainability of bird and wildlife populations by providing them available habitats through limiting the number of harvested regions.
- In the literature, land allocation is defined with respect to the amount of area needed for cultivation, and in most cases, cropland is used for the cultivation of biomass crops. The model proposed by An et al. [8] determines the biomass amount required, where biomass is assumed to be provided from cropland and lands in a CRP. On the other hand, Zhang et al. [11] limit the cultivation of switchgrass production to only marginal land. Our model is differentiated from others by leaving the choice of land type to decision makers (landowners), since they can control cropland, grassland (pastureland), and marginal land in coordination. The model also enables DMs to quantify the availability of cropland to be used for switchgrass cultivation by incorporating a sustainability factor in the land-usage constraints.
- In this model, we have calculated the establishment cost for various seeding scenarios and production cost, which depend on the rental cost and the amount of fertilizers used. Furthermore, the savings from soil erosion prevention and CO_2 retained via soil carbon storage, which are not directly available in the literature, are calculated by incorporating a couple of sources. Therefore, this chapter also provides compact data for researchers looking for various aspects of environmental and economic input and output of switchgrass biomass production.

- In the literature, many constraints are not directly available: growth function of the switchgrass population; cost of production including fertilizers; harvesting cost including cost of mowing, raking, baling, staging, and loading; as well as the limitation of harvested areas to ensure sustainability of bird populations. In order to incorporate these constraints into our optimization model, we have generated formulations by evaluating the research-based instructions and data available in the literature. Although we have established the model particularly for switchgrass, it can also be used as a basis for and applied to biomass production from any other types of energy crops.

The remainder of this chapter is organized as follows. The problem is defined in section 2.2, while the mathematical model is described in detail in section 2.3. The calculation of input parameters and the application of the model to a real case study in Kansas are presented in section 2. 4. All computational results for the base case scenario and sensitivity analyses are given in section 2.5. Finally, some concluding remarks with future directions are provided in section 2.6.

2.2 Problem Statement

We focus on the following echelons for the switchgrass-based biofuel production shown in Figure 2.1: land allocation, establishment, biomass production, biomass harvesting, and biomass transportation to biorefinery. The land types to be allocated for switchgrass cultivation include cropland, grassland, and marginal land. Cropland defines the productive land where food crops are cultivated. Grassland is considered to have semi-productive soil covered by grasses. Marginal land refers to arid, degraded soil and lands that are in a CRP. After land type is determined, a seeding season (frost and spring) and a suitable seeding method (airflow, drill,

and no-till drill) are decided. Harvesting, which includes mowing, raking, baling, staging, and loading, is performed by late September. Finally, the harvested switchgrass biomass is transported to a biorefinery to be converted into bioethanol.

The objective of the mathematical model is to maximize the total economic value obtained from switchgrass biomass production while determining the optimal decision strategies for the following:

- Land allocation (seeding zones) for switchgrass cultivation.
- Seeding time along with seeding scenario to be implemented.
- Biomass cultivated zones to be harvested and time for harvesting.
- Amount of harvested switchgrass in a related zone at the time of harvesting.
- Allocation of budget to various farm operations (seeding, production, harvesting, and transportation).

2.2.1 Notation and Assumptions

Depending on the equipment used, the estimation of harvesting cost can vary considerably. The type of bale (large round or large square) also affects the cost. For the budget estimations in this chapter, we consider harvesting in large square bales weighing 397 kg each, which are easy to transport and store ([18], [19]).

Studies show that multiple harvesting in the same year decreases the total amount of biomass since the root system is weakened ([19], [20]). Therefore, single harvesting, which is suggested immediately after the first killing frost, is used in this model because it is stated to be the most economical and environmentally friendly harvesting method ([11]).

It has been shown that bioethanol producers prefer to obtain their biomass supply from within a 80-km radius of the biorefinery, due to the high cost of transporting bulky biomass [5]. Therefore, this study aims to maximize the economic value of switchgrass production, given that a predetermined facility is located in close proximity to the cultivation area.

Nomenclature

Indices

i Row of cultivation zone

j Column of cultivation zone

(i, j) Switchgrass cultivation zone

k Switchgrass seeding scenario

t Time period

l Transportation mode

Sets

I Set of rows of cultivation area

J Set of columns of cultivation area

K Set of seeding scenarios

T Set of time periods in planning horizon

L Set of transportation modes

M_t Set of time periods from the first period to period t ($M_t = \{1, \dots, t\}$)

CR Set of cultivation zones on croplands in cultivation area

Binary Decision Variables

$S_{ijk}(t)$ 1 if zone (*i*,*j*) is seeded at time period t with seeding scenario k, and 0 otherwise.

$X_{ij}(t)$ 1 if zone (*i,j*) is harvested at time period *t*, and 0 otherwise.

Continuous Decision Variables

$N_{ij}(t)$ Switchgrass yield in zone (*i,j*) at time period *t* (t)

$\bar{N}_{ij}(t)$ Harvested switchgrass biomass in zone (*i,j*) at time period *t* (t)

E_b Establishment budget ($)

P_b Production budget ($)

H_b Harvesting budget ($)

T_b Transportation budget ($)

Parameters

$P(t)$ Sale price of switchgrass at time period *t* ($ t^{-1})

SE_{ij} Soil erosion prevention economic value of switchgrass in zone (*i,j*) in each period ($)

CS_{ij} Carbon sequestration economic value of switchgrass in zone (*i,j*) in each period ($)

σ_k Carbon emissions penalty for seeding scenario *k* ($)

ρ Carbon emissions penalty for production and harvesting ($)

ω Carbon emissions penalty specific for yield production and operations ($ t^{-1})

τ Carbon emissions penalty for biomass transportation ($ t^{-1} km^{-1})

α Weight of switchgrass sales

β Weight of soil erosion prevention value

μ Weight of savings from the reduction of GHG emissions via carbon sequestration

A_{ij} Potential switchgrass yield from zone (*i,j*) (t)

π_t Growth factor of switchgrass after *t* years of establishment

Δ Fraction of facility capacity assigned to biomass from switchgrass

Cap_t Biomass capacity of facility at time period *t* (t)

TEC_k Total expected establishment cost for seeding scenario *k* ($)

MC_k Machinery cost for seeding scenario *k* ($)

SC_k Seeding cost for seeding scenario *k* ($)

FC_k Fertilization cost for seeding scenario *k* ($)

PC_k Pesticide cost for seeding scenario *k* ($)

REC_k Re-establishment cost of seeding scenario *k* ($)

R_k Re-establishment probability of seeding scenario *k*

ψ Fixed cost of switchgrass production per cultivation zone ($)

γ Variable cost of switchgrass production ($ t^{-1})

RC_{ij} Rental cost of cultivation zone (*i,j*) ($)

δ Fixed cost of harvesting per zone ($)

θ Variable cost of harvesting ($ t^{-1})

D_{ij} Distance of zone (*i,j*) to facility (km)

F_l Fixed cost of transportation mode *l* ($)

V_l Variable cost of transportation mode *l* ($ t^{-1} km^{-1})

A_b Total available budget in the planning horizon ($)

λ Sustainability factor defining the percentage of cropland, which is not allowed for biomass production

2.3 Mathematical Modeling

A mixed-integer linear programming model is formulated with the objective of maximizing economic values obtained from switchgrass-based biomass production as well as its beneficial environmental impacts. The optimal levels for various decisions regarding seeding and harvesting time periods and cultivation areas are determined by solving the MILP model. A detailed explanation of the objective function and the constraints of the proposed model are provided in the following sections.

2.3.1 Objective Function

The objective of the proposed model is the maximization of the weighted sum of the total economic value obtained from switchgrass production. The total economic value (*TEV*) includes revenue to be obtained from the sales of switchgrass biomass (*TB*), economic value of soil erosion prevention (*TS*), and savings from the reduction of GHG emissions via carbon sequestration (*TC*), as indicated by

$$TEV = \alpha TB + \beta TS + \mu TC \tag{2.1}$$

All terms are multiplied by α, β, and μ, respectively, in order to assign priorities of the decision maker, where the sum of α, β, and μ equals 1. The first term, direct revenue of the farmer from the sales of biomass production, is calculated as

$$TB = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \bar{N}_{ij}(t) P(t) \tag{2.2}$$

where $\bar{N}_{ij}(t)$ is the amount of harvested switchgrass biomass in zone (*i,j*) at time *t*, and *P(t)* is the sale price of switchgrass biomass at time *t*.

We also need to consider the cost of soil erosion to landowners and farmers. In most cases, farmers rent land from owners. Independent of whether the farmer is the owner or not, more fertilizer is needed to compensate for the impact of soil erosion, and eventually land value decreases due to loss of productivity. Studies show that growing switchgrass reduces soil erosion significantly ([21], [22]). Therefore, the second term represents savings from soil erosion via switchgrass cultivation as

$$TS = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \frac{N_{ij}(t)}{A_{ij}} SE_{ij} \tag{2.3}$$

where the ratio of $N_{ij}(t)$ to A_{ij} is the percentage of switchgrass yield grown at time *t* with respect to the potential yield in zone (*i,j*), and SE_{ij} is the economic value of the soil erosion prevention in zone (*i,j*) in each period.

Finally, since the storage of atmospheric CO_2 as soil organic carbon (SOC) increases the soil quality and since carbon sequestration can be potentially used as savings in carbon emission trading systems, the net CO_2 sequestration is also evaluated as a benefit of switchgrass cultivation ([23], [24]). The last term, *TC*, savings from net carbon emission reduction, is calculated by

$$TC = \sum_{ijt} \left(\frac{N_{ij}(t)}{A_{ij}} CS_{ij} - \sum_{k} S_{ijk}(t)\sigma_k - X_{ij}(t)\rho - \bar{N}_{ij}(t)(\omega + D_{ij}\tau) \right) \tag{2.4}$$

where CS_{ij} is the economic value of carbon sequestered in zone (*i,j*) in each period, σ_k is the carbon emissions penalty for seeding scenario *k*, ρ is the carbon emissions penalty for production operations depending on harvesting, ω is the carbon emissions penalty for production operations depending on yield, and, τ is the carbon emissions penalty for transporting harvested biomass.

2.3.2 Production Constraints

Total switchgrass amount grown in zone (*i,j*) in year *t*, $N_{ij}(t)$, is defined as

$$N_{ij}(t) = \sum_{k \in K} \sum_{z \in M_t} A_{ij} \pi_{t-z+1} S_{ijk}(z) \quad \forall i, j, t \tag{2.5}$$

where A_{ij} is the potential switchgrass yield in zone (*i,j*), $S_{ijk}(t)$ is the binary variable defining seeding scenario *k* in zone (*i,j*) at time *t*, and π_{t-z+1} is the switchgrass growth factor. It takes three years for switchgrass to reach its potential yield [19]. Therefore, π_{t-z+1} shows the portion of potential switchgrass yield reached by time period *t*, where *z* represents the time period of seeding.

The total number of seedings at each zone (*i,j*) is limited to one, and only one seeding scenario *k* can be used through period *t*

$$\sum_{t \in T} \sum_{k \in K} S_{ijk}(t) \le 1 \quad \forall i, j \tag{2.6}$$

Harvesting at each zone (*i,j*) at time *t* can only be made if that zone is already seeded through time period *t* by any seeding scenario *k* as

$$X_{ij}(t) \le \sum_{k \in K} \sum_{h \in M_t} S_{ijk}(h) \quad \forall i, j, t \tag{2.7}$$

Harvested switchgrass biomass in zone (*i,j*) at time period *t*, $\bar{N}_{ij}(t)$, cannot exceed the amount of switchgrass grown, $N_{ij}(t)$, in that zone

$$\bar{N}_{ij}(t) \le N_{ij}(t) \quad \forall i, j, t \tag{2.8}$$

On the other hand, the harvested switchgrass biomass in zone (*i,j*) at time period *t* can be, at most, equal to the potential switchgrass yield of zone (*i,j*), if $X_{ij}(t)$ is set to 1. If there is no harvest at time *t*, *i.e.*, if $X_{ij}(t)$ is set to zero, then $\bar{N}_{ij}(t)$ is zero:

$$\bar{N}_{ij}(t) \le A_{ij} X_{ij}(t) \quad \forall i, j, t \tag{2.9}$$

The total amount of the harvested biomass in each period is limited by the capacity of the facility:

$$\sum_{i \in I} \sum_{j \in J} \bar{N}_{ij}(t) \le \Delta Cap_t \quad \forall t \tag{2.10}$$

where Δ is the fraction of facility capacity assigned to biomass from switchgrass, and Cap_t is the biomass capacity of the facility at time period t.

2.3.3 Budget Constraints

The budget assigned for establishment, E_b, is defined by the total establishment cost of seeding in all zones (i,j) for all seeding scenarios k in the planning horizon as

$$E_b = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} TEC_k S_{ijk}(t) \tag{2.11}$$

where switchgrass establishment cost, TEC_k, is the sum of machinery, seeding, fertilization, and pesticide costs for seeding scenario k, as well as the expected re-establishment cost, REC_k, of a failed establishment trial. In order to find the expected establishment cost, REC_k is multiplied by R_k, the probability of establishment failure for seeding scenario k. Then TEC_k is used as an input and computed as

$$TEC_k = MC_k + SC_k + FC_k + PC_k + REC_k R_k \quad \forall k \tag{2.12}$$

The budget assigned for production, P_b, is defined by the total production cost of switchgrass cultivation as

$$P_b = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} ((\psi X_{ij}(t) + \gamma \bar{N}_{ij}(t)) + \sum_{k \in K} \sum_{h \in M_t} S_{ijk}(\mathrm{h}) RC_{ij}) \tag{2.13}$$

where ψ is the fixed cost of nitrogen application, and γ is the variable cost for phosphorus (P) and potassium (K) applications, since a fixed amount of N after harvesting and variable amounts of P and K for each tonne of harvested biomass are suggested for the best production practices of switchgrass ([19], [18]). The term RC_{ij}, the rental cost of zone (i,j), is multiplied by the seeding decision variable, which becomes 1 if switchgrass is seeded in that zone, and 0 otherwise.

Similarly, the budget assigned for harvesting, H_b, is defined by the overall cost of harvesting as

$$H_b = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} (\delta X_{ij}(t) + \theta \bar{N}_{ij}(t)) \tag{2.14}$$

where the total harvesting cost consists of the fixed cost, δ, of harvesting, and variable cost, θ , which depends on the amount of harvested switchgrass biomass. Mowing and raking have a fixed cost per harvested zone, while the cost of baling, staging, and loading depends on the harvested switchgrass biomass ([19]).

Various available transportation modes can be used to transport biomass to the biorefinery facility. The budget assigned for transportation, T_b, is defined as the total expenses related to transportation as

$$T_b = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \sum_{l \in L} (F_l X_{ij}(t) + V_l D_{ij} \bar{N}_{ij}(t)) \tag{2.15}$$

where F_l is the fixed cost incurred for the chosen transportation mode l, if zone (i,j) is harvested, and V_l represents the variable cost of mode l, which depends on the distance to the biorefinery and the harvested biomass amount ([19]).

The total cost of farm operations—establishment, production, harvesting, and transportation—which are given in detail in equations (2.11) to (2.15), cannot exceed the total available budget, A_b, in the planning horizon, as given below:

$$E_b + P_b + H_b + T_b \leq A_b \tag{2.16}$$

Equation (2.16) is formulized in the model in order to determine the value of optimal budget allocation to establishment, production, harvesting, and transportation operations.

2.3.4 Environmental Constraints

We formulate environmental constraints, considering the ecological consequences of switchgrass production, with the purpose of maintaining biodiversity and providing food supply safety.

The following constraint is introduced to the model to sustain continuity and diversity of bird populations

$$\sum_{m=i-1}^{i+1} \sum_{n=j-1}^{j+1} (1 - X_{mn}(\mathrm{t})) \geq X_{ij}(t) \quad \forall i, j, t \tag{2.17}$$

Constraint (2.17) ensures that if zone (i,j) is harvested, then one of its neighbor zones should remain unharvested in each time period t to ensure a nesting area for birds during winter. It has been also stated that diversity of bird species increases only when there is a mixture of harvested and unharvested fields in a region, since shortgrass bird populations grow on harvested fields, while tallgrass bird populations can survive better on unharvested fields ([16], [17]).

For sustainability of the food supply, a particular percentage of cropland should be kept for food crop production. Zones to be converted to energy crop production cannot exceed the allowable share, 1–λ, of cropland:

$$\sum_{(i,j)\in CR}\sum_{k\in K}\sum_{t\in T} S_{ijk}(t) \le (1-\lambda)\,|CR| \tag{2.18}$$

where |CR| refers to the cardinality of the set of croplands.

2.4 Case Study

The MILP model explained in section 2.3 is applied to the case of a biofuel production project in Hugoton, Kansas. This project was announced by the United States Department of Agriculture (USDA) as one of the Biomass Crop Assistance Program projects in 2011. The proposed area to be used for biomass production from switchgrass is up to 8,094 ha and is sponsored by Abengoa Bioenergy LLC. This planned biorefinery has 95 hm^3 of cellulosic ethanol capacity through the conversion of 330,000 t of crops ([25], [26]). We assume an ample capacity for the biorefinery, which does not limit the biomass production, where full capacity is assigned to biomass obtained from switchgrass. The cultivation area surrounding the biorefinery in the center of Hugoton has three different soil types: cropland, grassland, and CRP land, which we consider as marginal land in this study. The total area is divided into 21 by 21 rectangular arrays, leading to 441 zones, each 2.59 km^2 (1 square mile) in size. A total of 11 seeding scenarios are evaluated in this case study. Since the expected life of switchgrass is at least ten years, in order to obtain the maximum utilization of the investment on switchgrass production, the planning horizon is considered to be ten years [29]. The other necessary input parameters used in the model are provided with detailed explanations in the next section.

2.4.1 Input Parameters

In this section, we present the data collected from various resources in order to formulate our case study. Since we have different land types and seeding scenarios, for some parameters, we have consulted a combination of various publicly available sources in order to gather and calculate the data. The next subsections include those references that we have used for the purpose of data collection. This section also provides a valuable asset to researchers looking for compact data in this field.

2.4.1.1 Seeding Scenarios and Yields

Seeding scenarios and corresponding yield amounts for each scenario in different years are given in Table 2.1.

TABLE 2.1 SEEDING SCENARIOS AND CORRESPONDING YIELD AMOUNTS

Seeding scenario	Seeding scenario characteristics			Yield (t ha^{-1})		
	Land type	Seeding season	Seeding method	t=1	t=2	t=3–10
1	Cropland	Frost	Airflow	3.75	10	15
2	Grassland	Frost	Airflow	2.63	7	10.5
3	Cropland	Spring	Airflow	3.75	10	15
4	Cropland	Spring	Drill	3.75	10	15
5	Cropland	Spring	No-till drill	3.75	10	15
6	Grassland	Spring	Drill	2.63	7	10.5
7	Grassland	Spring	No-till drill	2.63	7	10.5
8	Marginal land	Frost	Airflow	1.87	5	7.5
9	Marginal land	Spring	Airflow	1.87	5	7.5
10	Marginal land	Spring	Drill	1.87	5	7.5
11	Marginal land	Spring	No-till drill	1.87	5	7.5

Seeding scenarios are defined by three characteristics: land type, seeding season, and seeding method. Land type includes cropland, grassland, and marginal land. There are two available seeding seasons: frost seeding and spring seeding. For seeding method, airflow and no-till drill are used as modern seeding methods because they lead to low soil erosion and less carbon

emissions, in contrast to drill seeding, which is used as the conventional (traditional) seeding method. In this study, we add four seeding scenarios of marginal land to those seven scenarios provided for cropland and grassland by Duffy and Nanhou [18].

The amount of switchgrass yield is mostly affected by land type and time passed since the establishment. Various yield amounts, ranging from 10–20 t ha^{-1} y^{-1}, are estimated for cropland. In this case study, for cropland, we use an average value, 15 t ha^{-1} y^{-1}, as the potential yield, which is a practical amount in Kansas ([27], [28]). We also consider lower and upper bound values on the yield level in the computational experiments in order to investigate the impact of possible changes in yield level. The potential switchgrass yield is reached at the third year after establishment [19]. The first-year switchgrass yields may only be 25% of the potential yield. In the second year of establishment, biomass yields can reach 66% of the potential yield, based on the discussion by Garland et al. [29] and West and Kincer [30]. For instance, in order to obtain the yield amount in cropland in the first year, the potential yield (15 t) is multiplied by 25%, thus leading to 3.75 t, while in the second year, it is multiplied by 66% to calculate the yield amount. On the other hand, the yield of grassland and marginal land drops to 70% and 50%, respectively, of that in cropland [31]. For instance, to compute the amount of switchgrass yield in marginal land in the first year, 3.75 t is multiplied by 50%.

2.4.1.2 Establishment Cost and Selling Price

Data regarding the establishment and re-establishment costs for various scenarios are provided in Table 2.2 ([18], [19]). The selling price of switchgrass is taken as \$120 t^{-1} [32], while establishment cost depends on many variables such as machinery, seed, fertilizer, and pesticide costs. In machinery cost, grassland seeding scenarios (2, 6, and 7) include the cost of additional

Roundup® spraying to prepare the land for cultivation. Pure live seed (PLS) in the amounts of 6.7 kg ha^{-1} and 5.6 kg ha^{-1} is used for frost seeding and spring seeding, respectively, on both cropland and grassland. PLS in the amounts of 11.2 kg ha^{-1} and 8.9 kg ha^{-1} is used for frost and spring seeding, respectively, on marginal land. Phosphorus in the amount of 33.6 kg ha^{-1} and potassium in the amount of 44.8 kg ha^{-1} are applied for establishment. Nitrogen fertilizer is usually not applied during the seeding year because this tends to stimulate weed growth more than switchgrass growth. Atrazine and 2,4-D pesticides are used on all types of lands.

TABLE 2.2 SWITCHGRASS ESTABLISHMENT, RE-ESTABLISHMENT, AND TOTAL EXPECTED ESTABLISHMENT COSTS

Seeding scenario	Establishment cost (\$ ha^{-1})	Re-establishment cost, REC_k (\$ ha^{-1})	Total expected establishment cost, TEC_k (\$ ha^{-1})
1	407.15	112	435.15
2	417.77	112	445.77
3	416.84	112	472.84
4	589.35	121.4	650.05
5	505.60	116	563.60
6	599.97	121.4	660.67
7	516.62	116	574.62
8	446.80	112	474.80
9	426.53	112	482.53
10	599.97	121.4	660.67
11	516.62	116	574.62

Re-establishment is required if there are not enough switchgrass stands a year later than seeding. Re-establishment cost consists of seeding, fertilizer, pesticide, and machinery costs. Since Roundup® is already used for land preparation in establishment, it is not included in the re-establishment cost. The probability of re-establishment is taken as 25% for frost seeding and 50% for spring seeding scenarios, as suggested in the literature [18]. Re-establishment cost is multiplied by the corresponding probability values and added to the establishment cost in order to compute the expected cost of establishment.

2.4.1.3 Production Cost

Annual production cost includes rental, fertilizer, and pesticide costs. Average land rental costs for one hectare of cropland, grassland, and marginal land in southwest of Kansas are $234.6, $23.7, and $75.3 [33], respectively. Fertilizers P and K are applied in the amounts of 0.42 kg and 9.47 kg, respectively, for each tonne of switchgrass harvested. A moderate amount of N (112 kg ha^{-1}) is used in this case study. Nitrogen application costs $137 ha^{-1}, while each kg of K and P costs $12. The cost of pesticide is $16.89 ha^{-1}[18].

2.4.1.4 Harvesting Cost

The harvesting operation includes mowing, raking, baling, staging, and loading. For the budget estimations in this chapter, it is assumed that harvesting is done in large square bales, each weighing 397 kg. Mowing and raking has a fixed cost of $31.61 ha^{-1}. The cost of baling is $7, while the cost of staging and loading is $2.8, leading to a total of $9.8 for each bale [18]. Since 2.5 bales are obtained for each tonne, the variable cost of harvesting is taken as $24.5 t^{-1} of switchgrass harvested.

2.4.1.5 Transportation Cost

The cost of transporting the biomass by truck is calculated based on the following formula: $5.70 + 0.1367X, where X is the distance of the cultivation zone to the facility in km, while 0.1367 is the variable cost in $ km^{-1} t^{-1}. On the other hand, transporting the biomass by rail costs $17.10 + 0.0277X [19]. In this study, distance to the facility is calculated based on a city-block distance, also known as the Manhattan distance. Among the transportation modes, only one mode of transportation, transportation by truck, is considered for this specific case because of its availability in Kansas.

2.4.1.6 Soil Erosion

Parameter values regarding the environmental benefits of switchgrass cultivation have also been computed. A recent study by the USDA considers farmer and societal costs of soil erosion by providing scientifically derived estimates. By summing the values of fertilizer saved ($1.95) and water quality benefits ($5.43), the USDA estimates that the yearly savings of the farmers and society from erosion is equal to $7.38 for each tonne of soil [21]. The USDA estimates soil erosion in Kansas to be 8.29, 1.34, and 2.69 t ha^{-1} for cropland, grassland, and marginal land, respectively. Multiplying these amounts by $7.38, the value of one tonne of soil per year, we estimate soil-erosion savings via switchgrass cultivation to be $61.18, $9.89, and $19.85 ha^{-1}-y^{-1} for cropland, grassland, and marginal land, respectively.

2.4.1.7 Carbon Sequestration and CO_2 Emissions

The amount of soil organic carbon sequestered, its CO_2 equivalence, and saving values due to carbon sequestration for each seeding scenario are given in Table 2.3.

TABLE 2.3 SOIL ORGANIC CARBON (SOC), CO_2 EQUIVALENCE, AND SAVINGS

Seeding scenario	SOC (t ha^{-1} y^{-1})	CO_2 equivalence (t ha^{-1} y^{-1})	Savings ($ ha^{-1} y^{-1})
1, 3, 4, 5	4.42	16.22	324.4
2, 6, 7	0.32	1.17	23.5
8, 9, 10, 11	3.2	11.74	234.8

SOC sequestration depends on soil type. Its value in cropland is taken as 4.42 t ha^{-1} y^{-1} [34]. On the other hand, sequestration rates of up to 2.4-4.0 t ha^{-1} y^{-1} are reported for switchgrass grown in the CRP in South Dakota [35]. Therefore, an average value of 3.2 t ha^{-1} y^{-1} is used for carbon sequestration on marginal land. Since grassland is expected to already be saturated with a high concentration of SOC, carbon sequestration via switchgrass cultivation is

less than 1 t ha^{-1} y^{-1} [36]. In this study, it is assumed to be 10% of that is on marginal land. To compute the equivalent CO_2 sequestered from the atmosphere, the SOC values in Table 2.3 are multiplied by 3.67 [37]. The average cost of CO_2 emissions is \$20 t^{-1}, according to the Emissions Trading System in the European Union (EU) [38]. The savings column is computed by multiplying CO_2 equivalence with \$20 t^{-1}. Carbon emissions that occur during seeding, production, harvesting, and transportation operations are provided in Table 2.4 ([39], [40]). CO_2 emitted during each sub-operation, including pesticide and fertilizer applications, is shown in the CO_2 emissions column. The number (amount) of these sub-operations (pesticides and fertilizers) in each operation is indicated in the usage column. Finally, the cost of CO_2 emissions is presented in the cost column and is equal to multiplying CO_2 emissions, usage, and \$20 t^{-1}. For instance, the cost of pesticide application in the seeding operation is obtained by 6.3 (kg kg^{-1}) * 5.25 (kg ha^{-1}) * \$20 t^{-1}, which equals \$0.66 ha^{-1}.

TABLE 2.4 CO_2 EMISSIONS AND THEIR EQUIVALENT COSTS FROM VARIOUS OPERATIONS

Operation	Sub-operation	CO_2 emissions		Usage [16]		Cost (\$)	
Seeding	Drill	35.3	kg ha^{-1}	1		0.706	\$ ha^{-1}
Seeding	No-till drill	5.8	kg ha^{-1}	1		0.116	\$ ha^{-1}
Seeding	Airflow	7.9	kg ha^{-1}	1		0.158	\$ ha^{-1}
Seeding	Pesticide	6.3	kg kg^{-1}	5.25	kg ha^{-1}	0.66	\$ ha^{-1}
Seeding	Fertilizer (P)	0.2	kg kg^{-1}	33.6	kg ha^{-1}	0.672	\$ ha^{-1}
Seeding	Fertilizer (K)	0.15	kg kg^{-1}	44.8	kg ha^{-1}	0.896	\$ ha^{-1}
Production	Pesticide	6.3	kg kg^{-1}	5.25	kg ha^{-1}	0.66	\$ ha^{-1}
Production	Fertilizer (N)	1.3	kg kg^{-1}	112	kg ha^{-1}	2.91	\$ ha^{-1}
Production	Fertilizer (P)	0.2	kg kg^{-1}	0.42	kg t^{-1}	0.00168	\$ t^{-1}
Production	Fertilizer (K)	0.15	kg kg^{-1}	9.47	kg t^{-1}	0.02841	\$ t^{-1}
Harvesting	Rake	1.7	kg ha^{-1}	1		0.034	\$ ha^{-1}
Harvesting	Bale	3.30	kg ha^{-1}	1		0.066	\$ ha^{-1}
Transportation	Truck	0.203	kg $t^{-1}km^{-1}$	1		0.00406	\$ t^{-1} km^{-1}
Transportation	Train	0.017	kg t^{-1} km^{-1}	1		0.0003	\$ t^{-1} km^{-1}

As given previously in equation (2.4), the net savings from CO_2 sequestration is obtained by subtracting the cost of carbon emissions in Table 2.4 from the savings via CO_2 sequestration shown previously in Table 2.3.

2.4.2 Experimental Design

In this section, we evaluate the impact of key parameters on results. These parameters include the objective function weights, yield levels, sustainability factor, and available budget amount for biomass production.

We investigate three different cases of weight selection for (α, β, μ) in the objective function given in equation (2.1) in order to understand the relation between environmental factors (soil erosion prevention, carbon sequestration, and GHG emissions) and the sale of switchgrass biomass. Another reason for analyzing these weights cases, which are (1 0 0), (0.33 0.33 0.33), and (0 0.5 0.5), is to reflect the perspectives and preferences of various stakeholders (farmers, co-ops, or government) on the problem.

We also investigate the impact of high, moderate, and low levels of switchgrass yield and present an analysis of their effects on the results. A high level of switchgrass yield indicates an upper limit of the yield that can be obtained from any type of land. On the other hand, low-level yield is studied as a worst-case scenario, where productivity of switchgrass is very low because of unexpected incidents such as extreme drought.

The sustainability factor, another parameter that is expected to affect results, gives the percentage of cropland that is not allowed for biomass production. The first value of the sustainability factor is set to 0%, which refers to the full availability of cropland for the cultivation of switchgrass. The second case, where the sustainability factor is set to 25%, is

stricter since it forces switchgrass cultivation on marginal land and grassland by limiting the available area of cropland for switchgrass cultivation to 75%. Finally, the sustainability factor is set to 50% in order to ensure safety of the food supply from cropland.

Finally, we also investigate the effect of three budget cases: limited, moderate, and ample. The budget level that is enough for switchgrass cultivation in all studied regions is taken as the ample budget. A moderate budget is equal to 75% of the ample budget, while 50% of the ample budget is considered to be a limited budget in this analysis.

2.5 Computational Results

The MILP model provided in section 2.3 is solved using CPLEX 12.2 on a personal computer with a 3.40 GHz, 16.0 GB memory. The model has 696 continuous variables and 17,078 integer variables. Model solution statistics are summarized for all cases in Table 2.5. The global optimum was achieved for all cases in less than 310 central processing unit (CPU) seconds. We observe that as the available budget and sustainability factor decrease, difficulty of the problem and thus computational time increases. If we emphasize the sales of switchgrass in the objective function, the solution time also increases due to additional decisions regarding the harvesting time and amount.

In the base case scenario, the objective function weights (α, β, μ) in equation (2.1) are set to (1 0 0), which gives full priority to the revenue obtained from the sale of switchgrass. The sustainability factor and budget in the base case scenario are 25% and moderate (525 M$), respectively. We also use a moderate level of switchgrass yield, shown in Table 2.1 in the base case scenario. The first four columns of Table 2.5 correspond to four different parameters that are investigated. In Table 2.5, four different sets of experiments are presented in each row-

block of the table. In each set of experiments, each parameter is set to three different values, as explained in section 4.2, in order to analyze its impact on the results, while the remaining parameters are fixed to the base case values.

TABLE 2.5 SUMMARY OF COMPUTATIONAL STATISTICS FOR DIFFERENT SCENARIOS

Objective function weights (α β μ)	Yield levels	Sustainability factor (%)	Budget level (M$)	Objective function value (M$)	CPU time (s)
(1 0 0)				931.5	303.1
(0.33 0.33 0.33)	Base	Base	Base	364.6	30.5
(0 0.5 0.5)				112.6	0.9
	Low			747.9	297.2
Base	Moderate	Base	Base	931.5	303.1
	High			942.0	296.8
		0		931.5	302.5
Base	Base	25	Base	931.5	303.1
		50		911.6	67.2
			350	631.3	296.8
Base	Base	Base	525	931.5	303.1
			700	1202.8	49.6

When we analyze the tightness of the constraints given the optimal solution in the base case, we observe that total switchgrass yield is equal to the potential switchgrass yield, constraint (2.5), while harvested switchgrass biomass is equal to switchgrass yield, constraint (2.8). Constraints (2.6), (2.7), and (2.9) are also binding. Inequality (2.10) is not a limiting constraint since we have considered an ample capacity in this case study. All constraints (2.11) to (2.16) regarding the budget allocation are binding. Inequality (2.17) limits harvested zones to ensure sustainability of bird populations, while constraint (2.18) is not binding in the base case since cropland utilization is already less than 75%.As mentioned in section 4, the model is applied to a case study in Hugoton. Figure 2.2 displays a map of the studied region in Hugoton, which is divided into 21 by 21 rectangular arrays of cultivation zones with the row and column numbers referring to zone (*i*,*j*) in the model. For example, zone (11,11) shows the location of

the facility, which is in the center of the Hugoton map, while cultivation zone (6,9) shows one section of grassland in the considered region. This map displays the considered area with the distribution of land types, the location of the facility, and residential areas while indicating optimal seeding zones in the first year of the planning horizon when the MILP model is solved for the base case scenario.

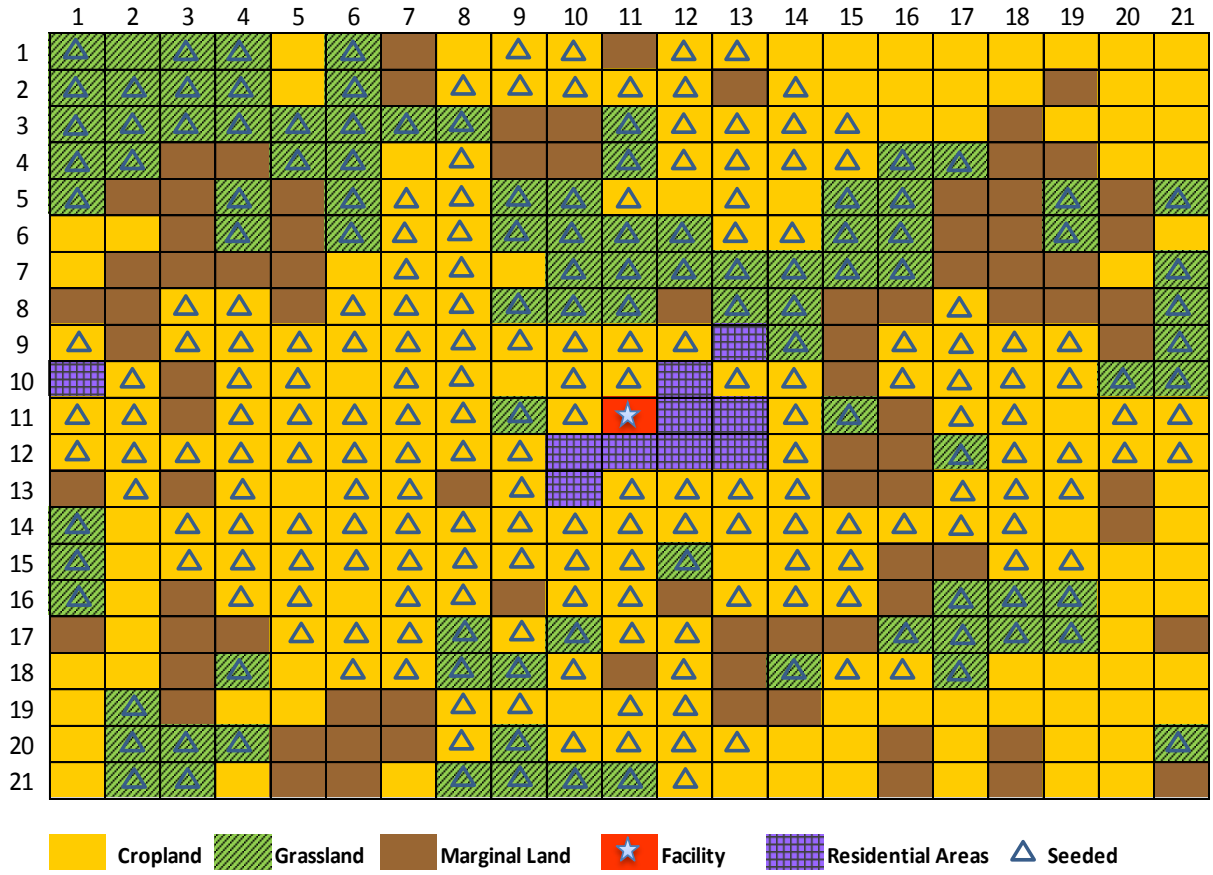

Figure 2.2 Hugoton area divided into 21 by 21 zones including land types, facility, residential areas, and optimal switchgrass seeding locations.

It can be seen that the closest zones to the facility are selected for switchgrass cultivation. In addition, grassland is selected for cultivation since it has a lower rental cost, while cropland becomes favorable due to its higher switchgrass yield. As the best seeding scenario, scenario 1 is selected for cropland, while scenario 2 is chosen for grassland. Both of

these scenarios involve airflow planting in frost seeding. Seeding time is always chosen as the first year of the planning horizon in order to increase the overall production amount. Out of 248 zones of cropland, 163 are utilized for switchgrass production, while 93 out of 94 zones of grassland are converted into switchgrass cultivation. In other words, 87.6% of available cropland is used, while this value increases to 99% for grassland. For this case, none of the 88 zones of marginal land is chosen for switchgrass cultivation.

The total area converted to switchgrass cultivation is as follows: 42,380 ha for cropland and 24,180 ha for grassland. The overall amount of biomass yield reaches 7.99 million tonnes (Mt), while 7.76 Mt of that amount is harvested in the ten-year planning horizon. The cost of switchgrass biomass harvested is calculated as \$67.63 t^{-1} for the base case scenario, which is similar to current values in the market [41].

Figure 2.3 shows the amount of biomass yield and harvested biomass in different types of lands.

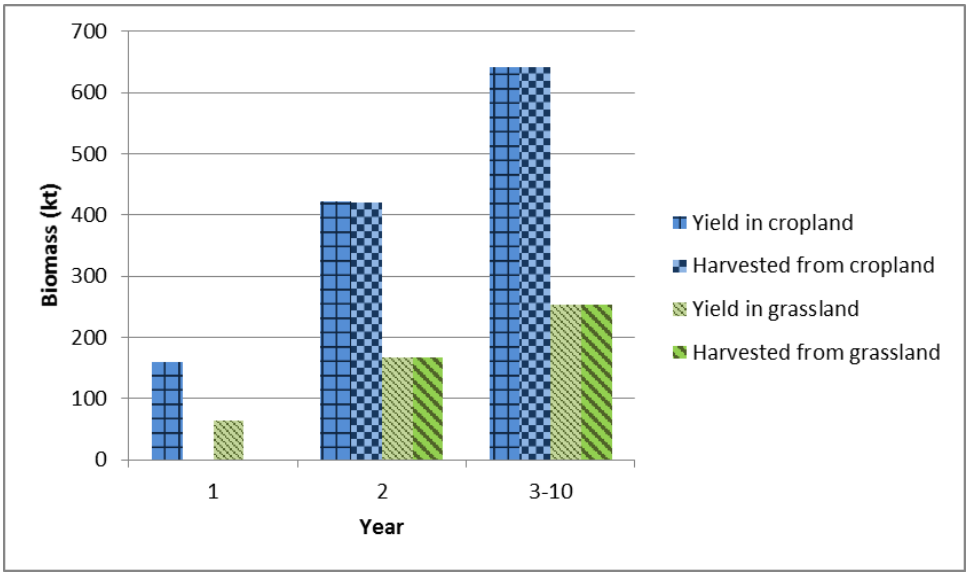

Figure 2.3 Biomass yield and harvested amount in the planning horizon.

It can be seen that the harvesting decision is deferred to the second year due to the limited budget and low yield in the establishment year. All switchgrass yield is harvested from years two to ten. This can be explained by the selection of the objective function weights in the base case scenario in which priority is given to the sales of switchgrass biomass.

We have also determined the optimal budget amounts to be allocated for operations involved in the biomass production. Figure 2.4 shows the share of 525 M$ for seeding, land rent, fertilization, harvesting, and transportation throughout the planning horizon for the base case scenario. As depicted in Figure 2.4, harvesting, fertilization, and rental costs require 210, 178.5, and 94.5 M$, respectively, and comprise 92% of the overall budget.

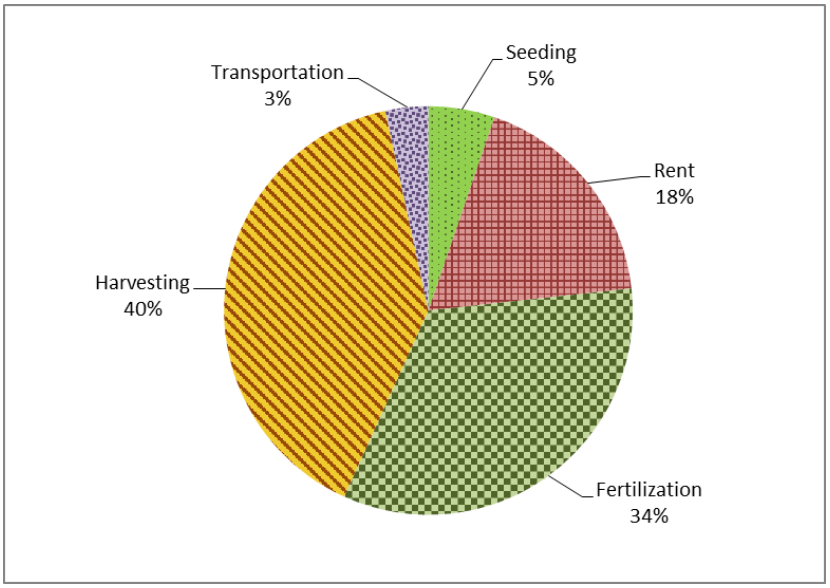

Figure 2.4 Optimal cost breakdown for the base case scenario.

Figure 2.5 displays the optimum budget level for different farm operations at each time period in the base case scenario. The rental cost is about 10 M$ in the first year and remains the same during the planning horizon. The budget amount allotted to seeding is about 33 M$ and is used only the first year of the planning horizon since all seeding decisions are made in

the first year. The allocation of harvesting and fertilization budget starts in the second year and increases in the third year. As the harvesting increases, budget allocated for fertilization and transportation also increases since their values depend on the harvested switchgrass biomass. The budget remaining after the first and second years is divided equally into eight years by the model.

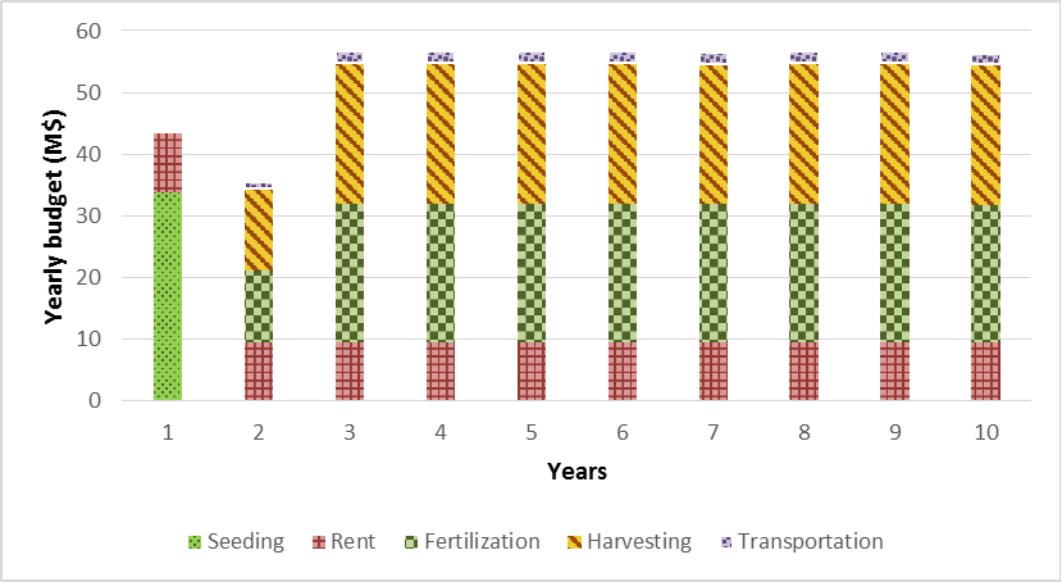

Figure 2.5 Optimal yearly budget allocation for farm operations of switchgrass biomass production in the base case scenario.

Figure 2.6 displays profitability ratios in the base case for various economical values obtained from switchgrass production. The profitability ratio is obtained by dividing net economical values (profits) of corresponding outputs by the budget value in the base case. Total economic benefits represent the summation of nominal values of sales of switchgrass with savings via carbon sequestration and soil erosion prevention. On the other hand, the objective function value is the amount of economical values after the terms in the objective function are multiplied with their corresponding weights. The highest profitability ratio for total economic

benefits is obtained when equal consideration is given to both economic and environmental factors.

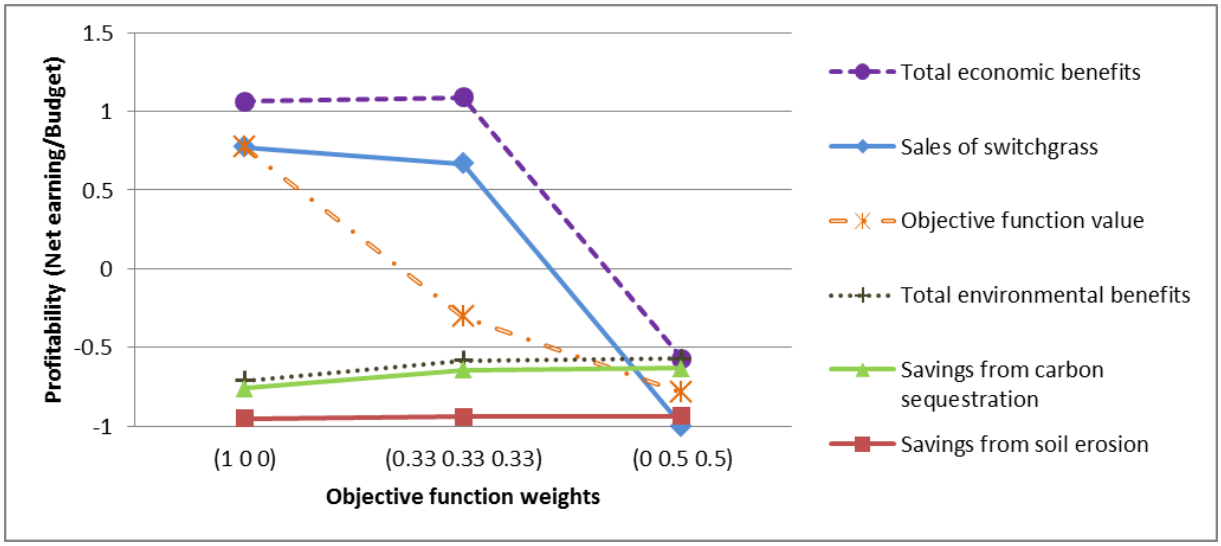

Figure 2.6 Profitability of various economical parameters based on changing weights.

In the following sections, we provide some scenario analyses by changing different parameter values in order to gain better insight into the nature of the problem. First, we investigate the impact of different objective function weights on the results. The second analysis addresses the effect of changing switchgrass yield levels on model outputs. Third, we perform another analysis in order to determine the impact of sustainability factor on the solution, and finally, we investigate the impact of different budget levels. The values used in these analyses are summarized in Table 2.5. Furthermore, we also conduct a separate sensitivity analysis that examines the effect of CRP incentives on the selection of marginal land.

2.5.1 Analysis of Objective Function Weights

Three different weight cases are investigated to understand the impact of objective functions on the results. For the first set of weights (1 0 0), priority is given to revenue from biomass sales, which emphasizes the problem only from the farm owner point of view. On the

other hand, the second set of weights (0.33 0.33 0.33) gives equal consideration to revenue and environmental consequences of biomass production, which may reflect the government's goals. The last set of weight (0 0.5 0.5) gives full consideration to the environment. The total economic value obtained from the sales of switchgrass, and savings from soil erosion and carbon sequestration for three different objective function weights is shown in Figure 2.7. The amount of switchgrass grown and harvested on different land types is also shown for three different objective function weights in Figure 2.8.

As shown in Figures 2.7 and 2.8, giving full consideration to the environment decreases the amount of switchgrass harvested to zero, which results in no sales. The equal-weight case (0.33 0.33 0.33) gives higher total economic value than that in the profit priority case (1 0 0), although the harvested amount decreases from 7.76 Mt to 7.30 Mt. This is because in the equal-weight case, savings from soil erosion and carbon sequestration increases faster than the decrease in sales of switchgrass on marginal land. In this case, cropland, grassland, and marginal land account for 50%, 13%, and 37%, respectively, of the overall biomass production. Giving equal consideration to the environment and sales of switchgrass, some production is shifted from grassland to marginal land since marginal land has ten and two times better savings for carbon sequestration and soil erosion, respectively, than savings from grassland. However, by further emphasizing environmental benefits, the model uses the entire harvesting budget to have almost 100% utilization of all land types including grassland. However, in this case, the change in soil erosion is minimal since switchgrass soil erosion prevention is not high for grassland, and further utilization of grassland does not provide much more additional benefit.

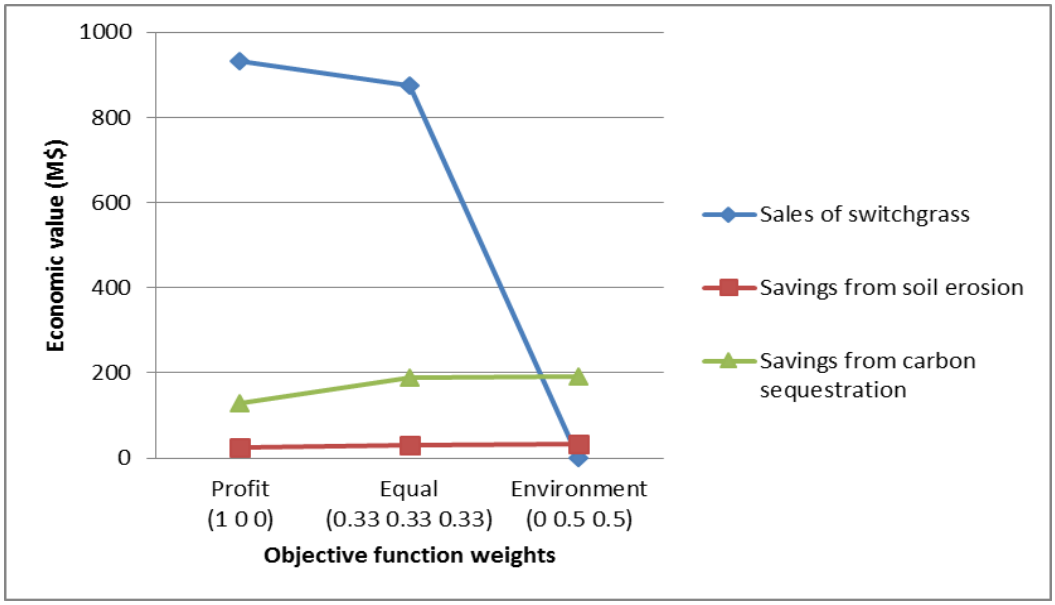

Figure 2.7 Economic value obtained from three objectives based on changing weights.

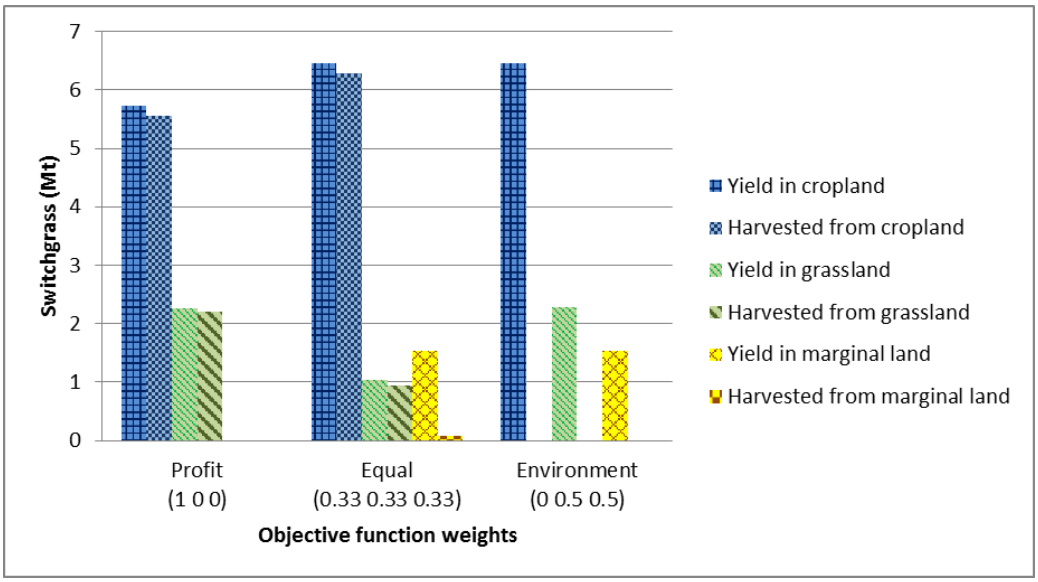

Figure 2.8 Switchgrass yield and harvested amount based on changing weights.

2.5.2 Analysis of Switchgrass Yield Levels

Very few researchers have taken into account stochasticity in model parameters. In this study, potential switchgrass yield is assumed to be mostly dependent on land types and establishment year. However, lower and upper bounds are set on the potential switchgrass

yield in order to reflect the impact of various factors such as changing weather conditions on potential yield. Potential yield in the low level is set to 33% less than that in the moderate level, as shown previously in Table 2.1. Similarly, potential yield in the high level is taken as 33% more than that in the moderate level. Figures 2.9 and 2.10 show the effect of different yield levels on the economic value and on harvested switchgrass from different land types, respectively. In the low-yield case, all land types are utilized for biomass harvesting since there is not enough biomass grown on cropland and grassland. On the other hand, increasing the potential yield to a moderate level removes marginal land from the solution. In other words, a moderate biomass amount in cropland and grassland leads to savings from the transportation cost, which can be used for more harvesting. Removing less-productive marginal lands from the solution leads to a higher economic value because the total biomass amount increases from 6.23 Mt to 7.76 Mt. However, further increasing the potential switchgrass yield provides only a slight improvement in the sales of switchgrass because, in this case, budget becomes a limiting factor. We still obtain a slight increase in sales because the same amount of biomass can be obtained from a closer region to the facility, which results in some savings from the transportation cost and leads to more harvesting. Another interesting result is obtained regarding savings from carbon sequestration. A higher potential yield level decreases savings from carbon sequestration since the model does not select marginal land, which leads to ten times more carbon sequestration than that of grassland.

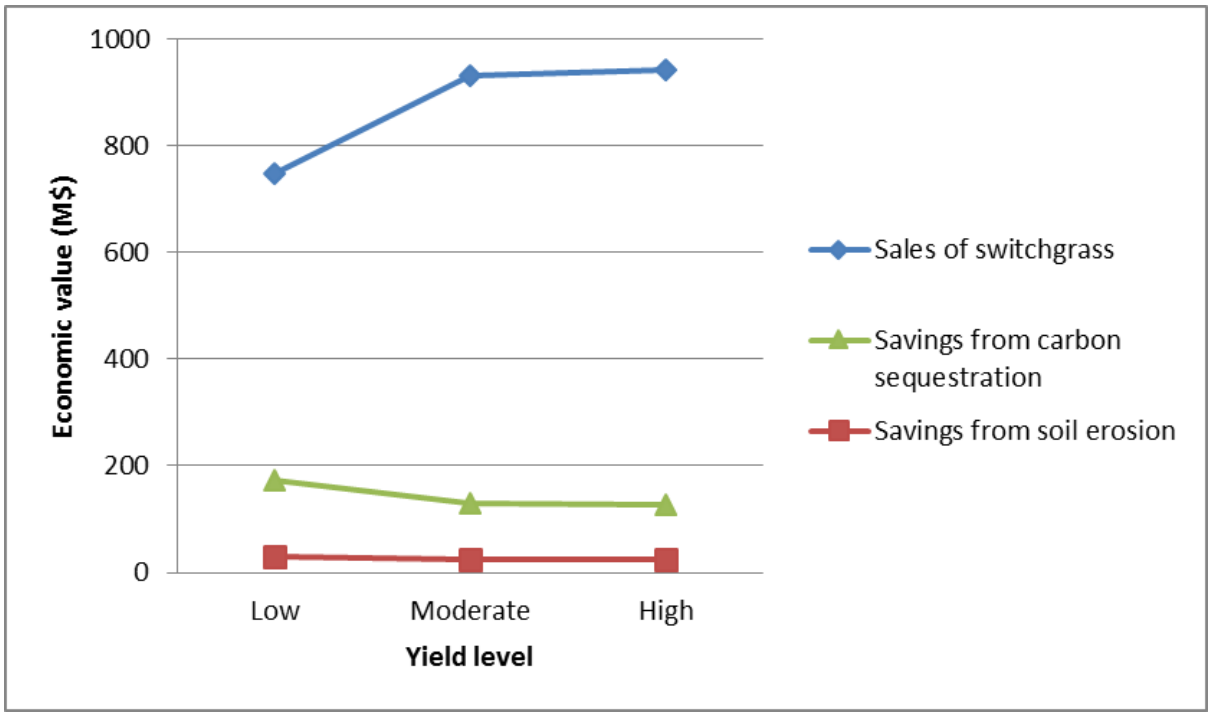

Figure 2.9 Economic value obtained from different objectives based on changing yield levels.

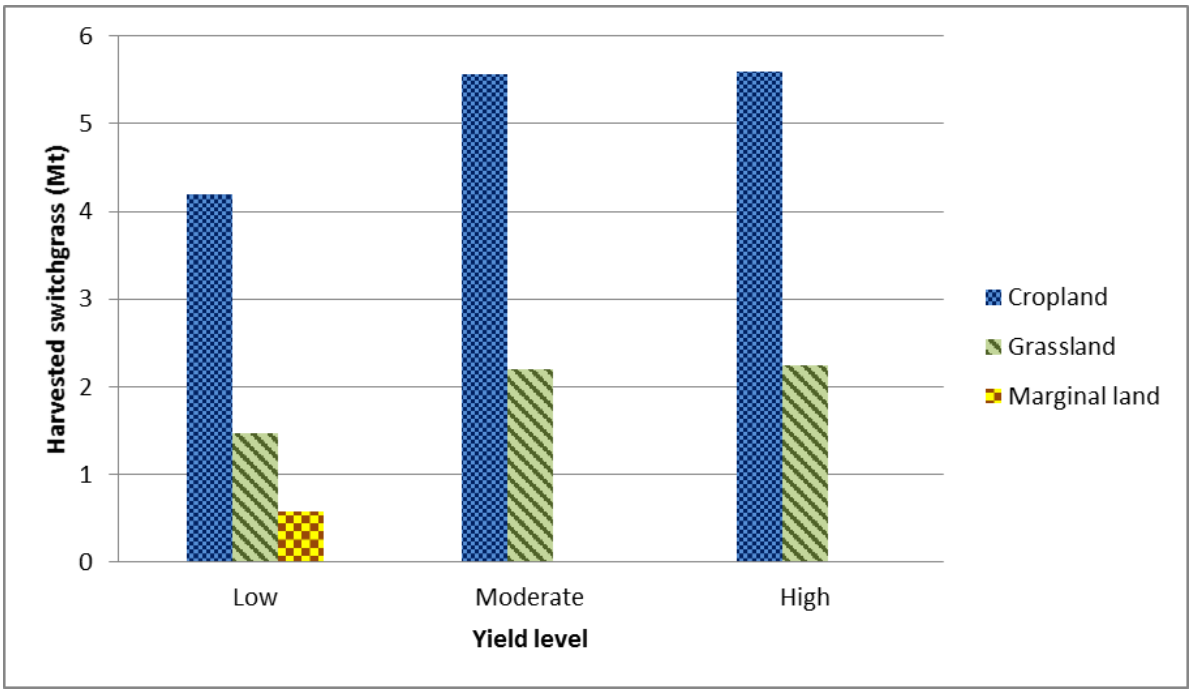

Figure 2.10 Harvested yield from different land types based on changing yield levels.

2.5.3 Analysis of Sustainability Factor

Figures 2.11 and 2.12 show the effect of the sustainability factor on economic value obtained for three objective functions and on the amount of harvested switchgrass from different land types, respectively. First, the full availability of cropland for biomass production is defined by setting the sustainability factor to 0%. Then it is increased to 25%. Finally, for full security of the food supply, the sustainability factor is increased to 50%. Based on Figures 2.11 and 2.12, there is no difference in results for sustainability factors of 0% and 25%, while we observe a slight decrease in economic value from the sale of switchgrass when the sustainability factor is set to 50%. Since utilization of cropland is already less than 75% in the base case, i.e., the sustainability constraint is not binding, changing the sustainability factor from 0% to 25% (i.e., limiting the usage of cropland for biomass production to 75%) does not affect the results.

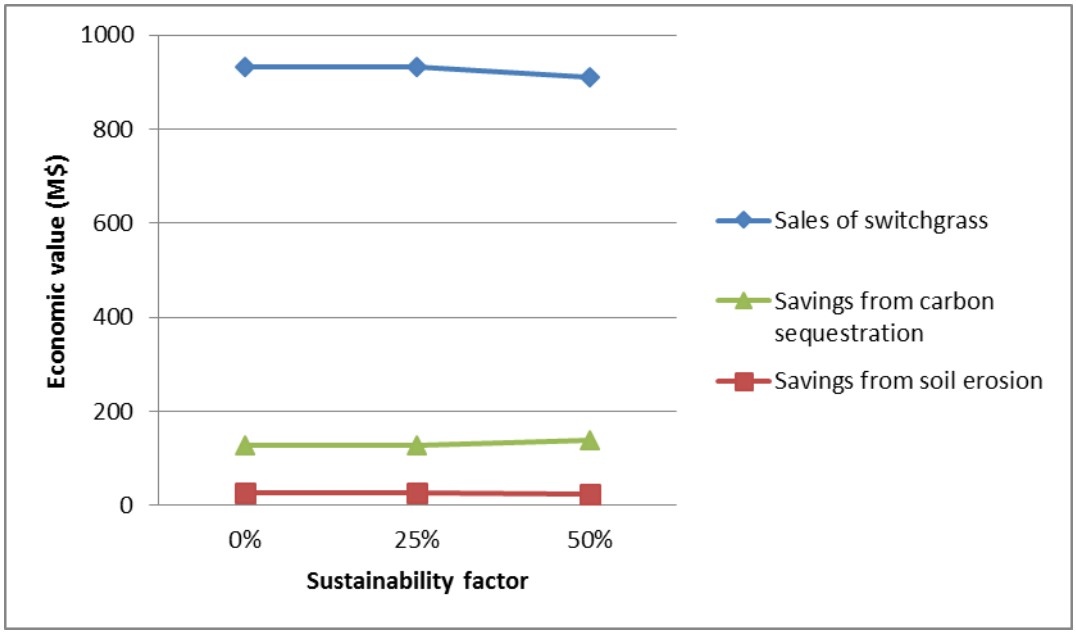

Figure 2.11 Economic value from three objective functions based on sustainability factor.

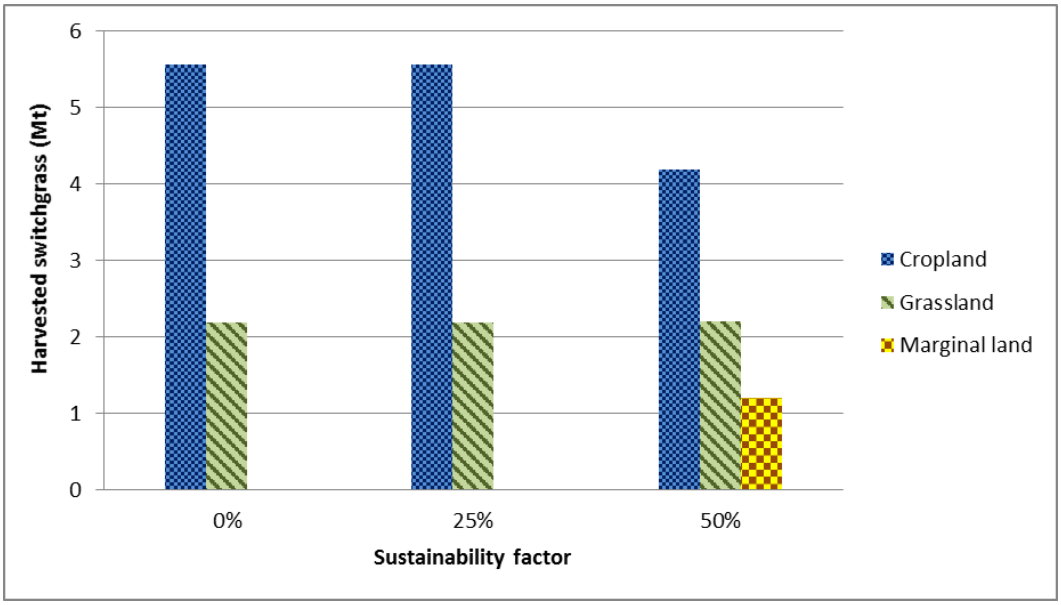

Figure 2.12 Harvested switchgrass based on sustainability factor.

The binding constraint on cropland utilization is the budget constraint. When we further increase the sustainability factor to 50% (i.e., limiting the usage of cropland to 50%), the model cannot use the same amount of cropland as in the base case. Therefore, in this case, the budget usage is shifted to marginal lands, which are not as productive, leading to a decrease in the harvested switchgrass biomass from 7.76 Mt to 7.50 Mt. By changing the allocation of land types between cases of 0% and 50% sustainability factors, one can conclude that food supply safety can be provided without losing too much economic value.

2.5.4 Analysis of Changing Budget Levels

We also investigate the effect of a changing budget on the results. The economic value and harvested switchgrass biomass are shown in Figures 2.13 and 2.14, respectively. Here, an ample budget represents a sufficient budget amount for seeding and harvesting on all types of land. A moderate budget is set to 75% of the ample budget, while a tight budget is considered to be 50% of the ample budget. Figure 2.13 shows that an increase in the budget results in an

increase in all objective functions in terms of economic value. However, the increment in sales in switchgrass biomass and savings from soil erosion is slower than the increment in the budget. This is because budget is used more for transportation from marginal land to the biorefinery, and marginal land is not very productive. On the other hand, the increase in savings from carbon sequestration is higher than the increment in the budget because marginal lands have more potential for carbon sequestration than all other land types. On the other hand, as shown in Figure 2.14, a change in the budget does not affect the switchgrass biomass harvested from grassland since it is already fully utilized even under the medium-budget case, while expanding the available budget affects cropland and marginal land. Changing the budget from tight (350 M$) to ample (700 M$) leads to an increase in harvested switchgrass biomass from 5.3 Mt to 10 Mt.

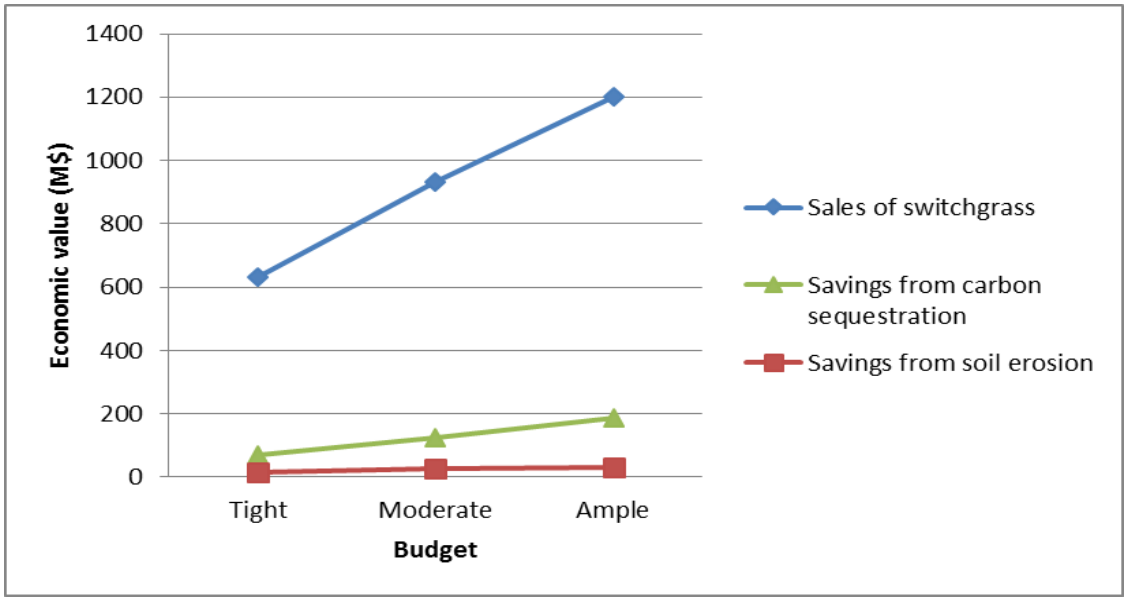

Figure 2.13 Economic value obtained from different objectives based on changing budget.

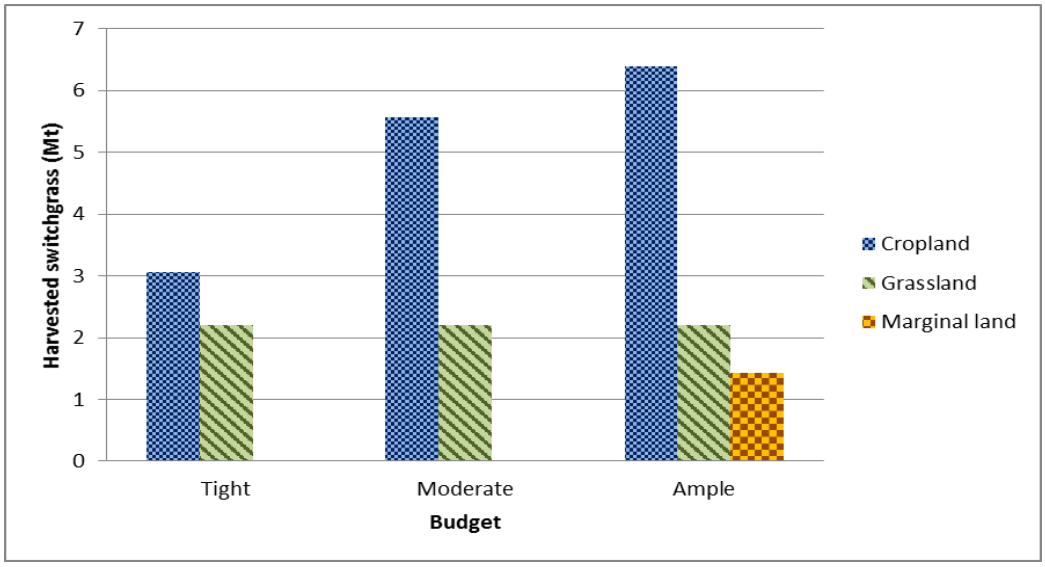

Figure 2.14 Harvested yield from different land types based on changing budget.

The increase in sales of switchgrass biomass with respect to budget is not linear since as the budget increases, a higher share of it is allocated for long-distance transportation, and the model also starts using less-productive land. For example, increasing the budget from low to medium only increases the utilization of cropland, which is more productive than grassland. However the rental cost of cropland is also high. When we increase the budget from medium to ample, cropland utilization reaches 75%, while marginal land becomes fully utilized. However, the rate of increase in sales of switchgrass decreases when the budget is changed from medium to ample since, in this case, although the rental cost of marginal land is lower than that of cropland, those lands are less productive. On the other hand, the rate of increase in savings from environmental benefits increases when the budget level is increased. That is because a higher budget level leads to utilization of more cropland and marginal land where switchgrass shows higher environmental benefits compared to grassland.

2.5.5 Sensitivity Analysis of CRP Incentives on Land Selection

We also study the effect of CRP incentives on the utilization of marginal land. Since some studies suggest that switchgrass cultivation could substitute for the CRP ([16], [35]), we analyze how much incentive is needed to make switchgrass cultivation favorable on marginal land over its production on cropland and grassland. Figure 2.15 shows how the amount of switchgrass harvested from different land types is influenced by the level of CRP incentives.

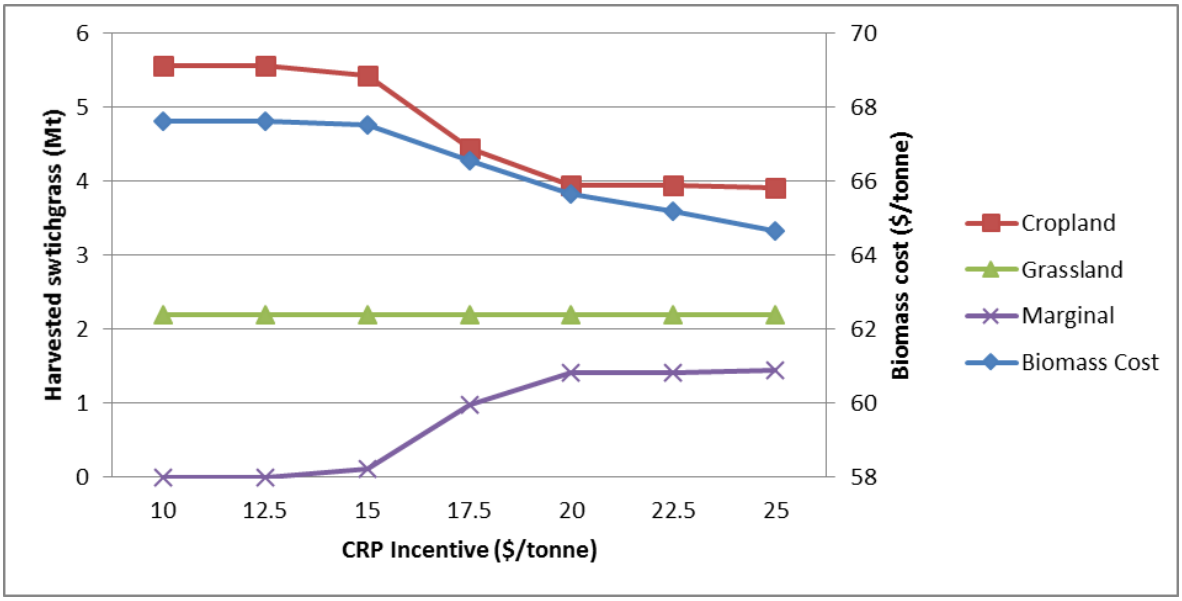

Figure 2.15 Impact of CRP incentives on switchgrass production and biomass cost.

If the government utilizes an incentive of $15 for each tonne of switchgrass produced on marginal land, then the total cost of biomass starts to decrease and marginal land starts to be utilized. On the other hand, an incentive of $20 for each tonne of biomass is sufficient for the maximum utilization of marginal land, while an incentive beyond $20 is overpayment to farmers for marginal land utilization. We observe another interesting result for the cost of biomass production when CRP incentives are considered. Without CRP incentives, the cost of harvested switchgrass biomass is $67.63 t^{-1} for the base case scenario. If a $20 incentive is

provided for marginal land, then this value decreases to about \$65.5 t^{-1}. Using CRP contracts as an incentive for switchgrass cultivation on marginal land may also decrease the switchgrass sales price, due to the decline in biomass production cost.

2.6 Concluding Remarks and Future Directions

In this chapter, we introduce a mixed-integer linear programming model that defines an optimal design for switchgrass cultivation on different land types in order to maximize the total revenue of biomass production as well as its beneficial environmental impacts. We apply the proposed model on a real case study of a biofuel production site in Hugoton, Kansas. This case study shows that given the current market prices, switchgrass cultivation on grassland and cropland is highly profitable. Given the limited budget, marginal land is not utilized for biomass production, unless the government utilizes CRP contracts as an incentive on marginal land for switchgrass cultivation.

In the proposed model with a ten-year time horizon, results indicate that for all types of land, planting switchgrass using the airflow method in the frost season of the first year maximizes the total economic value. It can be seen that harvesting starts in the second year of seeding for optimum allocation of a limited budget, since switchgrass yield is low in the first year and reaches its maximum potential in the third year. In this chapter, the effect of a sustainable food supply is also considered. Limiting biomass cultivation on cropland slightly decreases the overall biomass production since less-productive marginal land starts to be utilized. On the other hand, while giving full priority to revenue in the objective function maximizes the sales of switchgrass, it does not maximize the total economic value. Maximum benefit is obtained when equal consideration is given to revenue obtained from sales of

switchgrass and economic value of its environmental impacts. We also observe that the increase of switchgrass yield level from low to moderate increases the biomass amount and thus the total economic value, while the increase of yield level from moderate to high provides very slight improvement on the total economic value, due to limited budget and high harvesting cost.

This chapter provides a unique approach in terms of quantifying and modeling the environmental effects of switchgrass production as well as its economic impacts at the farm level. The model and methodology presented in this chapter could be extended in a number of possible ways. In this chapter, uncertainty regarding the yield, budget, and multi-objective function weights is handled by conducting sensitive analyses. In a future study, the stochasticity in yield levels, budget, and price of switchgrass biomass could be explicitly considered in a stochastic programming model where stochastic elements are modeled as random variables. Furthermore, price change can also be considered as a nonlinear function of yield.

We also represent the change of cost and environmental impacts of switchgrass production across space by considering different land types in our model. In particular, we model carbon sequestration and soil erosion prevention on a heterogeneous landscape as a linear function of yield. Although these environmental factors may be potentially time-varying, due to the unavailability of the data, we only consider the impact of yield, which is time-varying until it reaches its maximum value, on environmental factors. An extended version of this model could consider a potential decrease in savings from environmental benefits, particularly from carbon sequestration, in time due to saturation of the soil with soil organic carbon. We collect and synthesize various types of data regarding the establishment cost, carbon

sequestration, and CO_2 emissions in order to build a model that accounts for important economic and environmental factors that affect switchgrass production. However, the environmental impacts could be further extended by considering the effects of switchgrass cultivation on water quality and the populations of other species in addition to bird species if adequate data is acquired.

In the future, in order to deal with a larger-size landscape and more complex problems, cutting planes and decomposition algorithms could be utilized to decrease the model solution times. This model could also be extended to biomass production from any other types of energy crops, in order to identify the most efficient management and planning strategies for biomass production. In addition, economic and environmental analysis could be investigated for other energy crops along with currently cultivated food crops, and optimum allocation of lands could be determined for biomass and food supply.

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CHAPTER 3

FOOD VS BIOFUEL: AN OPTIMIZATION APPROACH TO THE SPATIO-TEMPORAL ANALYSIS OF LAND-USE COMPETITION AND ENVIRONMENTAL IMPACTS

3.1 Introduction

The growing demand of energy and dependency on fossil fuels motivates researchers to seek sustainable ways of energy production. Biofuel, an environmentally friendly renewable energy source, is considered a substitute for fossil fuels. In addition, the increasing price of oil and environmental problems make biofuel a promising alternative energy. A number of sources, such as food crops, energy crops, and forest residues, can be used in biofuel production. In order to ensure the transition from fossil fuels to biofuel, some mandates have been developed by governments in different countries including the U.S. The Renewable Fuel Standard was set by the U.S. Congress in 2007 to provide a strategic plan for biofuel production [1].

Biofuels help to secure energy and fight against climate change by reducing CO_2 emissions. However, they also arouse questions and debates. For example, corn (*Zea mays* L.), a food source, has also been utilized in biofuel production, which leads to concern about security of the food supply and sustainable energy generation. Subsidies in corn production cause displacement of grasslands and other crops, thus impacting biodiversity. Furthermore, using corn for ethanol production leads to an increase in food prices [2], [3]. Some researchers claim that ethanol production from corn requires more energy input than its output, while others contend that corn-based ethanol provides a net energy return [4], [5]. On the other hand, efficient production methods and hybrid corn have increased the overall productivity of corn

cultivation. Currently more than 25% of total corn yield is used in ethanol production in the U.S. [6]. According to RFS2, ethanol made from grain can comprise up to 15 billion gallons of a 36-billion-gallon annual ethanol goal [1].

Another source of biofuel is cellulosic plants (energy crops), such as switchgrass (*Panicum virgatum*), which is native to North America and has many environmental benefits. Switchgrass requires low fertilization, prevents soil erosion, tolerates variable soil conditions and drought, reduces GHG emissions, and enriches the soil quality via carbon sequestration [7]. Ethanol production from both food and energy crops is also known to reduce GHG emissions [8]. RFS2 requires the annual use of at least 16 billion gallons of biofuel from energy crops by 2022 [1].

The growth of ethanol production from first- and second-generation crops has motivated researchers to find more efficient and economical ways of designing biofuel production and the supply chain. Xie et al. [9] propose a mixed-integer linear programming (MILP) model for transporting cellulosic feedstock with three different transportation modes. The overall supply chain cost is minimized by providing optimal locations for biorefineries, hubs, and terminals. Cobuloglu and Büyüktahtakın [10] develop an MILP model that integrates economic and environmental impacts of switchgrass biomass production. Their model defines the best seeding method, harvesting time and amount for different land types, and budget allocation to farm operations under various scenarios. Kim et al. [11] develop an MILP model that maximizes the overall profit of biofuel production from forestry biomass to find the best transportation method, biomass locations, and biorefinery capacity and technologies. Similar

studies have recently been conducted for planning biofuel supply chains of cellulosic and food crops [12], [13], [14].

In addition to designing biofuel supply chains, there are a significant number of experimental and data collection studies on farm operations of corn and switchgrass production. Van Dam et al. [15] conduct a large-scale cost-estimation study and economic analysis for switchgrass and soybean production in Argentina. On the other hand, Khanna et al. [16] develop a simulation study to analyze the impact regarding the biomass prices of different crop types on land allocation. Their model also defines commodity prices, production, and consumption in each year. Another economic analysis of food and ethanol production from corn grain is presented by Bai et al. [17] who propose a game-theoretic mathematical model that defines the optimal location for biorefineries, land allocation, and price of feedstock. Khanna et al. [18] study the competition between two energy crops, switchgrass and Miscanthus, for electricity production. In their model, they consider environmental impacts such as GHG emissions and carbon sequestration with the objective of maximizing total profit.

Some studies define the relation between food price and ethanol demand. According to Mueller et al. [19], the contribution of ethanol demand in increasing food price is about 3% to 30%. According to the partial equilibrium model-based simulation of Sexton et al. [20], biofuels are responsible for 25% to 60% of increasing corn prices. In addition to the price of corn, land availability is an important factor affecting food security. Rathmann et al. [21] states that ethanol demand has led to a shift from wheat to corn and from soybeans to sugarcane in order to produce ethanol in the U.S. and Brazil, respectively. A study by Thompson and Meyer [22]

indicates that if biofuels are produced from food crop residues, then they may potentially decrease food prices due to the allocation of more land to food crop cultivation.

Many studies deal with a particular aspect of switchgrass and corn production. These studies analyze their environmental (soil erosion, carbon sequestration and emissions, and nitrogen uptake and pollution) and economic effects (cost of seeding, production, harvesting, and transportation), some of which we utilize to compile information in the data section of this chapter (see, e.g., [23], [24], [25]). To our knowledge, none of the previous studies simultaneously considers economic benefits, overall environmental impacts of food and energy crop production, and their competition on land allocation in a mathematical programming model for making optimal production decisions at the farm level. There is a need for such an optimization model that can provide strategic production, operation, and management plans to farmers (decision makers) under various budget and land allocation scenarios, while considering different economic and environmental priorities and sustainability of the food supply. Our model maximizes the total economic benefits of farmers and considers the environmental effects of food and biofuel production from corn and switchgrass simultaneously. This study allows farmers to make an economic projection in order to optimally allocate their lands to switchgrass and corn production during a given planning horizon. Also, our study provides economic and environmental profitability ratios of switchgrass and corn under a number of scenarios.

Contributions of this study are as follows:

- This is the first spatio-temporal optimization model that integrates economic and environmental outcomes of biomass and food production on different land types

simultaneously. Corresponding trade-offs between food and biomass production are analyzed in this chapter.

- None of the reviewed literature considers nitrogen pollution and its contamination to groundwater in an optimization model, as has been formulized in this study. The effect of harvesting on the savings from soil erosion prevention and carbon sequestration are also considered in the model. This study ensures the biodiversity of bird populations by providing them available habitat through limiting the number of harvested regions on grassland and marginal land.
- The nonlinear relation of revenue and yield quantity is approximated with a piecewise linear function. For further economic analysis, this chapter also provides profitability ratios, budget allocation, and yield levels to be obtained for a variety of scenarios.
- Input data for economic and environmental parameters are calculated by utilizing various sources. In that regard, this chapter also provides researchers with compact economic and environmental data in biomass and food production from switchgrass and corn.
- This study guides farmers and decision makers by providing economically efficient and environmentally friendly management strategies. In this model, priority given to the economic and environmental effects of food and biofuel production can be decided by the DM. In order to ensure food security, our study advises managers (government, policy makers, etc.) to provide CRP incentives or to adjust the sustainability factor, which defines cropland availability for biofuel production.

The remainder of this chapter is organized as follows: The problem statement and mathematical notations are presented in section 3.2, while the mathematical formulation developed for corn and switchgrass is described in detail in section 3.3. Input data for parameters are given in section 3.4. A case study with all computational results along with the sensitivity analysis is described in section 3.5. Finally, conclusions and future directions are discussed in section 3.6.

3.2 Problem Statement

Our goal in this chapter is to provide a mathematical model to maximize total economic and environmental benefits of biofuel and food production. We consider switchgrass as an energy crop, due to its positive environmental impacts and low input requirements. It is also a perennial grass that is native to North America and a promising second-generation biofuel crop, which is shown to be profitable on different land types [10]. Corn is considered a food crop due to its availability and prevalent cultivation in the U.S. It is also currently used in biofuel production, leading to disputes over sustainability of the food supply.

Switchgrass and corn production shows different properties. Switchgrass has a minimum ten-year life expectancy. On the other hand, corn requires establishment each year and uses a larger amount of fertilizers, herbicides, and pesticides than switchgrass. In addition, corn and switchgrass production have different environmental effects. It has been shown that switchgrass production, particularly on marginal lands, has a positive effect on the environment, such as reduction in GHG emissions, storage of soil organic carbon, and prevention of soil erosion due to its long root system [26]. However, requiring more fertilizer and seeding every year, corn production is not very benign to soil. Production of corn and

switchgrass is impacted by many factors, such as input, yield amount, budget allocation to farm operations, and related environmental influences. Therefore, one needs a compact decision-making system in order to obtain the best economic and environmentally benign management strategies for biofuel and food production from switchgrass and corn.

The stages of food and biofuel production start with seeding and end with transporting the yield to facilities. Figure 3.1 presents each stage of production and corresponding decisions.

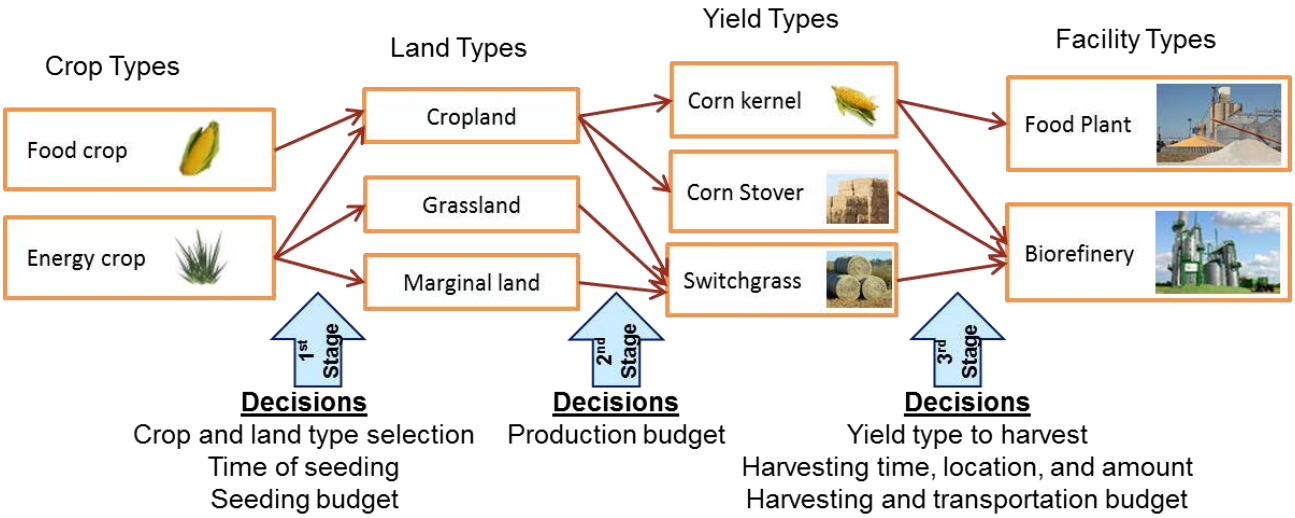

Figure 3.1 Flow chart and decisions made in food and biofuel production.

In the first stage, the model allocates food and energy crops to different land types, which results in diverse economic and environmental impacts on each land type. Seeding switchgrass can be considered a strategic-level decision since investment in switchgrass has a return for ten years. Seeding time and related budget allocation are other decisions involved in this first stage. In the second stage, we determine the optimal amount of overall budget that should be allocated to production operations. The production budget depends on rental cost and fertilizer needed. It is time-varying since switchgrass grows to its potential yield until the end of the third year of seeding. At the third and final stage, in order to maximize the overall benefits (from

profit and environment), the yield type to be harvested, time of harvesting, harvesting zones, and harvesting amount are optimally determined. In addition, at this final stage, based on the harvested yield type, food and biomass yields are transported to processing facilities, and a budget is allocated for the transportation operation. Note that decisions involved in all three stages of biofuel and food production are made simultaneously in our model.

Among various seeding methods, the reduced tillage process is used for corn in this model because it is one of the most common practices for cultivating this grain [27]. On the other hand, for switchgrass production, we consider airflow planting, which is found to be an optimal seeding method for switchgrass in a previous study [10]. We assume that when corn is grown, corn grain is harvested since it is a valuable commodity. We also assume in this model that transportation is carried out by farmers and that truck delivery is the method of transportation. A list of indices, sets, binary and continuous decision variables, along with parameters used in the proposed mathematical model are provided in the nomenclature that follows.

Nomenclature

Indices

i Row of cultivation zone

j Column of cultivation zone

(i, j) Cultivation zone

k Crop type (1: switchgrass, 2: corn)

v Yield type (1: switchgrass, 2: corn grain for food, 3: corn grain for biofuel, 4: corn stover)

t Time period

Sets

I Set of rows of cultivation area

J Set of columns of cultivation area

K Set of crop types

V Set of yield types

T Set of time periods in modeling horizon

M_t Set of time periods from first period to period t ($M_t = \{1, \dots, t\}$)

CR Set of cropland zones in cultivation area

GR Set of grassland zones in cultivation area

MR Set of marginal land zones in cultivation area

Binary Decision Variables

S_{ijk}^t 1 if zone (*i,j*) is seeded with crop type *k* at time period *t*, 0 otherwise

X_{ijv}^t 1 if zone (*i,j*) is harvested for yield type *v* at time period *t*, 0 otherwise

Continuous Decision Variables

N_{ij}^t Switchgrass yield in zone (*i,j*) at time period *t* (tonnes)

$\bar{N}_{ij}^t$ Harvested switchgrass biomass in zone (*i,j*) at time period *t* (tonnes)

$\tilde{Y}_{ij}^t$ Corn grain used for food production in zone (*i,j*) at time period *t* (tonnes)

$\bar{Y}_{ij}^t$ Corn grain used for biofuel production in zone (*i,j*) at time period *t* (tonnes)

Y_{ij}^t Harvested corn stover in zone (*i,j*) at time period *t* (tonnes)

E_b Establishment budget used ($)

P_b Production budget used ($)

H_b Harvesting budget used ($)

T_b Transportation budget used ($)

Parameters

α Weight of profit

β Weight of environmental effects

p_v^t Sale price of yield type *v* at time period *t* ($/tonne)

A_{ijv} Potential yield of yield type *v* in zone (*i,j*) (tonnes)

SE_{ijk} Economic value of soil erosion prevention in zone (*i,j*) via crop type *k* ($)

ϕ Soil erosion prevention reduction constant for harvested yield

CS_{ijk} Economic value of carbon sequestration in zone (*i,j*) via crop type *k* ($)

ξ Carbon sequestration reduction constant for harvested yield

σ_k Carbon emissions penalty of seeding crop type *k* ($)

ρ_v Carbon emissions penalty of harvesting yield type *v* ($)

ω_v Carbon emissions penalty of production operations for yield type *v* ($/tonne)

τ Carbon emissions penalty of transporting yield ($/tonne-km)

η Economic damage caused by nitrogen pollution ($/kg)

fe_k Nitrogen fertilization applied for crop type *k* (kg)

μ_k Percent nitrogen uptake by crop type *k*

ψ Percent nitrogen contamination (leaching) in drinking water

π_t Growth factor of switchgrass after *t* years of establishment

e_v Biofuel conversion factor for yield type *v* (liter/tonne)

Δ Fraction of facility capacity assigned to biofuel production from switchgrass and corn biomass

C_t Biofuel production capacity of facility at time period *t* (liter)

B Total available budget in planning horizon ($)

TEC_{ijk} Total expected establishment cost for crop type *k* in zone (*i,j*) ($)

ϵ_k Fixed cost of producing crop type *k* per cultivation zone ($)

RC_{ij} Rental cost of cultivation zone (*i,j*) ($)

γ_v Variable cost of producing yield type *v* ($/tonne)

δ_v Fixed cost of harvesting yield type *v* per zone ($)

θ_v Variable cost of harvesting yield type *v* ($/tonne)

D_{ij} Distance of zone (*i,j*) to facility (km)

F_v Fixed cost of transporting yield type *v* ($)

V_v Variable cost of transporting yield type *v* ($/tonne km)

λ Sustainability factor defining percentage of cropland not allowed for energy crop production

3.3 Mathematical Model

We develop a multi-objective and multi-stage MILP model in order to maximize the total economic and environmental benefits from biomass and food production. We consider switchgrass and corn as energy crop and food crop, respectively. Switchgrass and corn stover have been utilized in biofuel production, while corn grain has been used in both biofuel and food production. This model determines the optimum land and budget allocation for various crop types and farm operations, along with the time of seeding and harvesting, and transported

yield amounts. We present a complete model formulation with detailed explanation of the objective function and constraints beginning with equation (3.1) to equation (3.35) as follows:

3.3.1 Objective Function

The goal of the proposed model is to maximize the benefits of biofuel production from switchgrass, corn stover, and corn grain as well as food production from corn throughout the entire planning horizon. The total benefit is comprised of two parts: economic and environmental. The first part defines the profit by subtracting the total cost of establishment (E_b) , production (P_b), harvesting (H_b), and transportation (T_b), (budget used) from the total revenue (TR). The second part is the net economic value of various environmental benefits, such as savings from total soil erosion prevention (TSE) and total carbon sequestration (TCS) minus environmental hazards such as loss from total carbon emissions (TCE) and total nitrogen pollution (TNP).

$$Maximize\ Total\ Benefit = \alpha\big(TR - (E_b + P_b + H_b + T_b)\big) + \beta(TSE + TCS - TCE - TNP) \quad (3.1)$$

where α and β are used to assign priorities of the decision maker to the economic and environmental terms.

3.3.1.1 Total Revenue

Total revenue of the farmer from the sales of food and biomass production over all lands and time periods is calculated as

$$TR = \sum_i \sum_j \sum_t \big(p_1^t \bar{N}_{ij}^t + p_2^t \tilde{Y}_{ij}^t + p_3^t \bar{Y}_{ij}^t + p_4^t Y_{ij}^t\big) \quad (3.2)$$

where $p_v(t)$ is the sale price of different yield types (v = 1, 2, 3, and 4, respectively) at time period t, and $\bar{N}_{ij}^t$, $\tilde{Y}_{ij}^t$, $\bar{Y}_{ij}^t$, and Y_{ij}^t are harvested amounts of switchgrass yield, corn grain for food, corn grain for biofuel, and corn stover, respectively, in zone *(i,j)* at time t. Prices of yield

types (switchgrass, corn grain, and corn stover) that go to biofuel production are taken to be constant because we assume that they are sold in contracts with a biorefinery. On the other hand, the price of corn grain for food is assumed to be affected by market conditions. The detailed explanation for the function of revenue and supplied quantity of corn grain along with its piecewise linearization are provided below.

Supply-Price Relation for Corn Grain

We model the changes of price of corn grain according to the supplied amount. For corn grain in the food market, price is expected to decrease as the supplied amount increases, when other factors such as customer preferences, demand, and alternative food prices are held constant. We define the supplied corn grain as $\tilde{Y}^t = \sum_i \sum_j \tilde{Y}_{ij}^t$. The price is described as a function of corn grain supply and defined as $p_2^t = U_1^t - U_2^t \tilde{Y}^t$, where U_1^t and U_2^t are non-negative constants. Thus, the revenue function, $R^t(\tilde{Y}^t)$, can be written as

$$R^t\left(\tilde{Y}^t\right) = U_1^t \tilde{Y}^t - U_2^t\left(\tilde{Y}^t\right)^2 \quad \forall\, t \in T \tag{3.3}$$

In order to linearize equation (3.3), we construct its piecewise linear lower approximation. In this approximation, the supplied yield is divided into different segments: *s = 1,…,S*, where each segment *s* is bounded below by Z_{s-1} and above by Z_s. An example of the revenue function and its piecewise linear lower approximation using three segments are shown in Figure 3.2. The corn price in the food market, p_2^t, is divided into subprices in each segment *s*, $\tilde{p}_{2s}^t$, which decrease as the supplied amount increases but are constant in each segment *s*, as shown in Figure 3.3 in the data section for three segments [28]. We define E_s^t as a non-negative variable representing the yield amount of corn grain for food obtained in segment *s*. Note that the value of E_s^t gives the yield amount of corn grain for food exceeding Z_{s-1} and is bounded

above by the difference of Z_s and Z_{s-1}. For example, if total corn grain yield for food is between Z_1 and Z_2, then the value of E_1^t is $Z_1 - Z_0$, E_2^t is equal to $\tilde{Y}^t - Z_1$, and E_3^t becomes zero.

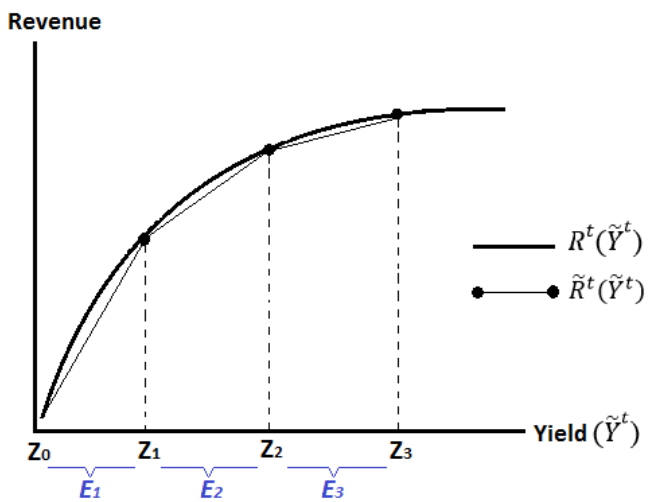

Figure 3.2 Revenue-yield relation and piecewise linear lower approximation.

In a generalized case, each E_s^t can be defined by the following inequality

$$E_s^t \leq max\{0, min\{Z_s, \tilde{Y}^t\} - Z_{s-1}\} \quad \forall\, s \in S, t \in T \tag{3.4}$$

Note that since our problem is a maximization model, the E_s^t value will be equal to its upper bound as given in the inequality (3.4) at optimality. For a given period t, the piecewise linear lower approximation function for revenue from corn grain, $\tilde{R}^t(\tilde{Y}^t)$ can then be written as

$$\tilde{R}^t(\tilde{Y}^t) = \sum_s \tilde{p}_{2s}^t E_s^t \quad \forall\, t \in T \tag{3.5}$$

Equation (3.5) ensures that total corn grain sales (revenue) is equal to the summation of corn grain sales over all segments s at time period t. Since the term E_s^t defined in inequality (3.4) is non-linear, we linearize E_s^t in equation (3.5) by replacing inequality (3.4) with the following linear inequalities:

$$E_s^t \leq \tilde{Y}^t - Z_{s-1} + Z_s(1 - R_s^t) \quad \forall\, s \in S, t \in T \tag{3.6}$$

$$E_s^t \leq (Z_s - Z_{s-1})\, R_s^t \quad \forall\, s \in S, t \in T \tag{3.7}$$

where we introduce a binary decision variable, R_s^t, which takes the value 1, if $Z_{s-1} \leq \tilde{Y}^t$, and 0, otherwise. If $Z_{s-1} \leq \tilde{Y}^t$ holds, then E_s^t is bounded above by the total corn grain yield, $\tilde{Y}^t$, minus the lower bound of segment *s*, Z_{s-1}, in inequality (3.6). In this case, E_s^t is also restricted by its range (upper-bound, Z_s, minus lower-bound, Z_{s-1}), as given in inequality (3.7), and will attain the minimum of these two bounds defined in inequalities (3.6) and (3.7). If $\tilde{Y}^t < Z_{s-1}$ holds, then R_s^t takes the value 0, thus ensuring a non-negative and non-restricting upper bound on E_s^t by inequality (3.6) and a zero upper bound by inequality (3.7). Note that, in this case, E_s^t will attain the value of zero when the linear approximation of the maximization problem, shown in equations (3.1) to (3.35), is solved.

3.3.1.2 Soil Erosion Prevention

Each crop type has different effects on soil erosion. *TSE* represents the economic value of soil erosion prevention as

$$TSE = \sum_i \sum_j \sum_t \left(SE_{ij1} \left(\frac{N_{ij}^t - \phi \bar{N}_{ij}^t}{A_{ij1}} \right) + SE_{ij2} \left(\frac{\tilde{Y}_{ij}^t + \bar{Y}_{ij}^t}{A_{ij2}} - \phi \frac{Y_{ij}^t}{A_{ij4}} \right) \right) \tag{3.8}$$

where SE_{ijk} is soil erosion savings in zone *(i,j)* by crop type *k* (1 and 2, respectively). As the yield amount in a given zone reaches its potential, the full amount of soil erosion savings is realized. However, if switchgrass or corn stover is harvested, then the savings from soil erosion decreases by the harvested amount since harvesting the yield makes the soil more vulnerable to rain and wind. For that purpose, a reduction constant, ϕ, is utilized to reflect the effect of harvesting on the savings. To calculate the total soil erosion savings, SE_{ijk} is multiplied by the proportion of remaining yield to its potential.

3.3.1.3 Carbon Sequestration

The storage of atmospheric CO_2 as soil organic carbon increases soil productivity. That carbon sequestration can also be realized as savings as follows:

$$TCS = \sum_i \sum_j \sum_t \left(CS_{ij1} \left(\frac{N_{ij}^t - \xi \bar{N}_{ij}^t}{A_{ij1}} \right) + CS_{ij2} \left(\frac{\tilde{Y}_{ij}^t + \bar{Y}_{ij}^t}{A_{ij2}} - \xi \frac{Y_{ij}^t}{A_{ij4}} \right) \right) \tag{3.9}$$

where CS_{ijk}, the economic value of carbon sequestration in zone *(i,j)* via crop type *k* (1 and 2, respectively), is multiplied by the ratio of yield amount to potential yield. In a similar manner to soil-erosion savings, if harvested, the savings from carbon sequestration is expected to decrease with the reduction constant, ξ.

3.3.1.4 Carbon Emissions

The economic value of carbon emissions during farm operations has been formulized as

$$TCE = \sum_i \sum_j \sum_t \left(\sum_k \sigma_k S_{ijk}^t + \sum_v \rho_v X_{ijv}^t + \omega_1 \bar{N}_{ij}^t + \omega_2 \tilde{Y}_{ij}^t + \omega_3 \bar{Y}_{ij}^t + \omega_4 Y_{ij}^t \right)$$
$$+ \sum_i \sum_j \sum_t D_{ij} \tau \left(\bar{N}_{ij}^t + \tilde{Y}_{ij}^t + \bar{Y}_{ij}^t + Y_{ij}^t \right) \tag{3.10}$$

where σ_k is the carbon emissions penalty of seeding crop type *k*, ρ_v is the carbon emissions penalty of harvesting yield type *v*, and ω_v is the carbon emissions penalty of production operations of yield type *v* (1, 2, 3, and 4, respectively). Finally, D_{ij} and τ are the distance in km and the carbon emissions penalty per tonne-km, respectively, for transporting the harvested amount.

3.3.1.5 Nitrogen Pollution

The cost of nitrogen pollution, in particular contamination to groundwater, has been considered in this model using the following equation:

$$TNP = \eta \sum_i \sum_j \sum_t \left(\sum_{h \in M_t} S_{ij1}^h fe_1 (1 - \mu_1) \psi + S_{ij2}^t fe_2 (1 - \mu_2) \psi \right) \tag{3.11}$$

where η, the economic value of damage caused by nitrogen pollution, is multiplied by nitrogen leakage. In order to obtain the amount of nitrogen contaminating groundwater, fe_k, the nitrogen applied for crop type *k* (1 and 2, respectively) is multiplied by the percent remaining after uptake by crop type *k*, (1-μ_k). Then, ψ, the percent of leaching to drinking water, is employed.

3.3.2 Constraints on Grown Yield

Yield amounts for switchgrass, corn grain, and corn stover that can be obtained from zone *(i,j)* at time period *t* are formulized using the following equations, respectively:

$$N_{ij}^{t} = \sum_{z \in M_t} A_{ij1} \pi_{t-z+1} S_{ij1}^{z} \quad \forall\, i \in I, j \in J, t \in T \tag{3.12}$$

$$\tilde{Y}_{ij}^{t} + \bar{Y}_{ij}^{t} = A_{ij2} S_{ij2}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.13}$$

$$Y_{ij}^{t} \leq A_{ij4} S_{ij2}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.14}$$

where equation (3.12) defines the total amount of switchgrass grown in zone *(i,j)* at time period *t*, N_{ij}^{t}. This is equal to the potential yield amount multiplied by the growth factor of switchgrass, π_{t-z+1}, which is also affected by time of seeding in that zone, S_{ij1}^{t}. Equality (3.13) ensures that the summation of corn grain for food and corn grain for biofuel obtained in zone *(i,j)* at time period *t* should be equal to the potential corn grain yield, A_{ij2}, if it is seeded. Similarly, constraint (3.14) ensures that harvested corn stover cannot exceed the potential stover yield in zone *(i,j)* at time period *t*.

3.3.3 Seeding Constraints

Constraints regarding seeding rules for switchgrass and corn are defined as follows:

$$\sum_{t} S_{ij1}^{t} \leq 1 \quad \forall\, i \in I, j \in J \tag{3.15}$$

$$S_{ij2}^{t} + \sum_{h \in M_t} S_{ij1}^{h} \leq 1 \quad \forall\, i \in I, j \in J, t \in T \tag{3.16}$$

Inequality (3.15) ensures that switchgrass can be seeded only once at each zone *(i,j)* during the planning horizon. Inequality (3.16) prevents corn seeding, S_{ij2}^{t}, on zones where switchgrass is previously seeded. It also imposes seeding for only one crop type for each zone *(i,j)* at each time period *t*.

3.3.4 Harvesting Constraints

Harvesting of switchgrass, corn grain, and corn stover are defined, respectively, as

$$X_{ij1}^{t} \leq \sum_{h \in M_t} S_{ij1}^{h} \quad \forall\, i \in I, j \in J, t \in T \tag{3.17}$$

$$X_{ij2}^{t} + X_{ij3}^{t} = S_{ij2}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.18}$$

$$X_{ij4}^{t} \leq S_{ij2}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.19}$$

where inequality (3.17) ensures that switchgrass can be harvested in zone *(i,j)* at time period *t*, only if it is seeded on or before time period *t*. Equation (3.18) forces the harvesting of corn grain in zone *(i,j)* at time *t*, if it is seeded. However, inequality (3.19) allows the model to decide whether or not to harvest corn stover, X_{ij3}^{t}, when corn is seeded.

3.3.5 Harvested Yield Constraints

The amount of harvested switchgrass biomass (first two equations), corn grain for food, corn grain for biofuel production, and corn stover is defined, respectively, as follows:

$$\bar{N}_{ij}^{t} \leq A_{ij1} X_{ij1}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.20}$$

$$\bar{N}_{ij}^{t} \leq N_{ij}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.21}$$

$$\tilde{Y}_{ij}^{t} \leq A_{ij2} X_{ij2}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.22}$$

$$\bar{Y}_{ij}^{t} \leq A_{ij3} X_{ij3}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.23}$$

$$Y_{ij}^{t} \leq A_{ij4} X_{ij4}^{t} \quad \forall\, i \in I, j \in J, t \in T \tag{3.24}$$

where inequalities (3.20), (3.22), (3.23), and (3.24) ensure that harvested switchgrass, corn grain for food, corn grain for biofuel production, and corn stover in zone *(i,j)* at time period *t* cannot exceed the potential amount of each yield type when there is harvesting. Otherwise, all harvesting amounts are set to zero. For switchgrass, in addition to inequality (3.20), constraint (3.21) limits the harvested amount by switchgrass yield, N_{ij}^{t}.

3.3.6 Biofuel Capacity Constraint

The capacity constraint for the biorefinery is included in the model as

$$\sum_i \sum_j \left(e_1 \bar{N}_{ij}^{t} + e_3 \bar{Y}_{ij}^{t} + e_4 Y_{ij}^{t}\right) \leq \Delta C_t \quad \forall\, t \in T \tag{3.25}$$

where e_v, the biofuel conversion factor for yield type *v* (1, 3, and 4) multiplied by corresponding harvested yields cannot exceed the fraction of facility capacity assigned to biofuel obtained from switchgrass and corn at time period *t*.

3.3.7 Budget Constraints

The total budget assigned to establishment, E_b, production, P_b, harvesting, H_b, and transportation, T_b, cannot exceed the available budget, B, in the planning horizon as presented by

$$E_b + P_b + H_b + T_b \leq B \tag{3.26}$$

where the cost of each farm operation—E_b, P_b, H_b, and T_b—has been formulized in constraints (3.27) to (3.30), respectively, as

$$\sum_i \sum_j \sum_k \sum_t TEC_{ijk} S_{ijk}^{t} = E_b \tag{3.27}$$

$$\sum_i \sum_j \sum_t \left(\left(\epsilon_1 + RC_{ij}\right) \sum_{h \in M_t} S_{ij1}^{h} + \left(\epsilon_2 + RC_{ij}\right) S_{ij2}^{t}\right)$$
$$+ \sum_i \sum_i \sum_t \left(\gamma_1 \bar{N}_{ij}^{t} + \gamma_2 \tilde{Y}_{ij}^{t} + \gamma_3 \bar{Y}_{ij}^{t} + \gamma_4 Y_{ij}^{t}\right) = P_b \tag{3.28}$$

$$\sum_i \sum_j \sum_t \left(\left(\sum_v \delta_v X_{ijv}^t \right) + \theta_1 \bar{N}_{ij}^t + \theta_2 \tilde{Y}_{ij}^t + \theta_3 \bar{Y}_{ij}^t + \theta_4 Y_{ij}^t \right) = H_b \tag{3.29}$$

$$\sum_i \sum_j \sum_t \left(\left(\sum_v F_v X_{ijv}^t \right) + D_{ij} \left(V_1 \bar{N}_{ij}^t + V_2 \tilde{Y}_{ij}^t + V_3 \bar{Y}_{ij}^t + V_4 Y_{ij}^t \right) \right) = T_b \tag{3.30}$$

Equation (3.27) states that the establishment cost, E_b, is equal to the multiplication of total expected establishment cost for crop type *k* in zone *(i,j)*, TEC_{ijk}, and the seeding decision variable of crop type *k* in zone (*i,j*), $S_{ijk}(t)$. Equation (3.28) defines the value of production cost, which involves fixed and variable costs. The fixed cost, ϵ_k, includes the cost of fertilizer for producing crop type *k* and the rental cost of zone (*i,j*), RC_{ij}. The variable cost of fertilizer depends on the amount of harvested yield type *v* (1, 2, 3, and 4), γ_v. Equation (3.29) defines the cost of harvesting by incorporating a fixed cost, δ_v, and a variable cost, θ_v, of harvesting crop type *v*. In a similar fashion, equation (7.4) defines the transportation cost by incorporating a fixed cost of transporting yield type *v*, F_v, and a variable cost of transporting yield type *v*, V_v. The variable cost also depends on the distance between zone (*i,j*) and the demand point given by D_{ij}.

3.3.8 Biodiversity and Sustainability Constraints

In addition to the environmental impacts of biomass and food production as defined in the objective function, we have also considered their effects on the biodiversity of bird populations and sustainability of the food supply, respectively, as

$$\sum_{m=i-1}^{i+1} \sum_{n=j-1}^{j+1} (1 - X_{mn1}^t) \geq X_{ij1}^t \quad \forall\, t \in T, and\ (i,j) \in GR\ or\ MR \tag{3.31}$$

$$\sum_{(i,j) \in CR} \sum_{h \in M_t} S_{ij1}^h \leq (1 - \lambda)|CR| \quad \forall\, t \in T \tag{3.32}$$

Inequality (3.31) prevents harvesting in at least one of the neighboring zones of zone (*i,j*), if switchgrass has been harvested in zone (*i,j*) of grassland or marginal land in order to provide

nesting areas for tallgrass and shortgrass bird species. Inequality (3.32) ensures sustainability of the food supply by limiting switchgrass seeding on cropland to a certain proportion, $(1-\lambda)$, which is multiplied by the cardinality of the set of croplands.

3.3.9 Integrality and Non-Negativity Constraints

Seeding and harvesting decisions for switchgrass and corn are defined to be binary variables, as given in equations (3.33) and (3.34), while switchgrass yield and harvested switchgrass, corn grain for food, corn grain for biofuel, and corn stover are forced to be non-negative in equation (3.35) as given below:

$$S_{ijk}^{t} \in \{0,1\} \quad \forall\, i \in I, j \in J, k \in K, t \in T \tag{3.33}$$

$$X_{ijv}^{t} \in \{0,1\} \quad \forall\, i \in I, j \in J, v \in V, t \in T \tag{3.34}$$

$$N_{ij}^{t}, \bar{N}_{ij}^{t}, \tilde{Y}_{ij}^{t}, \bar{Y}_{ij}^{t}, Y_{ij}^{t} \geq 0 \quad \forall\, i \in I, j \in J, t \in T \tag{3.35}$$

3.4 Case Study and Data

This proposed mathematical model is applied to ethanol and food production in the city of Hugoton, Kansas. Ethanol production capacity of the biorefinery in Hugoton is about 95 million liters (25 million gallons) per year. The technology used in this biorefinery is capable of producing ethanol from cellulosic feedstock, food crops, and food crop residue, which we consider to be switchgrass, corn grain, and corn stover, respectively [29]. We do not utilize the capacity constraint in our analysis as a limiting factor in order to obtain better insight into the other problem parameters. The cultivation area in Hugoton includes different land types such as cropland, grassland, and marginal land. The studied area is divided into 21 rows and 21 columns, where the size of each zone is defined as 260 ha (one square mile). Switchgrass is produced on all land types, while corn production is only considered on cropland. We also

consider corn in the food market in order to include the analysis of both food and biofuel production. Since the life expectancy of switchgrass is at least ten years, the planning horizon is taken as ten years, and each time period is set as one year in this study.

3.4.1 Data

In this section, we present the data used in the case study. The details of switchgrass production data along with its calculation can be found in a previous study [10].

3.4.1.1 Yield Amount

The yield amount of switchgrass, corn grain, and corn stover are given in Table 3.1. The expected life of switchgrass is ten years, and it reaches its maximum potential yield at the third year [10]. We take the maximum potential yield of switchgrass to be 15 tonnes per hectare in Kansas cropland. Switchgrass yield in the first and second years is 25% and 66%, respectively, of the maximum potential yield. In order to obtain switchgrass yield in grassland and marginal land, the cropland yield values have been multiplied by 0.7 and 0.5, respectively [10]. The average corn yield is estimated to be 6.8 tonnes per hectare (110 bushels per acre) in Kansas [23]. Corn stover yield is taken as 1.1 times that of corn grain, based on the literature [30].

TABLE 3.1 YIELD TYPE, SEEDING LOCATION, AND CORRESPONDING YIELD AMOUNTS

Yield type	Land type	Yield (tonnes/ha)		
		t = 1	t = 2	t = 3–10
Switchgrass	Cropland	3.75	10	15
Switchgrass	Grassland	2.63	7	10.5
Switchgrass	Marginal land	1.87	5	7.5
Corn grain	Cropland	6.8	6.8	6.8
Corn stover	Cropland	7.48	7.48	7.48

In order to maintain the minimum requirements for soil erosion protection, only 50% of the corn stover yield (Table 3.1) is considered harvestable, while it changes between 20% and 80% in the literature [24], [31].

3.4.1.2 Establishment Cost

The establishment cost of switchgrass and corn is provided in Table 3.2. We use airflow planting during the frost season for switchgrass establishment, which is shown to be the optimal seeding method [10]. On the other hand, we use reduced tillage for corn seeding, since it is a common method in Kansas [23], [25], [27].

TABLE 3.2 SWITCHGRASS AND CORN ESTABLISHMENT COSTS

Crop type	Land type	Method	Total establishment cost, TEC_{ijk} ($/ha)
Switchgrass	Cropland	Airflow	435.15
Switchgrass	Grassland	Airflow	445.77
Switchgrass	Marginal land	Airflow	474.80
Corn	Cropland	Reduced tillage	342.76

3.4.1.3 Production Cost

Production cost includes rent and fertilizer application for each yield type (switchgrass, corn grain, and corn stover). Average land rental costs of cropland, grassland, and marginal land in southwest Kansas are $234.6, $23.7, and $75.3 per hectare, respectively. The total fixed cost of switchgrass production is $97.84 per hectare [32], which includes cost of application of 112 kg nitrogen ($80.95 per hectare) and pesticide ($16.89 per hectare). A variable cost is phosphorus and potassium fertilization, which is $12 per tonne of harvested switchgrass yield.

Fixed P and K are used for corn production in the amount of 39 kg and 33.6 kg per hectare (89.63$), respectively. The fixed cost including herbicide ($61), insecticide ($47), and lime ($8.22) application totals $205.85 per hectare. On the other hand, 167 kg of N is applied

for every 6.8 tonnes of corn grain obtained, which leads to a variable cost of $26 for every tonne of corn grain [23]. The approximate values of P and K replacement required for every tonne of corn stover are about 3.1 kg, and 16.25 kg, respectively, which leads to a total cost of $22.33 per tonne of corn stover harvested [23], [24].

3.4.1.4 Harvesting Cost

For switchgrass, mowing and raking has a fixed cost of $31.61 per hectare. The variable cost of harvesting is taken as $24.5 per tonne of switchgrass harvested. For corn grain, the fixed cost of harvesting is $64.54 per hectare, while the corresponding variable cost is $15.2 per tonne of corn grain [23]. The fixed cost of harvesting corn stover is $14 per hectare, while the variable cost is about $9 for every tonne of corn stover harvested [33].

3.4.1.5 Transportation Cost

For switchgrass, the cost of transporting biomass by truck is calculated based on the following formula: $5.70 + $0.1367X, where $5.70 is the fixed cost per hectare and $0.1367 is the variable cost per tonne-km represented by X. An additional variable cost, the unloading and handling of biomass at the biorefinery, is taken as $1.88 per tonne of biomass [24]. For corn grain, the transportation cost is taken as $0.5 for each tonne-km based on the literature [34]. The transportation cost of corn stover is calculated in the same way as for switchgrass.

3.4.1.6 Soil Erosion

The savings to farmers and society from erosion is equal to $7.38 per tonne of soil. The contribution of switchgrass to soil erosion savings is considered to be $61.18, $9.89, and $19.85 per hectare-year, respectively, for cropland, grassland, and marginal land in Kansas [35]. However, corn production with reduced tillage causes about 0.4–1 mm soil loss per year,

resulting in 5–12 tonnes of soil erosion per hectare [35]. Therefore, a loss of $36.9 per hectare due to soil erosion is assumed for corn production. Harvesting switchgrass and corn stover is assumed to decrease the related soil erosion savings by 70%, based on the literature [36].

3.4.1.7 Carbon Sequestration—Soil Organic Carbon

The amount of SOC increase from each crop type, its CO_2 equivalence, and corresponding savings are provided in Table 3.3. Carbon sequestered by switchgrass in cropland is taken as 4.42 Mg/ha/year [37]. An average value of 3.2 Mg/ha/year is used for carbon sequestration on marginal land, while 0.32 Mg/ha/year is considered on grassland. Minor carbon sequestration is achieved by corn production, which is 368 kg/ha/year [38], while 7.5 tonnes of corn stover per hectare are needed for that amount of carbon sequestration [39]. Therefore, for the case when half of the stover is harvested, the SOC levels are assumed to decrease by half [39]. Similarly, when switchgrass is harvested, the SOC levels shown in Table 3.3 are assumed to decrease. Since carbon storage in the current soil carbon pool takes about 25–45 years to reach equilibrium [40], carbon sequestration rates are not assumed to decrease in the ten-year planning horizon.

TABLE 3.3 SOIL ORGANIC CARBON (SOC), CO_2 EQUIVALENCE, AND SAVINGS

Crop type	Land type	SOC (Mg/ha-yr)	CO_2 Equivalence (tonnes/ha-yr)	Savings ($/ha-yr)
Switchgrass	Cropland	4.42	16.22	324.4
Switchgrass	Grassland	0.32	1.17	23.5
Switchgrass	Marginal land	3.2	11.74	234.8
Corn	Cropland	0.368	1.35	27

Each tonne of SOC stored in the soil is equal to 3.67 tonnes of CO_2 absorption from the atmosphere. The average cost of CO_2 emissions is $20 per tonne, according to the Emissions

Trading System in the EU [10]. Therefore, savings is computed by multiplying $20 by the CO_2 equivalence.

3.4.1.8 CO_2 Emissions

The cost of carbon emissions that occur during seeding, production, harvesting, and transportation is provided in Table 3.4 [37], [38]. Carbon dioxide emitted during each sub-operation is given in the "CO_2 emissions" column. The usage numbers (or amount) of these suboperations (pesticides or fertilizers) in each operation are indicated in the "Usage in switchgrass" and "Usage in corn" columns. Finally the cost of CO_2 emissions (which is obtained by multiplying each tonne of CO_2 emissions by $20) is presented in the "Cost for switchgrass" and "Cost for corn" columns, respectively.

TABLE 3.4 FARM OPERATIONS, CO_2 EMISSIONS, USAGE OF SWITCHGRASS AND CORN, AND CORRESPONDING COST

Operation	Suboperation	CO_2 Emissions [41]		Usage in switchgrass [16]		Usage in corn [23], [24]		Cost for switchgrass		Cost for corn	
Seeding	Drill	35.3	kg/ha	-		1		-		0.706	$/ha
Seeding	Airflow	7.9	kg/ha	1		-		0.158	$/ha	-	
Seeding	Pest/herbicide	6.3	kg/kg	5.25	kg/ha	6.36	kg/ha	0.66	$/ha	0.801	$/ha
Seeding	Fertilizer (N)	1.3	kg/kg	-		24.55	kg/t	-		0.638	$/t
Seeding	Fertilizer (P)	0.2	kg/kg	33.6	kg/ha	39.2	kg/ha	0.134	$/ha	0.157	$/ha
Seeding	Fertilizer (K)	0.15	kg/kg	44.8	kg/ha	33.6	kg/ha	0.134	$/ha	0.101	$/ha
Production	Pesticide	6.3	kg/kg	5.25	kg/ha	5.59	kg/ha	0.66	$/ha	0.704	$/ha
Production	Fertilizer (N)	1.3	kg/kg	112	kg/ha	6.8*	kg/t	2.91	$/ha	0.1768*	$/t
Production	Fertilizer (P)	0.2	kg/kg	0.42	kg/t	3.1*	kg/t	0.0017	$/t	0.0124*	$/t
Production	Fertilizer (K)	0.15	kg/kg	9.47	kg/t	16.25*	kg/t	0.0284	$/t	0.0488*	$/t
Harvesting	-	8.5	kg/ha	-		1		-		0.17	$/ha
Harvesting	Rake	1.7	kg/ha	1		1*		0.034	$/ha	0.034*	$/ha
Harvesting	Bale	3.30	kg/ha	1		1*		0.066	$/ha	0.066*	$/ha
Transportation	Truck	0.203	kg/t-km	1		1		0.0059	$/t-km	0.0041	$/t km

*Additional cost of fertilizer required when harvesting corn stover

3.4.1.9 Nitrogen Pollution

Nitrogen is an essential fertilizer in crop production; however, it is also highly associated with the risk of polluting groundwater [36]. It is stated that a single harvest system removes only 50% of the N applied [40], while other studies indicate that N uptake changes about 14%–75% for switchgrass [42], [43]. Therefore, we take N uptake by switchgrass as an average value of 60%. On the other hand, N uptake by corn is 45% when four-year observation data is averaged [44]. We assume that 10% of the remaining N is dissolved in rain water or contaminates the groundwater. The cost related to health issues regarding N pollution in drinking water is estimated to be $0–5.5 per kg of N contaminated into water [45]. We take the N pollution cost as $4 per kg but also perform sensitivity analysis using different cost values for N pollution.

3.4.1.10 Conversion Rate

Ethanol production from switchgrass and corn grain is reported as 333 liters per tonne and 386 liters per tonne, respectively [46]. The rate of ethanol production from corn stover is equal to 336 liters per tonne [47].

3.4.1.11 Yield Price

The price of switchgrass is reported to be $94–130 per tonne [48]; therefore, we take the switchgrass biomass price as $100 per tonne in this study. The nominal corn price is taken as $160 per tonne, while the corn stover price is set at $50 per tonne, based on the study of Maung and Gustafson [30].

We take the price of corn grain for biofuel as $168 per tonne because the price of corn has increased by 5% with the introduction of biofuel demand based on the model of Rajagopal

et al. [49]. This price is taken as constant since corn grain for biofuel is sold based on contracts. For the price of corn grain that goes to the food market in the linearized model, the production level is considered in three segments: low, medium, and high, where each level has a different but constant price value in the corresponding segment. The relation between corn grain production and its price can be seen in Figure 3.3. Given the constant demand, when production is at a low quantity, the supply curve moves to the left (S_{low}), which increases the price of corn grain. On the other hand, when producing more than a medium quantity, the supply curve moves from medium (S_{medium}) to right (S_{high}), which decreases the corn price. The relation of revenue and supply amount can also be observed in Figure 3.3, where the slope of each section gives the price of corn grain in the corresponding segment. In the low-production case (cultivation in less than 33% of cropland), the price of corn grain for food, $\tilde{p}_{21}$, is taken to be 10% more than the nominal price ($\tilde{p}_{22}$ = \$160), which makes it \$176 per tonne. In the high-production case (cultivation in more than 66% of cropland), the corn price in the market, $\tilde{p}_{23}$, is assumed to decrease by 10%, which is equal to \$144 per tonne.

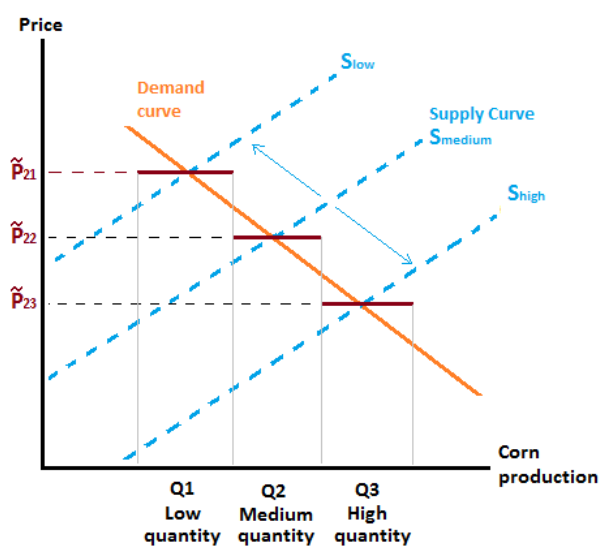

Figure 3.3 Price and supply relation of corn grain for food production.

3.5 Computational Results

The proposed MILP model of biofuel and food production is solved using CPLEX 12.2. Table 3.5 provides values of the changing parameters, which are considered in our sensitivity analysis—namely, objective weights, yield levels, sustainability factor, and budget level. It also provides the objective function value, the profit from switchgrass and corn, and their environmental benefits. A solution is reached in less than nine minutes for all cases. The solution time increases as higher priority is given to profit, and the budget and sustainability factor are set to their corresponding medium levels. In the base case, priority is given to profit so weights (α β) in the objective function, as shown previously in equation (3.1), are set to (1 0). The base case has a medium-yield level (as provided previously in Table 3.1) and a moderate budget (75% of the ample budget). The sustainability factor is set at 75% in the base case.

TABLE 3.5 SUMMARY OF COMPUTATIONAL STATISTICS FOR DIFFERENT SCENARIOS

Objective weights (α β)	Yield levels	Sustainability factor	Budget level (M$)	Objective function value (M$)	Profit (M$)		Environmental benefits (M$)		CPU time (s)
					Switchgrass	Corn	Switchgrass	Corn	
(1 0)*	Table 1*	75%*	750*	236.078	156.7	79.4	40.4	-22.8	522
(0.5 0.5)	Base	Base	Base	129.144	149.1	74.9	50.1	-15.8	406
(0 1)				109.329	-92.6	0	109.3	0	0.66
Base	Low+	Base	Base	56.958	55.9	1.1	14	-4.7	3.03
	High+			381.101	224.8	156.3	33.4	-19.4	237.2
Base	Base	100%	Base	209.001	100.6	108.4	18.5	-33.8	66.1
		50%		261.020	198.9	62.1	50.	-16.6	278.9
Base	Base	Base	500	185.823	133.6	52.3	19.9	-13.8	210.2
			1000	273.102	155.0	118.1	40.4	-37.9	178.9

*Shows base case values for parameters considered in sensitivity analyses.

+Values in Table 3.1 are decreased and increased by one third to obtain low- and high-yield levels, respectively.

Figure 3.4 shows land types and optimal seeding locations of switchgrass and corn cultivation zones for the base case. Here, different land types are represented by different colors. We assume that the biorefinery and food plant are located in the same zone at the

center of the grid. The optimal solution indicates that corn is located in zones that are close to the facility, while switchgrass production on cropland mostly surrounds the corn production areas. Of the considered area, grassland and marginal land have 99% and 96% utilization, respectively. Since the budget in the base case is not ample, utilization in cropland is 70%. Switchgrass uses 25% of this 70%, while the remaining 45% is utilized by corn. Switchgrass is seeded only in the first year, and corn is repeatedly seeded in the same locations during each year of the planning horizon.

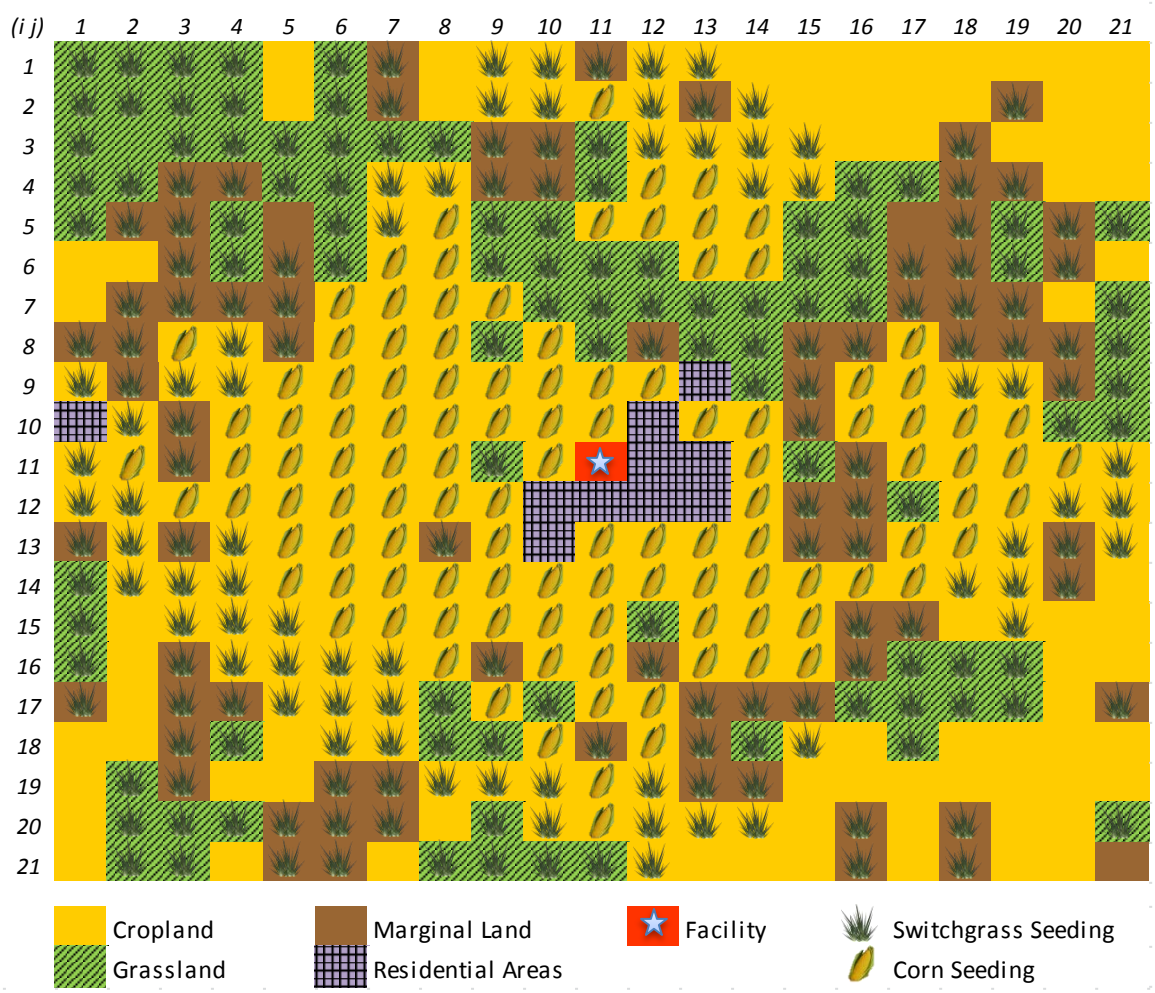

Figure 3.4 Land types in Hugoton, Kansas, and their allocation to switchgrass and corn production.

Figure 3.5 presents optimal production amounts for switchgrass and corn in different years. We observe that switchgrass yield and harvested biomass increase in the first three years and then remain constant. Switchgrass is not harvested in grassland and marginal land in the first year since it has a very limited yield on those lands in the first year. On the other hand, corn grain and stover yield do not change by year. Since corn grain for food has a high price when produced in a low quantity, corn grain grown in 33% of cropland is sold as food; the remaining corn grain goes to biofuel production. All of the available stover is harvested with a constant rate during the planning horizon.

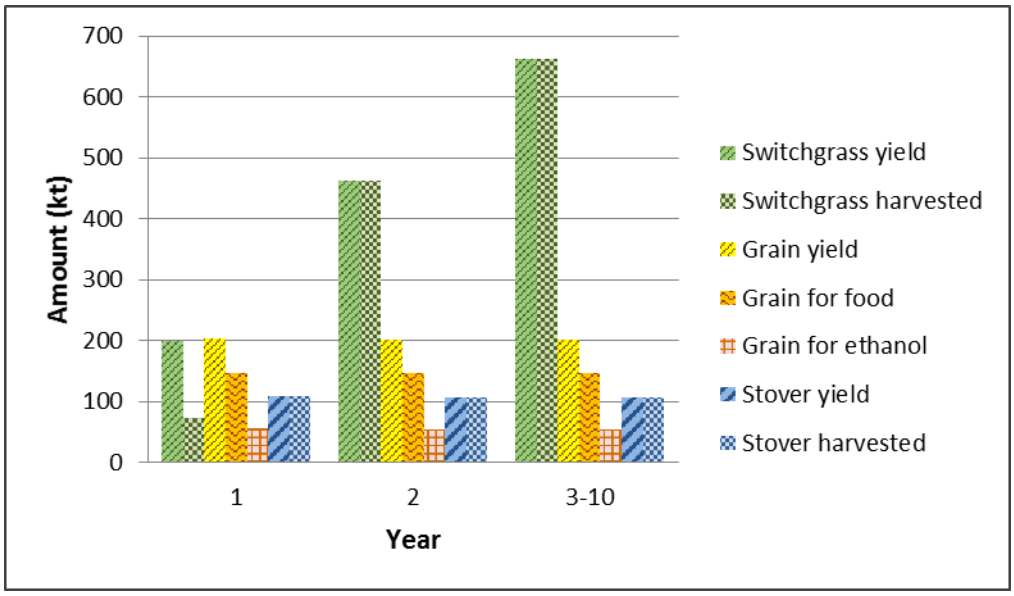

Figure 3.5 Yield and biomass amount from switchgrass and corn during years of planning horizon.

Optimal cost breakdown and shares of switchgrass and corn in different farm operations for overall production can be seen in Figure 3.6a. Of the total available budget, 53% is allotted to seeding, producing, and harvesting switchgrass, while 41% of the total budget is consumed by seeding, producing, and harvesting corn. When analyzing the allocation of budget to different farm operations, it can be seen that production uses 47% of the overall budget, while

harvesting, seeding, and transportation account for 29%, 18%, and 6%, respectively. Optimal cost breakdowns of the allocated budget for switchgrass and corn are shown separately in Figures 3.6b and c, respectively. As shown, the production and harvesting of switchgrass uses 87% of the optimally allotted budget. On the other hand, that sum decreases to 64% in the case of corn, since the seeding cost of corn becomes very important in its cultivation (Figure 3.6c). The budget saved from switchgrass seeding for the following years is mostly allocated for its harvesting. The transportation cost of corn is lower than that of switchgrass, since the harvested, i.e., transported, amount is lower than that of switchgrass, and corn production zones are closer to the demand point. For both crop types, production cost (including rent, fertilizer, and herbicide application) is almost half of the optimally designed budget for each crop.

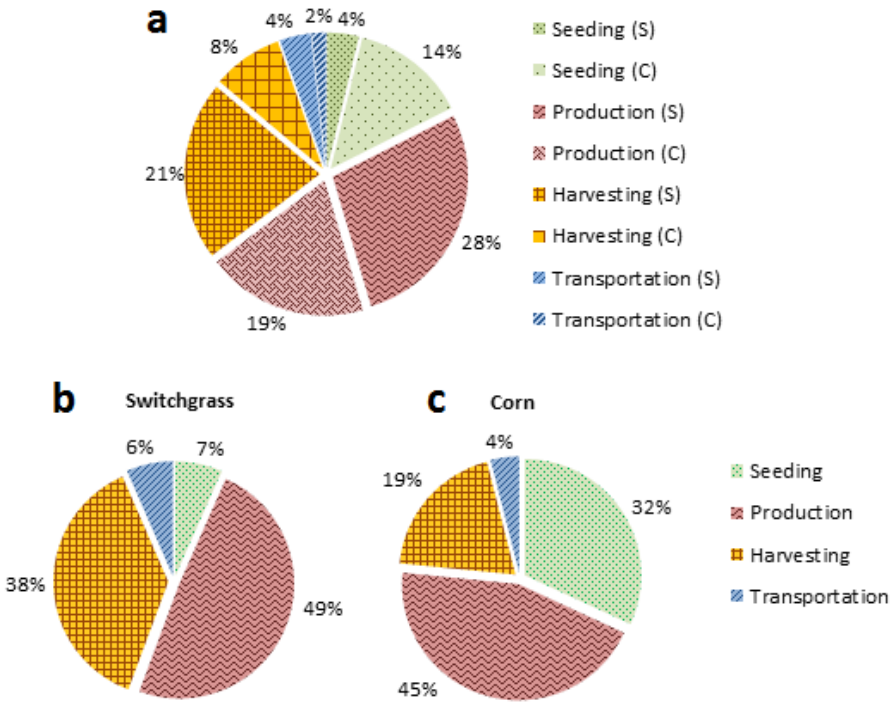

Figure 3.6 Optimal cost breakdown: (a) for both switchgrass (S) and corn (C) in base case scenario, (b) for switchgrass in base case scenario, (c) for corn in base case scenario.

Figure 3.7 displays the optimal yearly budget allocation to farm operations of switchgrass and corn cultivation. For switchgrass, seeding only takes place in the first year and uses almost 30 M$ of the overall budget. Production, harvesting, and transportation costs significantly increase from the first year to the maximum level in the third year, then remain constant until the end of the planning horizon, since switchgrass yield and harvested biomass do not change from years three to ten. Switchgrass uses about 45 M$ each year from year three until year ten. For corn production, the budget is equally divided into about 31 M$ for each year of the planning horizon. When we break down the cost further into harvested amount, we observe that the overall cost of seeding per tonne of switchgrass is $4.9, while this increases to $51.4 per tonne of corn grain. Seeding switchgrass in only the first year of the planning horizon makes it more competitive than corn in seeding cost.

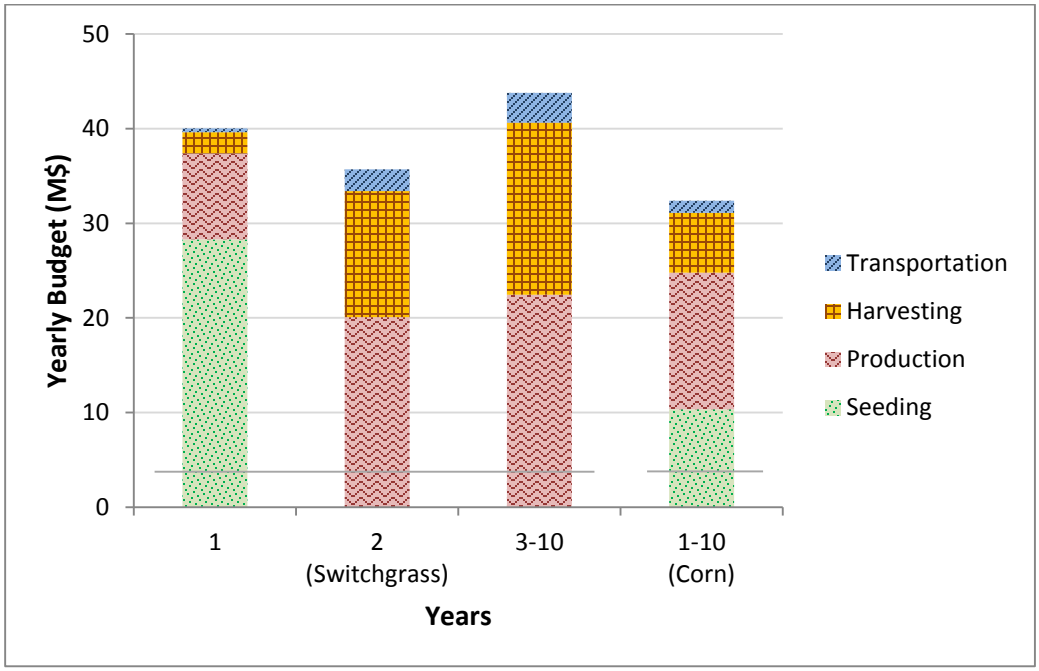

Figure 3.7 Optimal yearly budget allocation for farm operations of switchgrass and corn in base case scenario.

We also use a quadratic programming (QP) version of the model where we consider nonlinear equation (3.3) instead of equations (3.5), (3.6), and (3.7) in the revenue function in order to compare the results of QP with its piecewise linear lower approximation. In QP, equation (3.3) is utilized as a revenue function of corn grain. As expected, without linearization of the revenue function for corn grain in the food market, complexity and size of the problem considerably increases and causes a memory shortage, and a solution is not obtained for the base case. However, after decreasing the planning horizon to nine years in the base case, the QP solution is observed in less than five minutes. We have found that the objective value difference between piecewise linear approximation and QP is 1%. We observe similar results in both QP and its piecewise linear lower approximation, while in the QP model, the sale of corn grain in the food market is slightly higher than its sale in the linearized model.

3.5.1 Sensitivity Analysis

In this section, we investigate the effect of various key parameters on the optimal solution. We perform sensitivity analyses by varying objective weights, budget levels, sustainability factors (of food supply), and yield levels. This section also demonstrates the response of the model for handling possible uncertainty ranges in these parameters.

3.5.1.1 Objective Weights

We analyze the priorities of different stakeholders and decision makers in determining the optimal solution of the problem by changing the objective function weights (α β). The objective weights are set to (1 0), (0.5 0.5), and (0 1), in order to give priority to profit only, equally to profit and environment, and to environment only, respectively. Optimal results for different priorities are summarized in Figures 3.8a, b, c, and d.

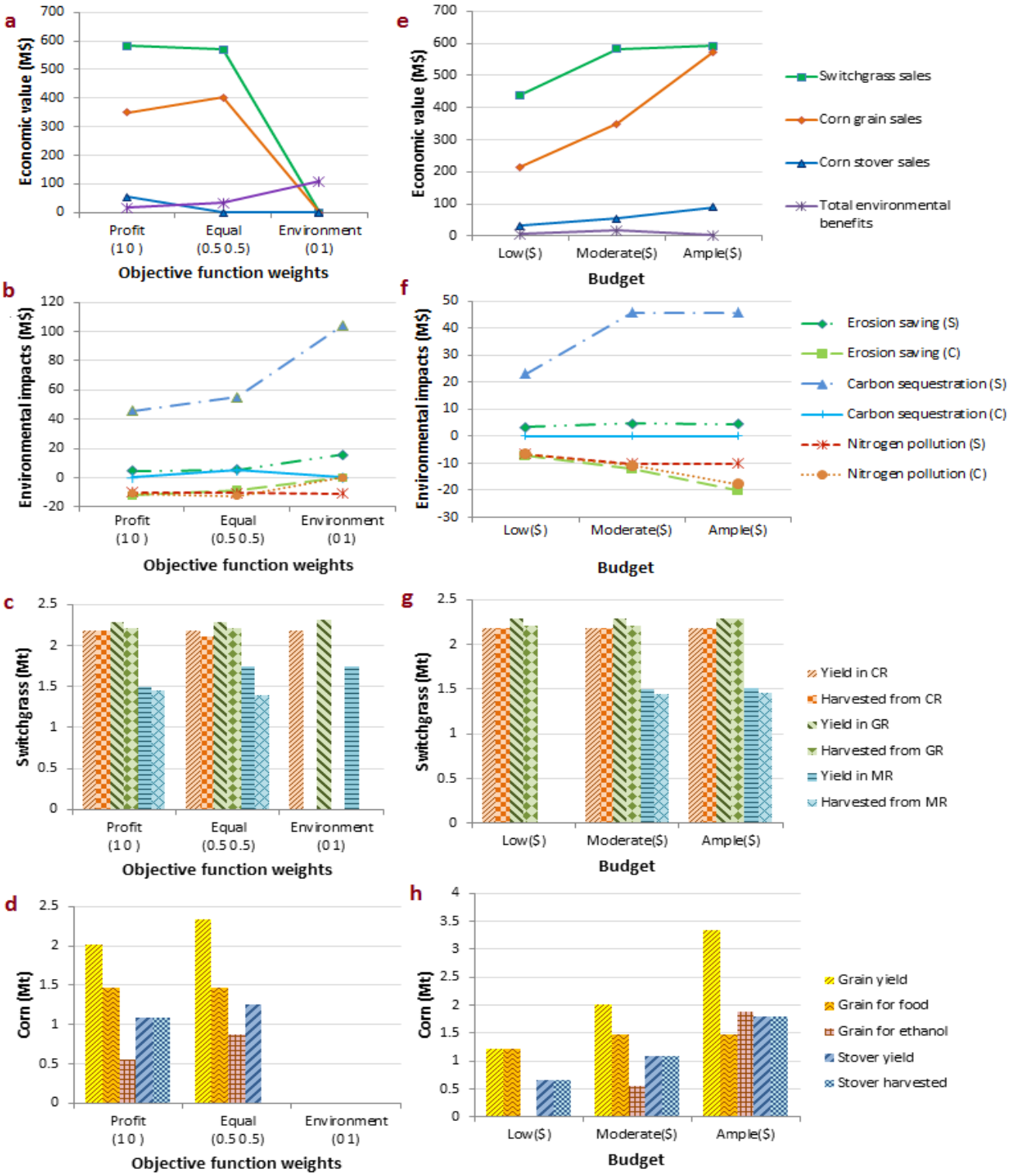

Figure 3.8 Impact of objective function weights and budget on economic values, environmental impacts, and switchgrass and corn yield amounts.

When priority is given to profit only, all yield types are almost fully harvested. However, when equal priority is given to profit and environment, corn stover sales go to zero (Figure 3.8a), because harvesting corn stover has negative effects on soil erosion prevention and carbon sequestration. Figure 3.8b shows that carbon sequestration of corn increases due to not harvesting stover in the equal priority case. In this case, the budget saved from not harvesting corn stover is used in the production of corn grain, which increases the sales of corn grain. In the same case, Figures 3.8a and c show that overall switchgrass sales decrease compared to the profit-priority case, since harvesting in marginal land decreases in order to obtain greater environmental benefits. Further increasing priority on the environment leads to no sales from switchgrass, corn grain, and corn stover, because harvesting has a negative effect on the environmental benefits (soil erosion prevention, carbon sequestration, and nitrogen pollution), and corn is not produced in this case. However, Figure 3.8c shows that switchgrass utilizes all zones available in different land types, while Figure 3.8d indicates that corn production is completely abandoned when priority is given to the environment. This is because even if corn stover is not harvested, the loss from soil erosion and nitrogen pollution is greater than any savings via carbon sequestration when corn is produced.

3.5.1.2 Budget Levels

We also analyze the effect of changing budget on the model outputs. Here, ample budget is set to a budget amount (1,000 M$), which would be enough to cultivate switchgrass and corn over the entire studied region. The moderate budget is set to 75% of the ample budget, while the limited budget is considered to be 50% of the ample budget. The economic value of sales and the environmental impacts of switchgrass and corn production for changing

budget levels are presented in Figures 3.8e and f, respectively. The impact of the budget level on the amount of switchgrass yield and harvested biomass can be seen in Figure 3.8g, while details for corn yield types are given in Figure 3.8h. As expected, when the budget increases from limited to moderate, the sales of switchgrass, corn grain, and corn stover increase (Figure 3.8e). In this case, Figure 3.8f shows that while carbon sequestration of switchgrass increases, nitrogen pollution increases as well.

Based on Figures 3.8e and g, increasing the budget from limited to moderate leads to utilization of marginal land for switchgrass production. We observe an increase in corn grain production for biofuel since the price of corn grain for food decreases as its quantity increases (Figure 3.8h). However, further increasing the budget from moderate to ample does not change any results related to switchgrass cultivation, since it already utilizes all allowable zones for its cultivation with the moderate budget case. On the other hand, an ample budget increases the sales of corn grain, particularly for biofuel (Figures 3.8g and h). In return, that causes more loss from soil erosion and nitrogen pollution (Figure 3.8f).

3.5.1.3 Sustainability Factor

In order to better understand land allocation for switchgrass and corn production, namely competition between biofuel and food production, the sustainability factor is also analyzed. Sustainability of the food supply is ensured by allotting a certain percentage of cropland to only food crop production, which is corn in the considered application. In other words, when the sustainability factor is taken as 50%, switchgrass can only be cultivated on the remaining half of the cropland. When the sustainability factor is 75%, only 25% of cropland is allowed for switchgrass cultivation. And, finally, by setting the sustainability factor at 100%,

switchgrass production is not allowed on cropland. Figure 3.9a presents the economic value obtained from the sales of switchgrass and corn along with the total environmental benefits for different sustainability factors. Figure 3.9b provides details of the economic value obtained from environmental benefits, while Figures 3.9c and d show the yield and harvested amounts of switchgrass and corn, respectively. When the sustainability factor is 50%, harvested switchgrass biomass and its sales reach maximum values. In this case, the environmental benefits also increase since switchgrass has higher environmental benefits on cropland than does corn. This result implies that increasing the security of the food supply decreases the environmental benefits. Limiting switchgrass cultivation on cropland from 50% to 0% (changing the sustainability factor from 50% to 100%) shifts its production from cropland to marginal land. Forcing switchgrass out of cropland also provides more space and budget for corn production. In other words, switchgrass surpasses corn on cropland since it is shown that switchgrass utilizes all allowable share of cropland when the sustainability factor is not set to 100%. Corn only uses the remaining cropland.

3.5.1.4 Yield Levels

We also observe the response of the model to different yield levels. In order to represent the low-productivity case, the low-yield level is set at 33% less than the medium-yield level, which is given in Table 3.1. In a similar manner, the high-yield level is set as 33% more than medium-yield level. Results regarding the economic value, detailed environmental benefits, and yield and harvest of switchgrass and corn are summarized in Figures 3.9e, f, g, and h, respectively. The results indicate that if the yield level is low, there is no switchgrass cultivation on marginal land since it is not profitable (Figure 3.9g).

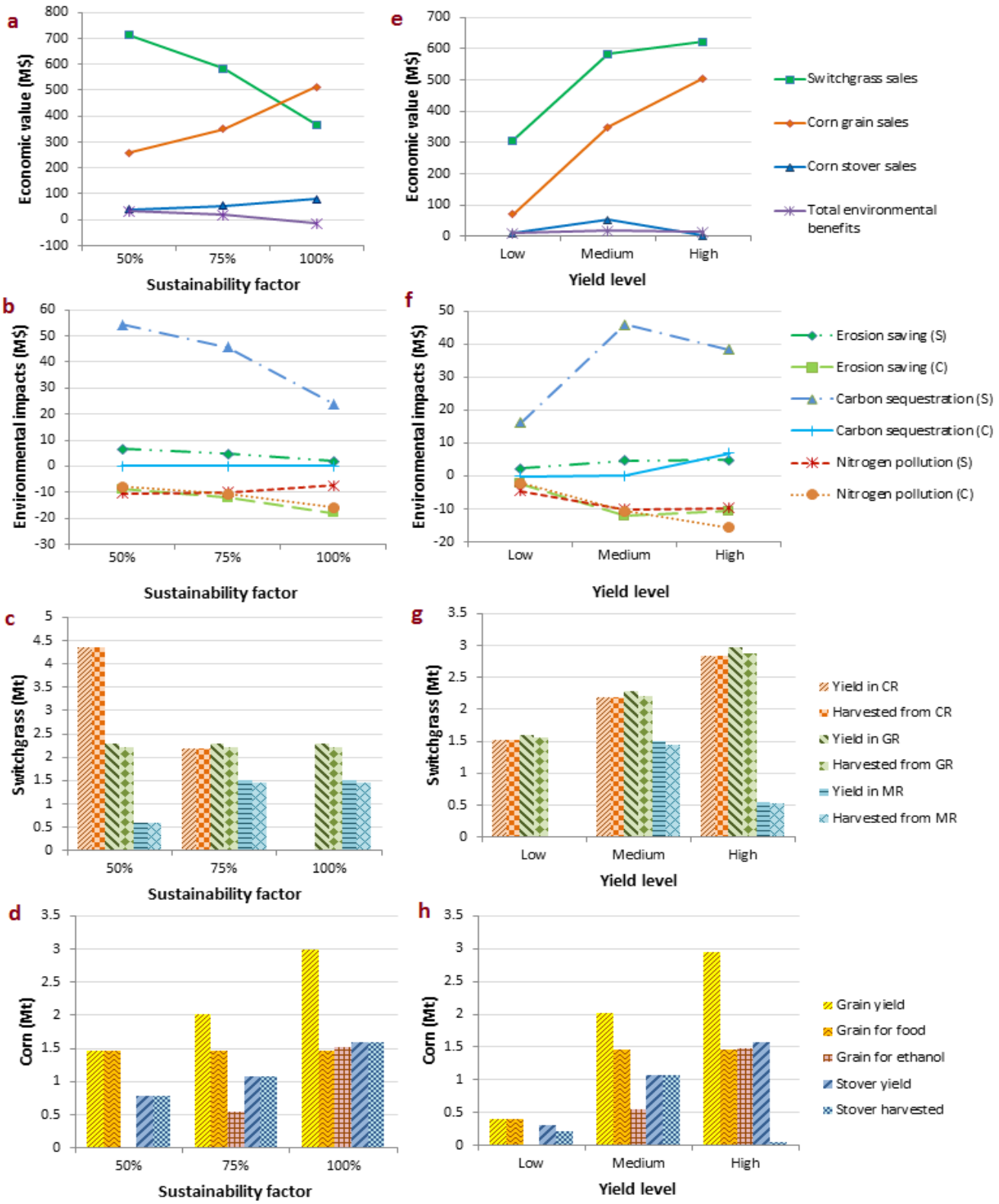

Figure 3.9 Impact of sustainability factor and yield level on economic values, environmental impacts, and switchgrass and corn yield amounts.

The increase in yield level from low to medium makes all land types profitable, which in return positively impacts switchgrass and corn sales (Figures 3.9e and g). However, the further increment from a medium- to high-yield level shows a restricted gain in the sales and harvested amount since the budget becomes a limiting factor (Figures 3.9e and g).

As an interesting result, in the high-yield-level case, switchgrass production decreases on marginal land since the model tends to use the related budget to harvest more switchgrass on cropland and grassland (Figure 3.9g). As switchgrass cultivation is reduced on marginal land, the environmental benefits decrease as well (Figure 3.9f). In a similar manner, when the yield level is increased from the medium to high level, the model prefers harvesting more corn grain than corn stover (Figure 3.9h). That decrement in harvested corn stover positively affects carbon sequestration.

3.5.2 Special Cases for Economic and Environmental Impacts

Further experiments are conducted for marginal land utilization, profitability ratios, and the effect of nitrogen pollution, in order to obtain better insight into the economic and environmental outcomes of the problem.

3.5.2.1 CRP Incentives on Marginal Land

Based on the literature, switchgrass can also increase the soil quality of marginal land by sequestering carbon and restricting soil erosion [50]. Currently, most marginal lands are either under CRP contracts or they remain idle. Therefore, we analyze the effect of CRP incentives on marginal land utilization for switchgrass production. In this analysis, the budget is set to 350 M$ (limited but enough to cultivate both corn and switchgrass), in order to observe the model's land allocation preferences, while all remaining parameters are set to base case values. Figure

3.10 shows the change in harvested yield types for different CRP incentives. If the budget is very limited (350 M$), unless supported by government, marginal land is not used for switchgrass production. It can be seen that with an incentive of about $7.5 per tonne of switchgrass, its production on marginal land becomes more profitable over corn production on cropland. It can also be seen that, in order to shift switchgrass production from cropland to marginal land, an incentive of more than $12.5 per tonne is required. Finally, with $17.5 per tonne of switchgrass on marginal land, the utilization of marginal land reaches a maximum and becomes more profitable than cropland for switchgrass production.

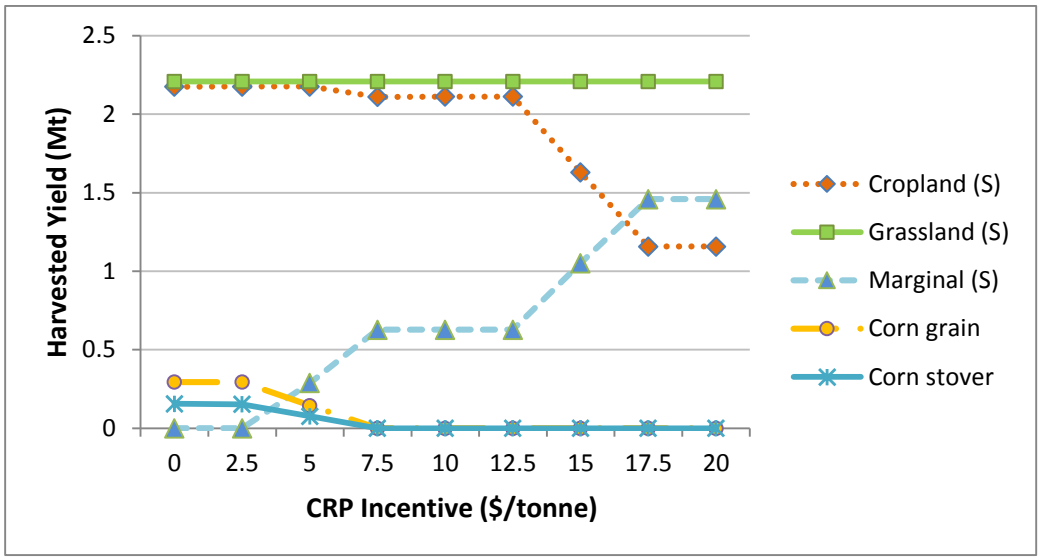

Figure 3.10 CRP incentives on marginal land utilization and its impact on switchgrass (S) and corn (C) production.

3.5.2.2 Profitability Analysis

In this section, profitability ratios of sales and environmental benefits of each crop type, which are shown in Figure 3.11, are analyzed. The base case setting with changing objective function weights is used in this analysis. The profitability ratio is obtained by dividing the economic value (of sales and environmental benefits) of a crop type to the budget it uses.

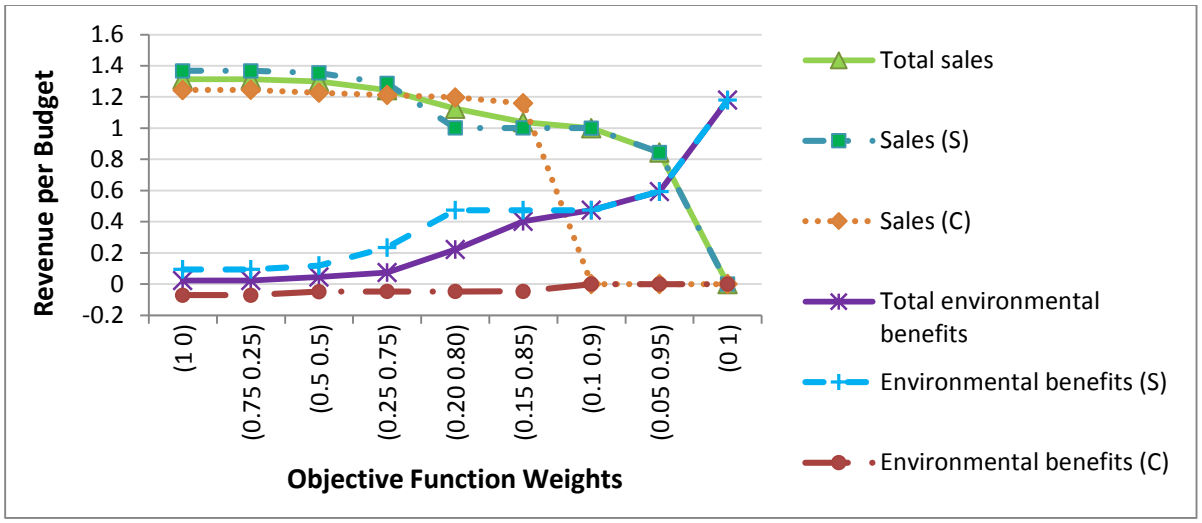

Figure 3.11 Profitability values for sales and environmental benefits of switchgrass (S) and corn (C) based on changing objective function weights.

Priorities of various stakeholders (farmers, co-op, or government) are reflected by considering various objective function weights. Although not depicted in Figure 3.11, the profitability ratio of sales of switchgrass cultivated on only grassland and cropland is more than 1.4 when the objective weight is (1 0). Decision variables and results of the model start to change if the objective weight of environmental impacts is increased to 0.75. In this case, switchgrass harvesting on marginal land and corn stover harvesting stop. When we set objective weights to (0.2 0.8), switchgrass harvesting stops on cropland as well. That causes a decrease in overall profitability of switchgrass sales while increasing environmental benefits due to no harvesting on cropland. Further increasing the weight on environmental benefits to 0.9, corn cultivation completely stops. However, switchgrass cultivation continues on all land types for all cases, while harvesting on grassland continues until the (0.05 0.95) weight case. Preventing switchgrass harvesting on all land types at the (0 1) weight case maximizes the profitability of environmental benefits, as expected. Although total environmental benefits cannot be as high

as sales, the profitability of environmental benefits of switchgrass reaches 1.2, since the budget used for switchgrass production is also very low due to no harvesting and transportation.

3.5.2.3 Changing Cost of Nitrogen Pollution

We also analyze the relation between the cost of nitrogen pollution and cultivation decisions since it is difficult to associate a certain dollar value for N pollution. When priority is given to profit or priority is equally distributed over profit and environment, the impact of changing N pollution cost is negligible. Therefore, this analysis is conducted under base case values but with full priority on the environment. The results of changing cost associated with N pollution are presented in Figure 3.12.

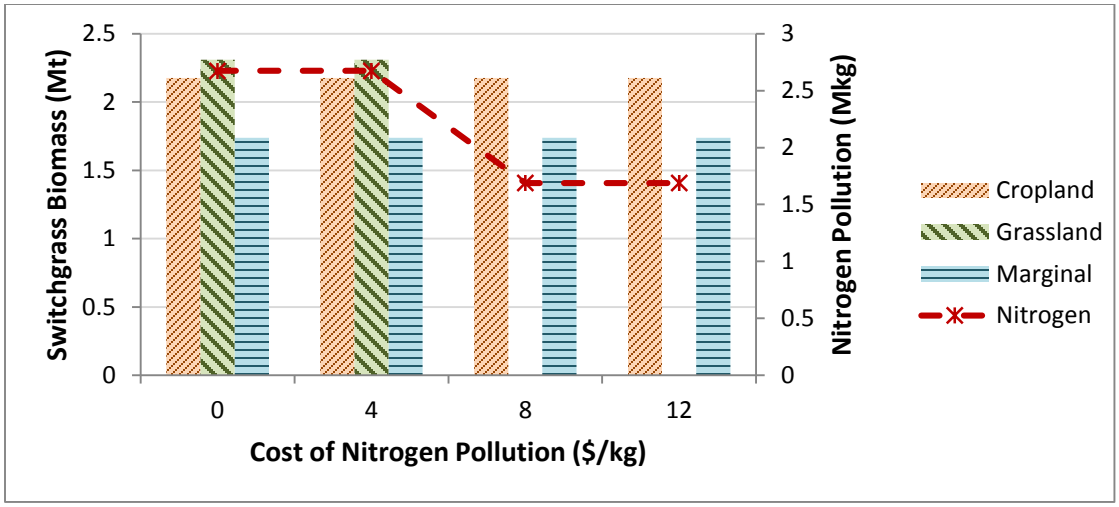

Figure 3.12 Impact of nitrogen pollution cost on overall nitrogen pollution and switchgrass yield on cropland, grassland, and marginal land.

In the case of full priority on the environment, there is no corn production while switchgrass is cultivated but not harvested. It can be seen that having no cost or a cost of $4 per kg of N pollution does not change the results, since savings via carbon sequestration outweighs the impact of N pollution. However, when we assign a higher cost to N pollution, as much as $8 per kg, switchgrass production on grassland fully stops, since the environmental benefits (such as

soil erosion prevention and carbon sequestration) on grassland cannot offset the cost of N pollution. We also observe that even if we further increase the cost of N pollution to $12, switchgrass cultivation on cropland and marginal land is sustained, since the overall environmental benefits on these land types are still positive.

3.6 Conclusion and Future Work

In this chapter, we develop a multi-objective mixed-integer mathematical programming model to analyze the competition between energy and food crops, with specific consideration given to switchgrass and corn. The proposed model integrates economic benefits and environmental impacts of switchgrass and corn cultivation. Economic benefit is represented as profit by subtracting the total cost of seeding, production, harvesting, and transportation (budget used) from the sales of switchgrass, corn grain, and corn stover. Environmental impacts include savings from soil erosion prevention and carbon sequestration, along with the economic loss due to carbon emissions and nitrogen pollution. Spatio-temporal changes in these economic and environmental impacts are also included in the model. Switchgrass production is allowed on cropland, grassland, and marginal land, while corn production is only considered on cropland. Capabilities and outcomes of the model have been demonstrated with an application to a biofuel production project in Hugoton, Kansas. We present the optimal results of budget allocation, land type selection, time of seeding and harvesting, and the amount of yield and harvested biomass from each crop type. The response of the model is analyzed by changing the values of key parameters and presented in the sensitivity analysis in section 3.5.1.

In the base case scenario, we observe that switchgrass is seeded in the first year, while corn is seeded in the same zones that are closer to the demand point in each year of the planning horizon. In this case, the majority of the budget is allocated for producing and harvesting switchgrass, while the seeding budget is more significant for corn than it is for switchgrass. Furthermore, the optimal budget allocation among planning years changes in the first two years, then stays constant from year 3 to year 10 for switchgrass production. It can be seen that giving equal priority to profit and the environment leads to no harvesting of stover, while a higher priority on the environment completely eliminates corn production and maximizes switchgrass cultivation without harvesting. When the budget is changed from low to high, switchgrass production is extended to marginal land, and corn grain starts to be produced for biofuel. It is also shown that, without a sustainability factor, which will secure food production, switchgrass will take over all zones in cropland since profitability of its production is higher than corn. Therefore, decision makers or government are encouraged to provide strict regulations on cropland usage or pay farmers directly for producing second-generation crops on marginal lands in order to secure food production on cropland in the future. The last sensitivity analysis is performed on corn and switchgrass yield levels. Results show that higher yields will decrease the production of switchgrass on marginal land and the harvesting of corn stover.

We also conduct further analysis on CRP incentives, profitability, and cost of nitrogen pollution. It can be seen that with a CRP incentive of about $7.5 per tonne of switchgrass harvested from marginal land, these land types can be more preferable to cropland in the case of a limited budget. Most profitable crop types vary spatially from high to low as follows: switchgrass on grassland, switchgrass on cropland, corn grain for food, corn stover, switchgrass

on marginal land, and corn grain for biofuel. It is shown that corn stover is not harvested for biofuel production when environmental impacts are considered. It can also be concluded that if carbon sequestration and soil erosion prevention are not valued, additional incentives are needed for switchgrass cultivation on marginal land. However, CRP incentives on marginal land may lead to different land allocations.

In the future, this model could be easily adapted to different regions and crop types. As an alternative energy crop, Miscanthus, another perennial, could be considered. As a food crop instead of corn, wheat cultivation could be considered since wheat grain and wheat straw are used in food and biofuel production in a similar manner to that of corn grain and corn stover. The uncertainty of the parameters and their effect on the model results can be analyzed by robust optimization or stochastic optimization models. The model could be applied to larger landscapes where zones represent counties of a given state. This may require the addition of storage places and associated costs to the model. In this case, optimal facility location could also be decided by the model. Switchgrass and some other energy crops, such as Miscanthus, may show invasive properties in different regions [51], [52]. Therefore, preventive decisions can be integrated into the model to minimize the risks associated with invasiveness of new second-generation biofuel crops. Finally, our model could be applied under various scenarios, in order to analyze the competition between food and energy supply and provide effective management strategies leading to higher economic and environmental benefits.

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CHAPTER 4

A STOCHASTIC MULTI-CRITERIA DECISION ANALYSIS FOR SUSTAINABLE BIOMASS CROP SELECTION

4.1 Introduction

Discovery of the best energy source for sustainable economic development has been a hot topic for decades. There is a need for sustainable energy production since fossil-based energy is known to be limited and not environmentally friendly. Ethanol is an alternative fuel, which has the potential to replace fossil-based fuel and is practically used in many countries. Various biomass sources are used to produce ethanol. In some countries, such as Brazil, ethanol is mostly produced from sugarcane, and it has had a significant share of the fuel market in 2009 [1]. On the other hand, ethanol is mostly produced from corn biomass in the U.S. which is the number one producer and consumer of ethanol in the world [2]. The variability of biomass sources in different countries raises the question of what biomass type is the most sustainable source for ethanol production.

Sustainability is described as the long-term development integrating three dimensions: continuous economic growth, environmental friendliness, and improved social welfare [3], [4]. In order to address the economic dimension of the sustainable biomass crop selection, we consider the financial implications of biomass crop type such as biofuel conversion rate, yield amount, and input cost for different farm operations. Furthermore, other economic factors such as technology, length of crop life, and equipment requirement also make the selection of biomass crop a strategic and operational decision. The environmental dimension of sustainable biomass crop selection requires the consideration of soil erosion, carbon dioxide sequestration,

biodiversity, and pollution of water so that the biomass crop production will not harm the environment [5]. Finally, in order to address the social dimension of the sustainable biomass crop selection, associated social impacts such as unemployment rate, working conditions, and welfare of the society should be included in the decision-making process [6], [7]. Since the biomass crop should meet these various economic, environmental, and social aspects, selection of the most sustainable biomass crop type is a multi-criteria decision-making (MCDM) problem.

MCDM techniques are utilized in real-life problems when there is a set of alternatives along with various criteria involved in the decision making. In many cases, the criteria have different units, such as dollars, time, dimensions, etc., which also make the acquisition of convenient data very expensive and the comparison among the criteria difficult during the decision-making process. For this reason, researchers have proposed a number of methods for MCDM that have different performances and are capable of solving such complex problems [8], [9]. The analytic hierarchy process (AHP), which was developed by Saaty in the 1970s [10], is a MCDM tool for dealing with complex decisions, making it easy for decision makers to use in solving complex problems. In this chapter, we propose a stochastic AHP approach for sustainable biomass crop selection since this method is particularly effective for cases where there are multiple options and uncertainty in the evaluation.

The remainder of this chapter is organized as follows: In section 4.2, we review the literature regarding biomass crop type selection and define the problem statement. In section 4.3, we propose the criteria to be considered in the biomass crop type selection and explain potential and currently used crop type alternatives in Kansas. In section 4.4, we present, step by step, the proposed stochastic analytical hierarchy process. In section 4.5, we demonstrate the

application of the proposed model and present the results along with sensitivity analysis. Finally, we provide concluding remarks along with some discussion in section 4.6.

4.2 Literature Review

The nature of problem solving in MCDM methods involves a number of steps: defining the problem, eliciting relevant criteria, weighting the criteria and criteria elements, defining alternatives, and ranking alternatives. In a similar manner, the AHP provides a rational and comprehensive framework for structuring a problem, comparing and weighting the criteria in the structure, and ranking the alternatives [11]. Although it has been criticized for some issues such as the rank-reversal problem (i.e., introduction of a new alternative may change the previous rankings), studies have been undertaken to make the AHP more robust, consistent, and efficient. One of these studies involves the conversion of expert opinions to numbers, since the scale used in the evaluation of criteria has not always had crisp values. Therefore, a fuzzy model was introduced by Laarhoven and Pedrycz [12]. Various fuzzy AHP approaches and models were developed later by many researchers (see, e.g., [13], [14], [15], [16]).

The AHP has been widely applied in many problems, from the selection of energy alternatives to the selection of suppliers and even academic personal [17], [18], [19]. However, to the best of our knowledge, an AHP model has not been developed for sustainable biomass crop type selection. In the literature, different methods have been proposed in the biomass field. For example, Kahr et al. [20] evaluate the lignocellulosic ethanol potential of various agricultural residues by conducting real experiments. They test cellulosic biomass, such as wheat straw, rye straw, oat straw, and corn stover for second-generation ethanol. Santchurn et al. [21] evaluate four commercial varieties of sugar cane using a randomized complete block

design. They identify variable proportions of sucrose and fiber in these biomass genotypes. Vaezi et al. [22] develop a numerical algorithm for the selection of biomass alternatives for gasification purposes. However, they only focus on one particular aspect of biomass types.

Some studies utilize MCDM methods and the AHP in areas related to renewable energy and biomass. For example, Dael et al. [23] propose an AHP model for selecting the location in a region for biomass valorization. They identify four main criteria and 22 sub-criteria, and apply the model in Belgium in order to determine potentially interesting locations to establish a biomass project. Balezentiene et al. [24] offer a fuzzy method to prioritize energy crops for a reasonable energy crop-mix. They only consider energy crops that are suitable for the Lithuanian climate. Kabak and Dağdeviren [25] evaluate renewable energy sources using a hybrid MCDM model based on benefits, opportunities, costs, and risks, together with an analytic network process (ANP). They compare five renewable energy sources (hydro, geothermal, solar, wind, and biomass) in Turkey as an application of their model. For a similar purpose, Yazdani-Chamzini et al. [26] propose an integrated complex proportional assessment of alternatives along with AHP methodology to select the best renewable energy project by considering social, economic, technological, and environmental criteria. Saelee et al. [27] develop a technique for order of preference by similarity to an ideal solution (TOPSIS) multi-criteria model for the biomass type selection for boilers. They compare wood chips, palm shells, and wood pellets for boilers under the criteria of efficiency, price, ease to operate, global warming potential, and acidification potential. Mathematical models have also been developed for making strategic decisions in the biomass area. Cobuloglu and Büyüktahtakın [28] propose an MILP method in order to determine the best biomass production location, cropland,

grassland, and marginal land, for switchgrass (*Panicum virgatum*) under various economic and environmental conditions. They also provide an optimization model for the comparison of energy and the food crop, and analyze trade-offs on the farm level [29]. Ziolkowska [30] develops an optimization model for biofuel production by using a preference ranking organization method for enrichment evaluations (PROMETHEE) approach to define objective function weights. Their method includes economic, environmental, and social criteria.

4.2.1 Problem Statement and Proposed Model

Biomass crop type selection includes various conflicting criteria, as mentioned previously. The majority of studies focus on economic analysis. However, for the sustainability of energy production, social and environmental aspects of biomass crop selection are also very important since they eventually impact long-term economic viability of biofuel production. Therefore, a comprehensive list of economic, environmental, and social criteria needs to be identified. In addition, their relative importance in decision making for the biomass crop type selection process and ranking of different biomass crop types have not been determined yet. The solution methods in the literature do not quantify many of the factors that need to be considered in the sustainable biomass crop selection. In addition, to the best of our knowledge, biomass crop type selection has not been studied using the AHP.

In this chapter, we study biomass crop type selection by utilizing the stochastic analytic hierarchy process. The steps involved in this study are displayed in Figure 4.1. First, we develop the most important aspects and criteria to be involved in decision making with the help of expert opinions and a review of the literature. Then, the structure of the AHP, including levels of criteria, is established. We obtain judgments of decision makers in the third step. The

uncertain information obtained from DMs is converted into stochastic beta pairwise comparisons. Consistency is measured and judgments are evaluated by using the logarithmic least squares method (LLSM), also known as the geometric mean. Finally, weights of criteria and ranking of alternatives are obtained.

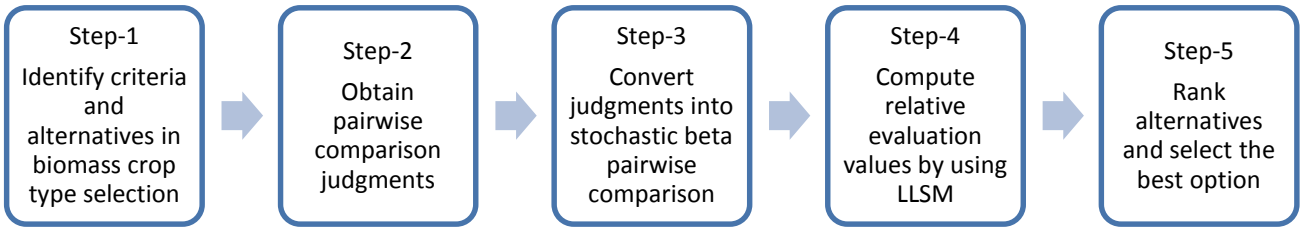

Figure 4.1 Proposed SAHP methodology for biomass crop selection.

Contributions of this research are as follows:

- In the literature, researchers use decision models to define the best biomass crop type with a limited number of criteria [20, 24, 29, 30]. To the best of our knowledge, this is the first AHP-based MCDM tool developed for biomass crop selection.
- In this chapter, we develop a stochastic AHP model that can handle various preferences of the DM, as well as crisp, linguistic, and fuzzy values simultaneously. The ranges of the expert opinions have been converted into crisp numbers by utilizing closed-form approximation of the median for beta distributions.
- To the best of our knowledge, comprehensive criteria to be considered in sustainable biomass crop selection have not been defined yet. This is the first study that provides a precise structure and complete list of the economic, environmental, and social criteria necessary for sustainable biomass crop selection by reviewing the literature and interviewing experts.

- In the application, the opinions of experts from different backgrounds have been analyzed in order to provide better insights about the problem. Thus, this is the first study that quantifies the importance of each criteria in decision making of sustainable biomass crop selection.

4.3 Proposed Crop Selection Criteria and Biomass Crop Alternatives

Biomass refers to the biological material obtained from plants, organics, and residues. It can be converted to biofuel, for use directly in transportation or as an additive to fuel. In general, biomass can be divided into three categories: food crops and their agricultural residues, energy crops (lignocellulose), and forest materials. Among these, crop types that have the potential to be used as biomass sources in Kansas are listed and explained briefly.

A complete list of criteria to be considered in biomass crop selection is not compactly given in any one study. Therefore, a number of sources have been consulted in order to identify aspects and criteria for biomass crop selection ([30], [31], [32], [33]). The main factors that can affect biomass crop type selection are listed as economic, environmental, and social aspects. The sixteen criteria under these aspects are presented in Figure 4.2.

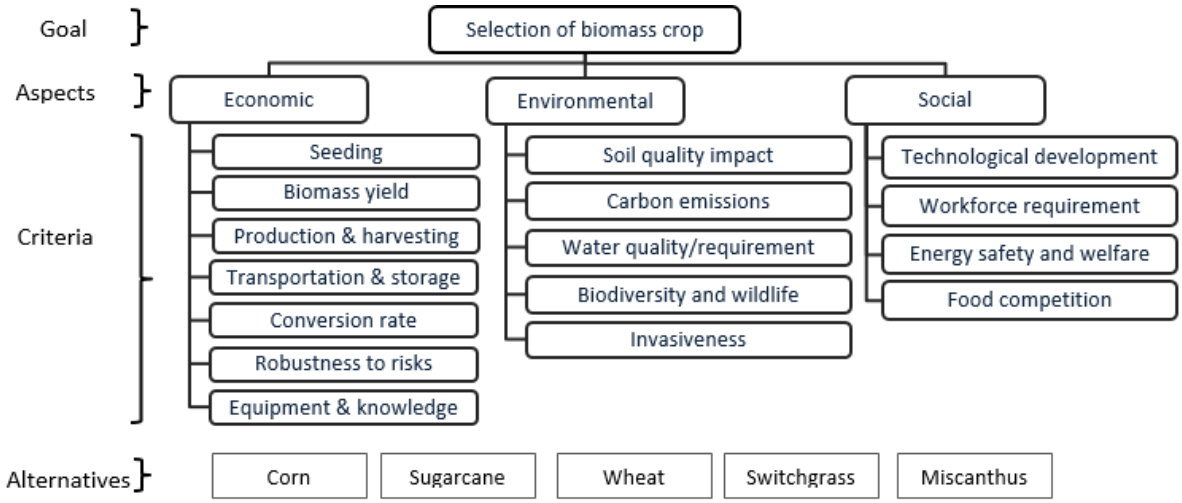

Figure 4.2 AHP decision model for biomass crop selection.

4.3.1 Economic Criteria

The following is a list of criteria under the economic aspect for biomass crop type selection:

- Seeding (C11): Measures the cost of establishment associated with land preparation, machinery, fertilizers, pesticide, and labor.
- Biomass yield (C12): Refers to the harvestable amount of biomass during the production of a certain crop.
- Production and harvesting (C13): Measures the cost of production including fertilizers, herbicides, irrigation, and labor, along with the harvesting cost of that certain biomass type.
- Storage and transportation (C14): Measures the cost of transportation and cost of storage requirements associated with a certain biomass type.
- Conversion rate (C15): Amount of gallons of ethanol obtained per tonne of biomass during the conversion of biomass into biofuel.
- Robustness to risks (C16): Includes strength of the crop type to all type of risks, such as drought, cold and hot weather, price fluctuations, and demand uncertainty in the market.
- Equipment and knowledge (C17): Refers to equipment availability and the practical knowledge of farmers about the cultivation of that particular crop type.

4.3.2 Environmental Criteria

Five criteria are related to the environmental aspects for selection of the biomass crop type:

- Soil quality impact (C21): Evaluates the capability of the biomass crop on decreasing soil erosion and requiring low fertilization during its cultivation.
- Carbon emissions (C22): Measures total CO_2 emissions and the carbon sequestration capability of a biomass crop type during its production.
- Water quality/requirement (C23): Considers the capability of the biomass type in increasing water quality and reducing water usage.
- Biodiversity and wildlife (C24): Refers to the effects of biomass cultivation on biodiversity and wildlife such as bird and insect populations.
- Invasiveness (C25): Includes risk and control cost of the biomass type associated with a high dispersal rate and the harmful effects, such as decreasing the hay value and damaging crop production over the region.

4.3.3 Social Criteria

The social aspects of biomass crop type selection are summarized below:

- Technological development (C31): Measures the potential development required to improve the ethanol conversion rate and productivity on farms.
- Workforce requirement (C32): Measures the creation of new jobs that occur as a result of certain types of biomass crop production.
- Energy safety and welfare (C33): Includes fossil fuel substitution capability of a crop type and its contribution to the wealth of society, such as the increment in gross domestic product when biomass production is initiated or increased.
- Food competition (C34): Evaluates the change of the food security by considering the potential allocation of cropland for biomass production.

4.3.4. Food Crops

Food crops are primarily used for food production. They are also utilized as biomass sources in ethanol production. Among food crops, corn and sugarcane are currently used for producing biofuel.

4.3.4.1 Corn

Corn is the largest biofuel source in the U.S., although its production involves high energy consumption. In other words, the output-input ratio is low since it requires good irrigation and high fertilization. The risk associated with price fluctuations is low for corn since it has a high demand in the market, either as ethanol or as food. However, using corn for energy production has been debated because of world hunger, which can be alleviated by increased corn production.

4.3.4.2 Sugarcane

After corn, sugarcane is the second most used biomass in biofuel production in the world [34]. It requires a warmer climate to grow. As the result of high biofuel production from sugarcane in Brazil, sugarcane conversion to biofuel is a developed technology, and sugarcane production has a low risk of price fluctuations. However, sugarcane production is sensitive to fertilizers, harvesting, irrigation, climate, and disease. Unlike corn and wheat, sugarcane is a perennial grass, and most of it can be converted to biofuel.

4.3.4.3 Wheat

Because of its high wheat production, Kansas is known as the “bread basket” of America. Wheat has a high protein content so it is a valuable food source for human beings, but

it is also used for ethanol production. It grows from its own seeds, and requires seeding and irrigation every year. Furthermore, farmers are familiar with its production.

4.3.5 Energy Crops

Energy crops, or lignocelluloses, are commonly used as feedstock. With the development of conversion technology, perennial crops have started to be called energy crops because of their low input and high energy yield.

4.3.5.1 Switchgrass

Switchgrass, a bunchgrass native to North America, is a perennial that does not need to be seeded every year. It has been promoted by the federal government because of its benefits to the environment, such as reducing soil erosion and greenhouse gas emissions. It can also grow on marginal lands that are not used for farming. It requires little irrigation and few fertilizers. Many studies have been undertaken to increase its conversion efficiency [35].

4.3.5.2 Miscanthus

Miscanthus (Miscanthus x giganteus), another energy crop commonly used in Europe for ethanol production, may exhibit some invasive properties in the U.S. because it is non-native to North America. This warm-season perennial grass is tolerant to cold weather and, therefore, has the potential to be grown as a source of biomass in Kansas. It can grow on less-productive land types, such as marginal lands. It requires irrigation for a higher yield, but compared to all other crop types, it has a very high yield [36].

4.4 Stochastic AHP Methodology

In this study, an SAHP methodology, which was proposed by Jalao et al. [37], and a fuzzy multi-criteria decision-making procedure, first proposed by Zeng et al. [38] and also used by

Kahraman and Kaya [17], are modified in order to evaluate and select the most appropriate biomass crop alternative. We decompose the decision problem into a hierarchy of more easily comprehended subproblems. First, a decision hierarchy with n criteria and m alternatives is built. Second, experts systematically evaluate the various elements of the hierarchy by comparing them to one another, two at a time (pairwise comparison). For that purpose, Saaty's linguistic and corresponding numerical scale, given in Table 4.1, is employed. Third, since experts might provide a range rather than a single number to compare two factors and the comparisons generally involve some level of uncertainty, imprecise numeric pairwise comparisons are modeled as stochastic pairwise comparison distributions. Fourth, the stochastic beta distribution is converted to crisp values. Fifth, priority weights of all pairwise comparison matrices are calculated by using the LLSM. Sixth, the consistency of matrices is checked; if inconsistency is encountered, then experts are required to update the corresponding comparison matrix. Seventh, individual evaluations are aggregated by employing a fuzzy weighted averaging operator. Eighth, and finally, an outranking method is employed to obtain the order of the best alternatives.

In making comparisons, experts must assign a definite number, on a scale of 1 to 9, in order to compute priority vectors. The fundamental scale for pairwise comparison is summarized in Table 4.1. Moreover, the corresponding reciprocals 1, 1/2, 1/3, …, 1/9 are used for a reverse comparison.

TABLE 4.1 SAATY'S PAIRWISE COMPARISON SCALE

Intensity of importance	Definition	Explanation
1	Equal importance	Two elements contribute equally to objective.
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong importance	Experience and judgment strongly favor one element over another.
7	Very strong importance	One element is favored very strongly over another
9	Extreme importance	Evidence favoring one element over another is of highest possible order of affirmation
Even scales of 2, 4, 6, and 8 are used to compromise slight differences between two classifications.		

The steps of the proposed method for biomass crop selection are explained in detail below:

Step 1: Structure the decision problem in a hierarchy with n criteria and k alternatives. For example, as shown in Figure 2, we consider a four-level AHP hierarchy for biomass crop selection, with 3 aspects, 16 criteria, and 5 alternatives.

Step 2: Compare elements using pairwise comparisons. Experts are required to compare every element pairwise in their corresponding section structured in the hierarchy. Experts can provide crisp values, most likely value (somewhat imprecise) with an upper and lower bound, or a range (totally imprecise) with a lower and upper bound for comparison of two elements. As indicated previously, Table 4.1 is employed for pairwise comparison since it is a widely used scale. Moreover, the corresponding reciprocals 1, 1/2, 1/3, …, 1/9 are used for a reverse comparison.

As an example, assume that an expert indicates that Miscanthus is "strongly more important" than corn in yield production. We obtain a numerical score, $a_{mc} = 5$. On the other hand, the expert can provide imprecise linguistic pairwise comparison because Miscanthus is at least equal, most likely moderately, or at most strongly more important than switchgrass in yield production. In this case, we obtain $a_{ms} = [1, 3, 5]$. Finally, if the expert provides a range in comparison because switchgrass is equally or moderately more important than corn, we obtain $a_{sc} = [1, 3]$.

Step 3: Convert imprecise preferences of experts into stochastic pairwise comparisons. Readers are referred to the study of Jalao et al. [37] for a discussion of beta distribution and stochastic pairwise comparison.

To obtain crisp values of stochastic pairwise comparison, a_{ij}, conversion is done according to probability density function $f_{ij}(a_{ij}|\theta_{ij})$ with parameters θ_{ij}. Based on the previous example, $a_{mc} \sim f_{mc} = 5$. And $a_{ms} = [1, 3, 5]$ is modeled as triangular distribution with lower limit (LL), most likely (ML), and upper limit (UL) as $a_{ms} \sim f_{ms}(LL, ML, UL) = T_{ms}(1, 3, 5)$. Finally, $a_{sc} = [1, 3]$ is modeled as uniform distribution as $a_{sc} \sim f_{sc}(LL, UL) = U_{sc}(1, 3)$. Because of the difficulty of priority weight calculation for these varying distributions, the stochastic pairwise comparisons are transformed into beta distributed pairwise comparisons, $\tilde{a}_{ij}$. The term $\tilde{a}_{ij}$ follows beta distribution, $B(\tilde{a}_{ij}|\alpha, \beta, LL, UL)$, with shape (α, β) and location (LL, UL) parameters, where $LL \leq \tilde{a}_{ij} \leq UL$ and $\alpha, \beta \geq 1$.

In order to explicitly model all a_{ij} as beta random variables $\tilde{a}_{ij}$, the shape $(\alpha_{ij}, \beta_{ij})$ and location (LL_{ij}, UL_{ij}) parameters are estimated based on the method of moments (MOM). Sample mean and variance are obtained by taking the first and second moments, respectively:

$$E\left[\tilde{a}_{ij}\right] = LL + \frac{\alpha}{\alpha+\beta}(UL - LL) \tag{4.1}$$

$$Var(\tilde{a}_{ij}) = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}(UL - LL) \tag{4.2}$$

Equating equations (4.1) and (4,2) to the sample mean ($\bar{a}_{ij}$) and sample variance (S_{ij}^2), respectively, we obtain the estimates of the shape parameters, $\hat{\alpha}_{ij}, \hat{\beta}_{ij}$, based on the following equations:

$$\hat{\alpha}_{ij} = \left(\frac{\bar{a}_{ij}-LL}{UL-LL}\right)\left(\frac{\left(\frac{\bar{a}_{ij}-LL}{UL-LL}\right)\left(1-\left(\frac{\bar{a}_{ij}-LL}{UL-LL}\right)\right)}{\frac{S_{ij}^2}{(UL-LL)^2}} - 1\right) \tag{4.3}$$

$$\hat{\beta}_{ij} = \left(1 - \frac{\bar{a}_{ij}-LL}{UL-LL}\right)\left(\frac{\left(\frac{\bar{a}_{ij}-LL}{UL-LL}\right)\left(1-\left(\frac{\bar{a}_{ij}-LL}{UL-LL}\right)\right)}{\frac{S_{ij}^2}{(UL-LL)^2}} - 1\right) \tag{4.4}$$

Applying the MOM for the conversion of stochastic pairwise comparisons to beta distributed pairwise comparisons, the outputs are summarized below:

$$\tilde{a}_{ij} = a_{ij} \quad if\ a_{ij}\ is\ crisp \tag{4.5}$$

$$\tilde{a}_{ij} \sim B\left(\hat{\alpha}_{ij} = 1, \hat{\beta}_{ij} = 1, LL_{ij}, UL_{ij}\right) \quad if\ a_{ij} \sim U\left(LL_{ij}, UL_{ij}\right) \tag{4.6}$$

$$\tilde{a}_{ij} \sim B\left(\hat{\alpha}_{ij}, \hat{\beta}_{ij}, LL_{ij}, UL_{ij}\right) \quad if\ \ a_{ij} \sim T\left(LL_{ij}, ML_{ij}, UL_{ij}\right) \tag{4.7}$$

where $\hat{\alpha}_{ij}$ and $\hat{\beta}_{ij}$ in equation (4.7) are obtained from equations 4.3 and 4.4, respectively. For these calculations, $\bar{a}_{ij} = (LL_{ij} + ML_{ij} + UL_{ij})/3$ and $S_{ij}^2 = (LL_{ij}^2 + ML_{ij}^2 + UL_{ij}^2 - LL_{ij}ML_{ij} - LL_{ij}UL_{ij} - ML_{ij}UL_{ij})/18$ (obtained from standard mean and variance formulations) are used.

Step 4: Convert beta distributed pairwise comparisons into crisp values. As the crisp values for each $\tilde{a}_{ij}$, the median value of beta distribution is used. The median of the beta distribution, $m(\hat{\alpha}_{ij}, \hat{\beta}_{ij})$, is obtained by employing the closed-form approximation proposed by proposed by Kerman [39]:

$$m(\hat{\alpha}_{ij}, \hat{\beta}_{ij}) \approx \frac{\hat{\alpha}_{ij} - 1/3}{\hat{\alpha}_{ij} + \hat{\beta}_{ij} - 2/3} \tag{4.8}$$

The median is bound below by the mode and above by the mean as follows:

$$\frac{\hat{\alpha}_{ij} - 1}{\hat{\alpha}_{ij} + \hat{\beta}_{ij} - 2} \leq m(\hat{\alpha}_{ij}, \hat{\beta}_{ij}) \leq \frac{\hat{\alpha}_{ij}}{\hat{\alpha}_{ij} + \hat{\beta}_{ij}} \tag{4.9}$$

where, in the case of $\hat{\beta}_{ij} \leq \hat{\alpha}_{ij}$, the order of the inequality (4.9) is reversed. Then, the numeric value of the median for comparison a_{ij}, considering LL_{ij} and UL_{ij} parameters, is obtained by using the following formula [40]:

$$a_{ij} = LL_{ij} + m(\hat{\alpha}_{ij}, \hat{\beta}_{ij}) * (UL_{ij} - LL_{ij}) \tag{4.10}$$

Step 5: Calculate the priority weights of elements. Let *n* be the number of elements, which can be represented by F_1, F_2, …,F_n in one section of the hierarchy. Then, a_{ij} represents the crisp value representing the quantified judgment on F_i over F_j. The pairwise comparison in the same section yields the following *n*-by-*n* matrix

$$A = \begin{array}{c} \\ F_1 \\ F_2 \\ \dots \\ F_n \end{array} \begin{array}{c} \begin{array}{cccc} F_1 & F_2 & \dots & F_n \end{array} \\ \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ 1/a_{12} & 1 & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ 1/a_{1n} & 1/a_{2n} & \dots & 1 \end{bmatrix} \end{array} \tag{4.11}$$

In this study, in order to obtain a priority weight of the elements in one section, we employ LLSM, which is also known as the geometric mean method, as follows

$$w_i = \frac{\prod_{j=1}^{n} a_{ij}^{1/n}}{\sum_{i}^{n} \left(\prod_{j=1}^{n} a_{ij}^{1/n} \right)} \tag{4.12}$$

Assume that F_i has t upper sections at different levels in the hierarchy, and $w_{section}^{(i)}$ is the section weight of the ith upper section, which contains F_i in the hierarchy. The final weight of w_i' of F_i can be obtained as

$$w_i' = w_i \prod_{i=1}^{t} w_{section}^{(i)} \tag{4.13}$$

Step 6: Check for inconsistency. For each matrix, calculate the inconsistency level, G, and compare it to the random consistency threshold, Ns (see source [41] for more details). When G < Ns is ensured, we move to the next step. In the case of inconsistency, we return to step 2. The expert is asked to update comparisons for the corresponding matrix.

Step 7: Aggregate opinions of the DMs by employing the fuzzy weighted averaging operator, $\tilde{S}_i$, which defines the weight of DM *i*. When we have *m* DMs, we determine the final scores as

$$\left(\tilde{F}S\right) = \sum_i^m \tilde{S}_i w_i' \tag{4.14}$$

where the summation of $\tilde{S}_i$ for all *m* should equal 1.

Step 8: Compute the overall evaluation values of alternatives. We determine the order of best alternatives with the calculation of their final scores. Final scores of the alternatives are obtained by multiplying their values under a sub-criterion with the weight of the corresponding sub-criterion.

4.5 Application to Biomass Crop Selection

In this section, the proposed SAHP model is applied to a biomass crop selection problem in the state of Kansas. The MCDM problem has three main criteria factors: economic, environmental, and social. Sixteen criteria are considered under the analytical hierarchy. In order to define the most appropriate biomass crop type in Kansas, various experts, including farmers, academics, and government officers are interviewed. Each expert provides their judgment for comparing each two elements under the same section and in the same level of the hierarchy. The comparison values provided by experts are either crisp numbers, a range, or

a most-likely value within a range. Table 4.2 shows the judgment of an expert for criteria under the environmental factor.

TABLE 4.2 PAIRWISE COMPARISON MATRIX FOR ENVIRONMENTAL CRITERIA

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}
Soil quality impact (C_{21})	1	*U*(7, 9)	1	*T*(7, 8, 9)	*U*(5, 7)
Carbon emissions (C_{22})		1	*U*(1/9, 1/7)	*U*(1/3, 1)	*U*(1/5, 1/3)
Water requirement (C_{23})			1	*T*(6, 7, 9)	*U*(5, 7)
Biodiversity and welfare (C_{24})				1	1/2
Invasiveness (C_{25})					1

After applying equations (4.5), (4.6), and (4.7) based on the distribution of evaluation (crisp, uniform, triangular), they are converted into stochastic beta pairwise comparisons, as provided in Table 4.3.

TABLE 4.3 STOCHASTIC COMPARISON MATRIX FOR ENVIRONMENTAL CRITERIA

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}
Soil quality impact (C_{21})	1	*B*(1, 1, 7, 9)	1	*B*(2.5, 2.5, 7, 9)	*B*(1, 1, 5, 7)
Carbon emissions (C_{22})		1	*B*(1, 1, 1/9, 1/7)	*B*(1, 1, 1/3, 1)	*B*(1, 1, 1/5, 1/3)
Water requirement (C_{23})			1	*B*(2.1, 2.6, 6, 9)	*B*(1, 1, 5, 7)
Biodiversity and welfare (C_{24})				1	1/2
Invasiveness (C_{25})					1

These stochastic pairwise comparison distributions are converted into crisp numbers by implementing equations (4.8) and (4.10). A comparison matrix with crisp values is displayed in Table 4.4.

TABLE 4.4 MEDIAN (CRISP) VALUES FOR ENVIRONMENTAL CRITERIA

	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}
Soil quality impact	1	8	1	8	6
Carbon emissions	0.125	1	0.127	0.667	0.267
Water requirement	1	7.875	1	7.306	6
Biodiversity and welfare	0.125	1.5	0.137	1	0.5
Invasiveness	0.167	3.75	0.167	2	1

Weights of each factor in the comparison matrix are calculated by using the LLSM method given in equation (4.12). After obtaining weights for each criteria by individual experts, they are aggregated by using the fuzzy weighted averaging operator given in equation (4.14). For this implementation, equal weight is assigned to each expert.

Table 4.5 shows the weights of the sub-criteria under environmental factors for a subset of experts and the aggregated value for overall experts. A complete list of aggregated final weights for each criteria and sub-criteria is given in Table 4.6. It can be seen that the economic factor has about 59% importance among the overall factors. Effect on the environment has about 26% importance, while the social factor has only 15% importance in biomass crop selection. The biomass yield amount of the crop has the highest weight among all economic criteria, while storage and transportation has the lowest importance.

The weights of economic criteria also show that decision makers are risk averse when selecting the biomass crop since weights associated with the robustness to risks as well as equipment and knowledge attained high values. We also observe that environmental outcomes of biomass production, such as water and soil quality, are also significant. On the other hand, the carbon footprint, which is also considered to be an environmental issue worldwide, is not highly weighted since it has an indirect effect on the farmer benefits. Finally, we observe that the effect of biomass crop selection on food competition is considered as the most important social criterion, while the remaining three social factors have about the same weight in decision making for biomass crop selection.

The scores of each biomass crop for the criteria under economic factor and total economic score are given in Table 4.7. Similarly, Table 4.8 and Table 4.9 provide scores of

biomass crop types for environmental and social criteria along with their total scores, respectively.

TABLE 4.5 WEIGHTS OF SUB-CRITERIA OF ENVIRONMENTAL CRITERIA AND AGGREGATION

Environmental	E1	E2	E3	E4	Aggregated
Soil quality impact	0.4901	0.4128	0.2769	0.2004	0.3451
Carbon emissions	0.0392	0.0388	0.2705	0.0474	0.0990
Water requirement	0.2426	0.4041	0.2553	0.5782	0.3701
Biodiversity and welfare	0.0646	0.0525	0.1150	0.0570	0.0723
Invasiveness	0.1635	0.0918	0.0823	0.1170	0.1136

TABLE 4.6 BIOMASS CROP SELECTION CRITERIA AND CORRESPONDING WEIGHTS

Main Criteria	**Weight**	**Sub-criteria**	**Weight**
Economic	0.589	Seeding	0.107
		Biomass yield	0.213
		Production and harvesting	0.120
		Storage and transportation	0.079
		Conversion rate	0.140
		Robustness to risks	0.152
		Equipment and knowledge	0.191
Environmental	0.245	Soil quality impact	0.265
		Carbon emissions	0.094
		Water quality/requirement	0.286
		Biodiversity and wildlife	0.124
		Invasiveness	0.232
Social	0.156	Technological development	0.207
		Workforce requirement	0.223
		Energy and welfare	0.249
		Food competition	0.321

TABLE 4.7 BIOMASS CROP SCORES FOR ECONOMIC CRITERIA

Crop type	**Economic criteria**							**Total economic score**
	C_{11}	**C_{12}**	**C_{13}**	**C_{14}**	**C_{15}**	**C_{16}**	**C_{17}**	
Corn	0.099	0.105	0.131	0.182	0.214	0.138	0.344	0.105
Sugarcane	0.144	0.148	0.115	0.063	0.077	0.120	0.104	0.067
Wheat	0.325	0.053	0.359	0.181	0.204	0.209	0.424	0.143
Switchgrass	0.231	0.293	0.185	0.241	0.286	0.309	0.076	0.134
Miscanthus	0.201	0.401	0.209	0.334	0.219	0.224	0.051	0.136

TABLE 4.8 BIOMASS CROP SCORES FOR ENVIRONMENTAL CRITERIA

Crop type	Environmental criteria					Total environmental score
	C_{21}	C_{22}	C_{23}	C_{24}	C_{25}	
Corn	0.075	0.051	0.105	0.120	0.220	0.030
Sugarcane	0.053	0.130	0.067	0.163	0.327	0.035
Wheat	0.152	0.062	0.143	0.119	0.292	0.047
Switchgrass	0.403	0.395	0.134	0.357	0.103	0.082
Miscanthus	0.317	0.362	0.136	0.240	0.059	0.066

TABLE 4.9 BIOMASS CROP SCORES FOR SOCIAL CRITERIA

Crop type	Social criteria				Total social score
	C_{31}	C_{32}	C_{33}	C_{34}	
Corn	0.109	0.122	0.150	0.126	0.020
Sugarcane	0.100	0.140	0.206	0.213	0.027
Wheat	0.113	0.095	0.057	0.154	0.017
Switchgrass	0.323	0.322	0.265	0.268	0.045
Miscanthus	0.356	0.320	0.321	0.239	0.047

After multiplying the scores of each biomass crop with the corresponding weights, we obtain the rankings as given in Table 4.10. It can be seen that two energy crops outrank the other food crops, with switchgrass and Miscanthus ranking 1 and 2, respectively.

TABLE 4.10 BIOMASS CROP ALTERNATIVES, WEIGHTS, AND RANKING

Crop alternatives	Weight	Ranking
Corn	0.1552	4
Sugarcane	0.1283	5
Wheat	0.2064	3
Switchgrass	0.2614	1
Miscanthus	0.2487	2

4.5.1 Sensitivity Analysis

In order to obtain better insight from the SAHP application on biomass crop selection, we depict the scores of different crop types on each factor, as shown in Figure 4.3.

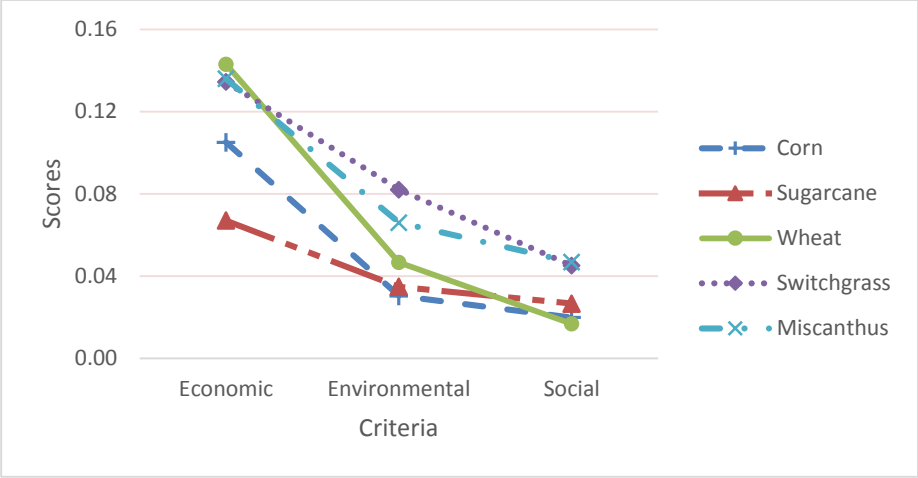

Figure 4.3 Weighted scores of biomass crop types in three main criteria.

It can be seen that since switchgrass has the significantly highest score in environmental criteria, it is chosen as the most sustainable crop type for biomass production in overall ranking. Due to its low scores in carbon emissions and biodiversity evaluations, corn is the least favorable crop type, based on the environmental criteria. However, wheat is very competitive in the economic criteria, due to farmers' knowledge regarding its production. Contrary to this, sugarcane is the least appropriate biomass crop in the economic criteria, since it has a low conversion rate, and high transportation and storage costs. In addition, farmers are not familiar with its production; therefore, it has a high risk. On the other hand, wheat has not much additional benefit to offer society than it does before and thus makes the lowest scores in energy safety, welfare, and workforce requirements.

We also perform a sensitivity analysis on the effect of the economic factor's weight on the results. Figure 4.4 presents those cases where the economic factor has 25% less weight and 25% more weight than the weight value computed, based on expert opinions on biomass crop selection.

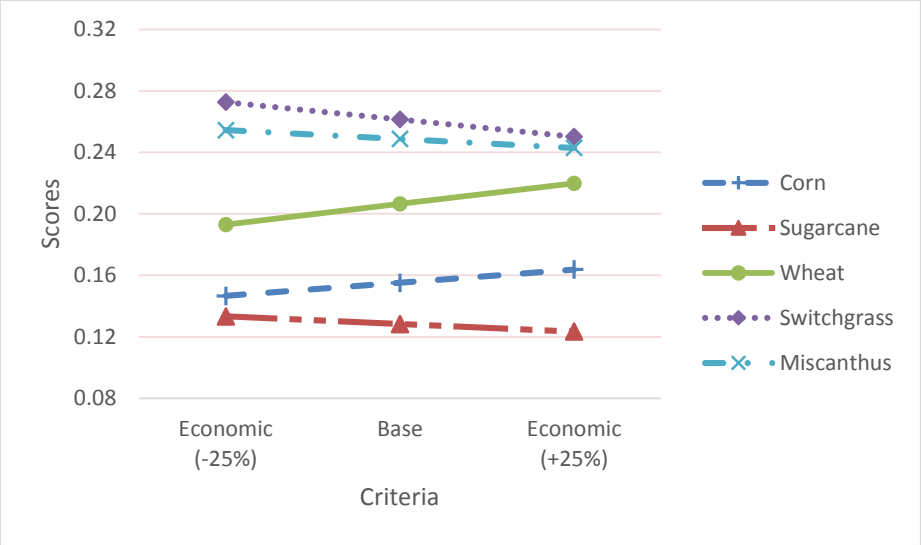

Figure 4.4 Overall scores of biomass crop types based on changing weights of economic factor.

We also analyze the effect of the environmental factor on results. Cases where the environmental factor has 25% less weight and 25% more weight than the value defined based on expert opinions for biomass crop selection are presented in Figure 4.5. As environment has more weight in biomass selection, switchgrass secures its ranking as number 1, since it has a better effect on the environment compared to other crop alternatives. On the other hand, the overall score of Miscanthus stays stable, while that of wheat and corn slightly decrease.

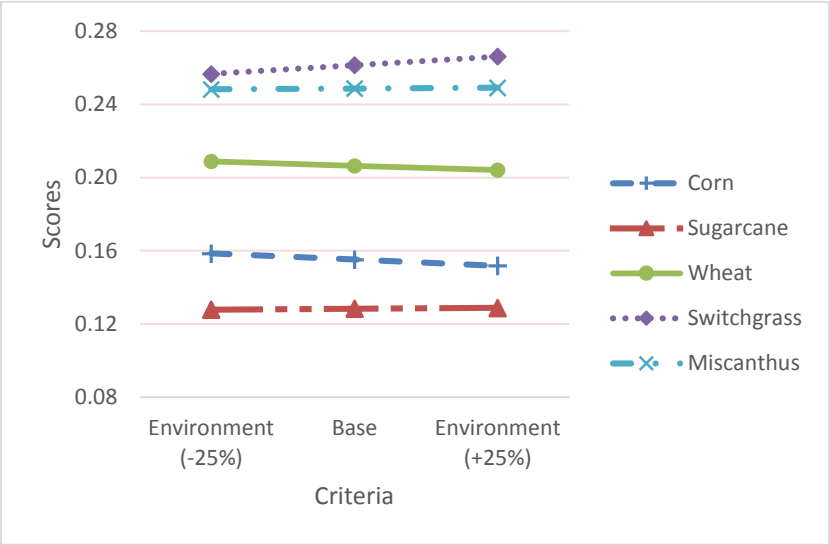

Figure 4.5 Overall scores of biomass crop types based on changing weights of environmental factor.

Since the weight of the social factor in biomass crop selection is comparatively low, the sensitivity analysis on the social factor shows that changing its weight in the 25% range only slightly affects the results. Since wheat has the lowest score in the social factor, its overall score decreases as social impacts become more important in decision making.

4.6 Conclusion and Future Work

Developing alternative solutions to energy production is one of the key points in sustaining economic growth and increasing the wealth of society. In this chapter, we study the selection of the most sustainable biomass crop type for biofuel production. The sustainability of a biomass crop is evaluated in terms of various environmental, economic, and social factors. By incorporating a literature review and expert opinions, the criteria to be considered in the selection and a hierarchy are constructed. A stochastic decision-making tool with AHP methodology, which allows experts to use crisp, fuzzy, or totally imprecise numbers in evaluation, is developed. Weight and importance of the criteria are determined. In order to deal with the possible bias in expert opinions, we interview a broad range of experts with different backgrounds. Applying the model to the available and candidate crop types in Kansas, it is shown that switchgrass is selected as the most appropriate biomass crop in the state. Miscanthus and wheat are determined to be the second and third best biomass alternatives, respectively. As the economic factor becomes more important, it can be seen that the overall score of switchgrass decreases, while the scores of wheat and corn increase. It is also shown that corn and wheat receive the lowest scores on environmental and social criteria, respectively.

In the future, the proposed SAHP structure could be used in different countries or regions in order to define the most sustainable biomass crop in that region. Other decision-making approaches such as ANP, TOPSIS, or VIKOR, or TOPSIS could also be used in biomass crop selection to compare results. In this chapter, we develop the most comprehensive decision-making criteria, including economic, environmental, and social factors, for sustainable biomass crop selection. However, as biomass and biofuel production becomes more common, the criteria to be considered in the decision-making structure and the corresponding weights may be updated depending on the significance of the criteria.

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CHAPTER 5

A TWO-STAGE STOCHASTIC MIXED-INTEGER PROGRAMMING MODEL FOR THE ANALYSIS OF BIOFUEL AND FOOD PRODUCTION

5.1 Introduction

Biofuel is considered a promising sustainable energy source that can substitute for scarce fossil fuel and is currently utilized in many countries. According to the Renewable Fuel Standards, annual biofuel production from grain can be 15 billion gallons, while at least 16 billion gallons should come from energy crops by 2022 [1]. However, biofuel production from food and energy crops increases the debate regarding competition between the security of food and the energy supply. In addition to differences in their economic impacts, food and energy crops have various environmental impacts. The trade-offs between economic and environmental benefits turn the decision making into a complex problem. In addition, it is important to incorporate uncertainties in yield amount with associated price level of energy and food crops in order to obtain better results relative to economic and environmental aspects. Thus, stakeholders in agriculture business need a decision analysis tool that can handle uncertainties, and incorporate economic and environmental impacts of food and biomass production.

Existing deterministic mathematical models use point estimates and mean values in decision making. Although sensitivity analysis is utilized to cover the range of possible values of a parameter, it lacks the ability to provide decision strategies that will be successful in the long run. One of the most critical aspects in biomass production is the variability in yield amount, since this is highly dependent on uncontrollable natural events, particularly changing weather

conditions such as drought and high precipitation. The supply amount of a crop also indirectly affects its price in the market. Uncertainty in yield amount and associated price level should be incorporated into a decision-making tool since it directly affects the cost of production, profitability, and land utilization. Stochastic programming can be used to deal with uncertain values of probabilistic parameters [2] [3]. Therefore, a more complete assessment of biomass and food production can be achieved with a stochastic model. In this chapter, we propose a stochastic mixed-integer programming (MIP) model that incorporates various economic and environmental effects of biomass and food production (BFP) and provides the best decision strategies at the farm level for decision makers. One of the objectives of this study is to explicitly model the yield uncertainty involved in BFP by considering various scenarios. Due to this problem's high complexity, we also aim to analyze the effect of different modeling techniques, such as deterministic and stochastic MIP, as well as its decomposition algorithm in order to solve the stochastic MIP problem more efficiently and increase the solution quality.

In the literature, rather than dealing with food and biofuel production simultaneously in a stochastic programming model, the majority of researchers focus on supply chain optimization. Gebreslassie et al. [4] define the optimal network design for hydrocarbon biofuel supply chain by considering feedstock seasonality, demand variations, and government incentives. They apply a multicut L-shaped decomposition algorithm to solve the stochastic MIP model. Chen and Fan [5] propose a two-stage stochastic MIP model via the Lagrangian relaxation method for designing a bioethanol supply chain network. Wiedenmann and Geldermann [6] develop a two-stage stochastic programming model to analyze the supply chain of agricultural raw materials under price and supply uncertainty. Here, first-stage decisions

involve the selection of suppliers for contract, while second-stage decisions define the value of penalty cost associated with unmet demand and quantity purchased from the no-contract supplier.

Very few optimization studies consider biomass and food production at the farm level, and many of them fall short on the stochastic nature of the problem. The model developed by Lin et al. [7] involves a problem scope from biomass harvesting to ethanol distribution by using Miscanthus. Similarly, Sharma et al. [8] formulate an MIP model for minimizing the transportation cost of switchgrass biomass to a biorefinery. They handle uncertainty in yield level by conducting sensitivity analysis. In another biofuel supply chain problem [9], MIP model is proposed for an optimal network design, while uncertainty of biomass availability and product demand are modeled with fuzzy numbers. However, the aforementioned models do not consider potential environmental effects of the supply chain in decision making.

In a limited number of studies, the environmental effects of BFP have been incorporated into a mathematical model. Cobuloglu and Büyüktahtakın [10] propose an MIP model for the optimal land allocation of switchgrass while accounting for soil erosion, carbon sequestration, and carbon emissions of biomass production. Uncertainty in yield amounts, budget levels, and cropland availability are dealt with using a sensitivity analysis. Most of the other studies only consider carbon emissions. Affuso and Hite [11] utilize a stochastic model by considering yield uncertainty and carbon emissions while allocating the land to the first-generation biofuel crops. Similarly, Liu et al. [12] consider carbon emissions for optimal design and planning of a biofuel supply chain in a deterministic MIP model. Giarola et al. [13] propose a stochastic MIP model for an ethanol supply chain in order to decide the best biomass types and technology under

uncertain biomass availability and the carbon trade value in the market. In order to find economically viable and environmentally friendly production strategies, Kantas et al. [14] incorporate carbon emissions and water pollution into a capacitated lot-sizing ethanol production model.

Our work differs from other studies in several aspects. In a previous study by Cobuloglu and Büyüktahtakın [15], economic and environmental effects of the competition between food and biomass production is analyzed in a deterministic model. Yield amount and associated price level is incorporated into the model with a piecewise linear function. Unlike Cobuloglu and Büyüktahtakın, we develop a stochastic programming model to analyze the economic and environmental impacts of BFP and incorporate uncertainty in two important parameters, yield and price level, into the stochastic MIP model.

Other contributions of this work can be summarized as follows

- Most stochastic models in the biofuel field are developed primarily for designing the supply chain. To the best of our knowledge, this is the first stochastic programming study that models the competition of food and biofuel production at the farm level.
- To the best of our knowledge, this is also the first stochastic programming study that incorporates both economic and environmental impacts, simultaneously, while considering yield uncertainty. In addition to costs such as seeding, production, harvesting, and transportation, a compact set of environmental impacts, namely soil erosion prevention, carbon emissions and sequestration, and nitrogen pollution, are integrated into the model.

- In this study, we utilize real data to obtain the probability of random events—yield amounts and price levels of crops. Thus, we first define the probability distribution of yield amounts. For the scenario generation, the probability density function is discretized into three values with associated probabilities. Then we find the corresponding price levels of each yield value by utilizing a linear regression.
- Due to the computational complexity of the stochastic MIP model, we customize the Benders decomposition algorithm for solving the BFP problem. Computational efficiencies such as solution quality and time of the deterministic, stochastic, and decomposition models are presented in the analysis section. We also provide the value of the stochastic solution (VSS) to demonstrate importance of incorporating uncertainty into the optimization model.
- This model has been developed for both energy and food crops, which in general can be utilized for other crops, such as wheat and Miscanthus. Efficiency of the proposed decomposition algorithm can also be tested in similar-type problems in the future.

The remainder of this chapter is organized as follows: The problem statement and the notations are presented in section 5.2. The stochastic MIP model as well as its decomposition are provided in detail in section 5.3. Input data for deterministic and uncertain parameters along with scenario generation are described in section 5.4. A case study with all computational results, comparisons, and sensitivity analysis is provided in section 5.5. Finally, conclusions and future directions are discussed in section 5.6.

5.2 Problem Definition

Our goal in this chapter is to provide a decision-making model that maximizes total economic and environmental benefits of biofuel and food production under uncertainty in the long run. We utilize switchgrass for biofuel production since it has environmental benefits, low input requirements, and high energy yield. It is also a perennial grass that is native to North America. Among different alternatives for food crops, corn is considered a source of both food and biofuel production in our study due to its prevalent cultivation in the U.S.

Switchgrass and corn have different economic and environmental benefits. Switchgrass is a low-input crop and has a minimum ten-year life expectancy. On the other hand, corn requires a high amount of fertilizer and needs seeding each year. Environmental benefits of switchgrass include reduction in GHG emissions, storage of soil organic carbon, and prevention of soil erosion due to its root system [16]. The environmental impacts of different crops change temporally and spatially. On the other hand, when compared with switchgrass, corn has few benefits while potentially damaging the environment. The yield of switchgrass and corn are both affected by weather conditions. In addition, the price level of corn grain in the food market is negatively correlated with its yield amount. Therefore, a compact decision-making system is needed not only to incorporate these economic and environmental trade-offs but also to handle the uncertainty of yield amounts and price levels.

Yield amounts of switchgrass and corn are affected by uncertain weather conditions. Yield amount is included in the model by considering three possible states of yield: high, medium, and low. The price of corn grain that goes to the food market is affected each year by the amount of corn yield. On the other hand, the price of switchgrass, corn stover, and corn

grain that go to a biorefinery is considered deterministic due to long-term contracts between farmers and the biorefinery. Figure 5.1 shows a scenario-tree, which represents the yield and price scenarios with associated probabilities (ε_s) for each scenario *s* in each time period of a ten-year horizon. In the first year, low-, medium-, and high-yield scenarios have probabilities ε_1, ε_2, and ε_3, respectively. In order to obtain the probability of each scenario in the second year, probabilities of each yield state (high, medium, and low) is multiplied with the probability of the previous scenario (parent node). Having three scenarios from each node results in 59,049 scenarios for a ten-year planning horizon. An example of the calculation of yield amount and price levels as well as associated probabilities for each scenario is presented in section 5.4.1.

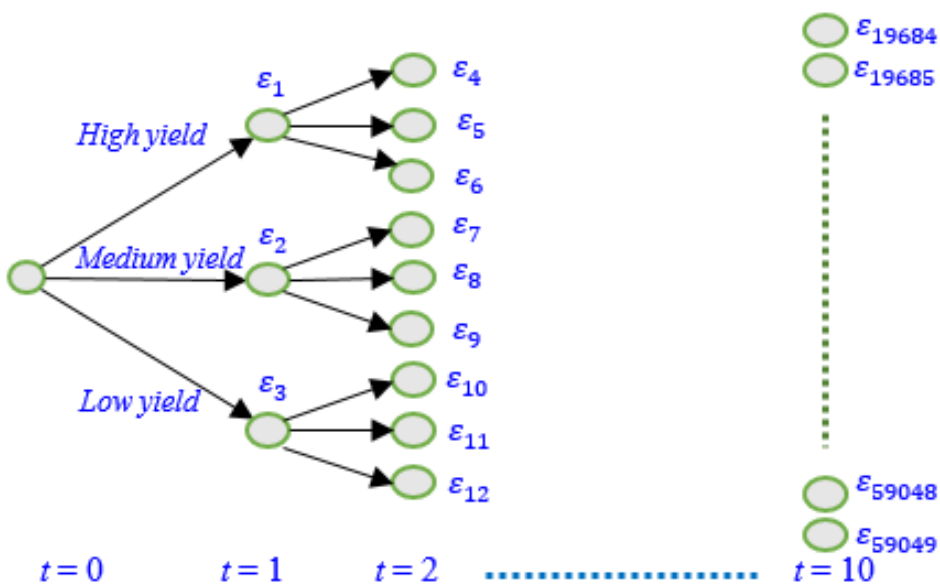

Figure 5.1 Scenario tree for uncertain yield amount and associated probabilities.

All sequential processes in BFP and outputs of the proposed stochastic programming model are displayed in Figure 5.2. Sequential processes considered in the model begin with the allocation of energy and food crops to different land types. Then, the cultivation of each crop type on different land types leads to various yield types. Once each crop is grown, the

harvesting of yield types is realized on the selected zones. Finally, harvested yield types are transported to different markets.

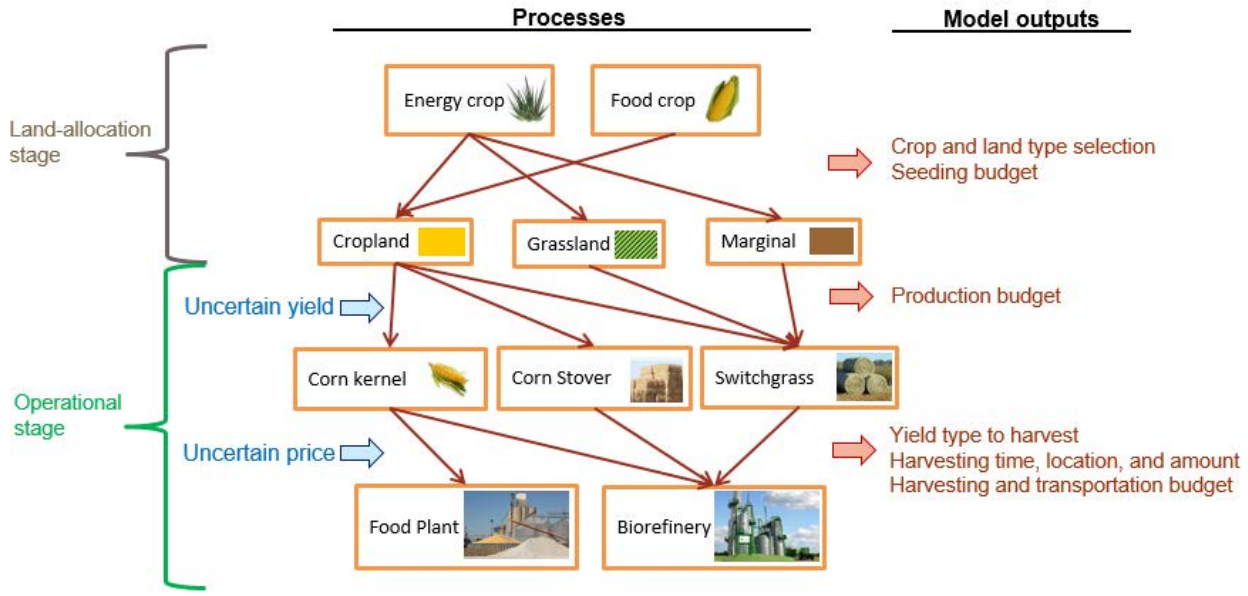

Figure 5.2 Model inputs and outputs as well as processes in food and biofuel production.

Model outputs demonstrate decisions for various processes. First, each zone of the different land types is allocated to a crop type. Based on the match between crop and land type, a seeding budget is defined. A production budget consisting of fertilization and rental cost is determined for producing switchgrass and corn in the allocated zones. Then, crop types to harvest, harvested zones, time period of harvesting, and amount of harvesting are defined. A portion of the overall budget is also allocated for harvesting operations. Finally, the quantity of harvesting also determines the budget required for transporting the harvested yield. Note that the model oversees all processes and provides decision making for each step simultaneously.

The establishment of switchgrass is considered a strategic decision since once allocated, it has ten years of life without reseeding. The remaining land allocated for corn is not assumed to change during the planning horizon. We also assume that utilized lands can be partially

harvested. Considering this setting, we propose a two-stage stochastic optimization model. In the first (land-allocation) stage, land allocation to different crop types is decided, and in the second (operational) stage, the amount of biomass and food yield, harvesting decisions, and quantity of harvesting are decided. These decisions also define the budget allocation for each farm operation.

Nomenclature

Indices

i Row of cultivation zone

j Column of cultivation zone

(i, j) Cultivation zone

k Crop type (1: switchgrass, 2: corn)

v Yield type (1: switchgrass, 2: corn grain for food, 3: corn grain for biofuel, 4: corn stover)

t Time period

s Scenarios for yield and price

Sets

I Set of rows of cultivation area

J Set of columns of cultivation area

K Set of crop types

V Set of yield types

T Set of time periods in modeling horizon

S Set of scenarios

CR Set of cropland zones in cultivation area

GR Set of grassland zones in cultivation area

MR Set of marginal land zones in cultivation area

Binary decision variables

S_{ijk} 1 if zone (*i,j*) is seeded with crop type *k*, 0 otherwise

Auxiliary Variables

TB Total benefit

TCE Total carbon emissions

TCE_1 Total carbon emissions released during seeding operations

TCS Total carbon sequestration

TNP Total nitrogen pollution

TR Total revenue

TSE Total soil erosion prevention

Continuous Decision Variables

X_{ijv}^t Harvesting percentage of zone (*i,j*) for yield type *v* at time period *t*

N_{ij}^t Switchgrass yield in zone (*i,j*) at time period *t* (tonnes)

$\bar{N}_{ij}^t$ Harvested switchgrass biomass in zone (*i,j*) at time period *t* (tonnes)

$\tilde{Y}_{ij}^t$ Corn grain used for food production in zone (*i,j*) at time period *t* (tonnes)

$\bar{Y}_{ij}^t$ Corn grain used for biofuel production in zone (*i,j*) at time period *t* (tonnes)

Y_{ij}^t Harvested corn stover in zone (*i,j*) at time period *t* (tonnes)

E_b Establishment budget used ($)

P_b Production budget used ($)

P_{b1} Production budget used for rent and fixed costs of seeding ($)

P_{b2} Production budget used primarily for variable costs ($/tonne)

H_b Harvesting budget used ($)

T_b Transportation budget used ($)

Z Decision variable representing subproblem and associated with optimality cuts

Π^1_{ijts} Dual variable associated with constraint (c9)

Π^2_{ijts} Dual variable associated with constraint (c10)

Π^3_{ijts} Dual variable associated with constraint (c11)

Υ^1_{ijt} Dual variable associated with constraint (c12)

Υ^2_{ijt} Dual variable associated with constraint (c13)

Υ^3_{ijt} Dual variable associated with constraint (c14)

ϟ^1_{ijts} Dual variable associated with constraint (c15)

ϟ^2_{ijts} Dual variable associated with constraint (c16)

ϟ^3_{ijts} Dual variable associated with constraint (c17)

ϟ^4_{ijts} Dual variable associated with constraint (c18)

ϟ^5_{ijts} Dual variable associated with constraint (c19)

$\varkappa_{ts}$ Dual variable associated with constraint (c20)

Ϫ_s Dual variable associated with constraint (c21)

Л^t_{ijvs} Dual variable associated with constraint (c22)

Parameters

α Weight of profit

β	Weight of environmental effects
p_v^t	Sale price of yield type *v* at time period *t* ($/tonne)
ε_s	Probability associated with scenario *s*
A_{ijv}	Potential yield of yield type *v* in zone (*i,j*) (tonnes)
SE_{ijk}	Economic value of soil erosion prevention in zone (*i,j*) via crop type *k* ($)
ϕ	Soil erosion prevention reduction constant for harvested yield
CS_{ijk}	Economic value of carbon sequestration in zone (*i,j*) via crop type *k* ($)
ξ	Carbon sequestration reduction constant for harvested yield
σ_k	Carbon emissions penalty of seeding crop type *k* ($)
ρ_v	Carbon emissions penalty of harvesting yield type *v* ($)
ω_v	Carbon emissions penalty of production operations for yield type *v* ($/tonne)
τ	Carbon emissions penalty of transporting yield ($/tonne-km)
η	Economic damage caused by N pollution ($/kg)
fe_k	Nitrogen fertilizer applied for crop type *k* (kg)
μ_k	Percent N uptake by crop type *k*
ψ	Percent N contamination (leaching) in drinking water
π_t	Growth factor of switchgrass after *t* years of establishment
e_v	Biofuel conversion factor for yield type *v* (liter/tonne)
Δ	Fraction of facility capacity assigned to biofuel production from switchgrass and corn biomass
C_t	Biofuel production capacity of facility at time period *t* (liter)
B	Total available budget in planning horizon ($)

TEC_{ijk} Total expected establishment cost for crop type *k* in zone (*i,j*) ($)

ϵ_k Fixed cost of producing crop type *k* per cultivation zone ($)

RC_{ij} Rental cost of cultivation zone (*i,j*) ($)

γ_v Variable cost of producing yield type *v* ($/tonne)

δ_v Fixed cost of harvesting yield type *v* per zone ($)

θ_v Variable cost of harvesting yield type *v* ($/tonne)

D_{ij} Distance of zone (*i,j*) to facility (km)

F_v Fixed cost of transporting yield type *v* ($)

V_v Variable cost of transporting yield type *v* ($/tonne km)

λ Food-security defining percentage of cropland allowed for only food crop production

5.3 Mathematical Solution Approaches

In this section, we explain the two-stage stochastic MIP model proposed for food and biomass production. In the following subsections, the stochastic model, customized Benders decomposition algorithm, along with the master problem (MP) (land allocation), primal subproblem (SP) (operational), and dual SP are presented.

5.3.1 Stochastic Model

Uncertainties involved in the decision-making process require the development of a stochastic model. Scenarios related to yield amount and price level along with their corresponding probabilities are integrated into the optimization model. The stochastic MIP model formulation is then given as follows

$$Maximize\ TB = \alpha\big(TR - (E_b + P_b + H_b + T_b)\big) + \beta(TSE + TCS - TCE - TNP) \quad (5.1)$$

Auxiliary variables:

$$TR = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(p_{1s}^t \bar{N}_{ijs}^t + p_{2s}^t \tilde{Y}_{ijs}^t + p_{3s}^t \bar{Y}_{ijs}^t + p_{4s}^t Y_{ijs}^t\right) \tag{5.2}$$

$$E_b = \sum_i \sum_j \sum_k TEC_{ijk} S_{ijk} \tag{5.3}$$

$$P_b = \sum_i \sum_j \left(\sum_k \left(\epsilon_k + RC_{ij}\right) S_{ijk} + \sum_t \sum_s \varepsilon_s \left(\gamma_1 \bar{N}_{ijs}^t + \gamma_2 \tilde{Y}_{ijs}^t + \gamma_3 \bar{Y}_{ijs}^t + \gamma_4 Y_{ijs}^t\right)\right) \tag{5.4}$$

$$H_b = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(\sum_v \delta_v X_{ijvs}^t + \theta_1 \bar{N}_{ijs}^t + \theta_2 \tilde{Y}_{ijs}^t + \theta_3 \bar{Y}_{ijs}^t + \theta_4 Y_{ijs}^t\right) \tag{5.5}$$

$$T_b = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(\sum_v F_v X_{ijvs}^t + D_{ij}\left(V_1 \bar{N}_{ijs}^t + V_2 \tilde{Y}_{ijs}^t + V_3 \bar{Y}_{ijs}^t + V_4 Y_{ijs}^t\right)\right) \tag{5.6}$$

$$TSE = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(SE_{ij1}\left(\frac{N_{ijs}^t - \phi \bar{N}_{ijs}^t}{A_{ij1s}}\right) + SE_{ij2}\left(\frac{\tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t}{A_{ij2s}} - \phi \frac{Y_{ijs}^t}{A_{ij4s}}\right)\right) \tag{5.7}$$

$$TCS = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(CS_{ij1}\left(\frac{N_{ijs}^t - \xi \bar{N}_{ijs}^t}{A_{ij1}}\right) + CS_{ij2}\left(\frac{\tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t}{A_{ij2s}} - \xi \frac{Y_{ijs}^t}{A_{ij4s}}\right)\right) \tag{5.8}$$

$$TCE = \sum_i \sum_j \left(\sum_k \sigma_k S_{ijk} + \sum_t \sum_s \varepsilon_s \left(\sum_v \rho_v X_{ijvs}^t + \omega_1 \bar{N}_{ijs}^t + \omega_2 \tilde{Y}_{ijs}^t + \omega_3 \bar{Y}_{ijs}^t + \omega_4 Y_{ijs}^t\right)\right)$$

$$+\sum_i \sum_j \sum_t D_{ij} \tau \left(\bar{N}_{ijs}^t + \tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t + Y_{ijs}^t\right) \tag{5.9}$$

$$TNP = \eta \sum_i \sum_j \sum_k S_{ijk} fe_k (1 - \mu_k) \psi \tag{5.10}$$

Subject to

Seeding constraints:

$$\sum_k S_{ijk} \leq 1 \quad \forall\, i, j \tag{5.11}$$

$$S_{ij2} \leq 0 \quad \forall\, (i,j) \in GR \text{ or } MR \tag{5.12}$$

$$\sum_{(i,j) \in CR} S_{ij1} \leq (1 - \lambda)|CR| \quad \forall\, t \tag{5.13}$$

Yield constraints:

$$N_{ijs}^t = A_{ij1s} \pi_t S_{ij1} \quad \forall\, i, j, t, s \tag{5.14}$$

$$\tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t = A_{ij2s} S_{ij2} \quad \forall\, i, j, t, s \tag{5.15}$$

$$Y_{ijs}^t \leq A_{ij4s} S_{ij2} \quad \forall\, i, j, t, s \tag{5.16}$$

Harvesting constraints:

$$X_{ij1s}^{t} \leq S_{ij1} \quad \forall\, i,j,t,s \tag{5.17}$$

$$X_{ij2s}^{t} + X_{ij3s}^{t} = S_{ij2} \quad \forall\, i,j,t,s \tag{5.18}$$

$$X_{ij4}^{t} \leq S_{ij2} \quad \forall\, i,j,t,s \tag{5.19}$$

Harvested yield constraints:

$$\bar{N}_{ijs}^{t} - A_{ij1s}\pi_t X_{ij1s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.20}$$

$$\bar{N}_{ijs}^{t} - N_{ijs}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.21}$$

$$\tilde{Y}_{ijs}^{t} - A_{ij2s}X_{ij2s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.22}$$

$$\bar{Y}_{ijs}^{t} - A_{ij3s}X_{ij3s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.23}$$

$$Y_{ijs}^{t} - A_{ij4s}X_{ij4s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.24}$$

Biofuel capacity constraint:

$$\sum_i \sum_j \left(e_1\bar{N}_{ijs}^{t} + e_3\bar{Y}_{ijs}^{t} + e_4 Y_{ijs}^{t}\right) \leq \Delta C_t \quad \forall\, t,s \tag{5.25}$$

Budget constraint:

$$E_b + P_b + H_b + T_b \leq B \tag{5.26}$$

Constraints on variables:

$$N_{ijs}^{t}, \bar{N}_{ijs}^{t}, \tilde{Y}_{ijs}^{t}, \bar{Y}_{ijs}^{t}, Y_{ijs}^{t} \geq 0 \quad \forall\, i,j,t,s \tag{5.27}$$

$$S_{ijk} \in \{0,1\} \quad \forall\, i,j,k \tag{5.28}$$

$$0 \leq X_{ij1s}^{t} \leq 1 \quad \forall\, i,j,t,s \tag{5.29}$$

The multi-objective formulation in the objective function maximizes the total benefits by using a weighted sum of the economic and environmental benefits. For the economic benefits, alpha is multiplied with profit, which is defined by subtracting the budget allocated to

farm operations, establishment, production, harvesting, and transportation from the total revenue. Net benefits of environmental impacts namely total soil erosion, total carbon sequestration, total carbon emissions, and total nitrogen pollution are multiplied by beta to determine their priority in decision making.

Economic impacts in the objective function are formulized in equations (5.2) to (5.6). Equation (5.2) defines the revenue by multiplying the amount of each yield type with its corresponding selling price. Equation (5.3) gives the establishment budget by multiplying seeding decisions with total establishment cost of seeding crop type *k* at zone (*i*,*j*). Equation (5.4) formulizes the production budget by incorporating fixed costs (fertilization and rent) with variables costs (fertilization), depending on the amount of each crop type. Similarly, equation (5.5) defines the harvesting budget by including fixed and variables costs of harvesting for each yield type. For the calculation of transportation budget, equation (5.6) incorporates a fixed cost for transporting each yield type and a variable cost, which depends on yield type and distance between zone (*i*,*j*) and demand point.

Economic values of environmental impacts in the objective function are formulized in equations (5.7) to (5.10). Equation (5.7) defines the economic value of soil erosion prevention by considering the effect of yield amount produced and harvested on different land types. Similarly, equation (5.8) determines the economic value of carbon sequestration by considering the production and harvesting of different yield types on different soil types. Equation (5.9) provides the total carbon emissions that occur during farm operations, such as seeding, production, harvesting, and transportation. Equation (5.10) calculates the negative economic

value of nitrogen pollution by considering the percentage of nitrogen leakage to ground water for each crop type.

The objective function is subject to seeding, yield, harvesting, capacity, and budget constraints. Equation (5.11) ensures that only one crop can be established in each zone. Equation (5.12) prevents the production of food crops on grassland and marginal land. For security of the food supply, equation (5.13) limits the allocation of energy crops to cropland with a percentage. Equations (5.14) to (5.16) determine the yield amount given that associated crop type is seeded in that zone for each scenario *s*. Equation (5.14) defines the switchgrass yield by multiplying the growth factor and maximum yield that can be obtained in a zone if it is seeded. Equation (5.15) states that total corn grain yield that goes to food or biofuel production equals the maximum corn yield production in the corresponding zone. Similarly, equation (5.16) ensures that corn stover yield cannot exceed the maximum yield grown in that zone in the case where corn is seeded. Equations (5.17) to (5.19) determine the harvesting regulations and policies for each scenario *s*. Equation (5.17) states that switchgrass can be harvested only if it is seeded. Equation (5.18) ensures that corn grain is harvested for either food or biofuel production once it is seeded. Similar to switchgrass biomass, Equation (5.19) ensures that it can be harvested only if corn is seeded in that zone. Equations (5.20) and (5.21) limit the amount of harvested switchgrass by multiplying its harvesting decision, growth factor, and maximum yield with the switchgrass amount available in that field. Equations (5.22) to (5.24) limit the amount of harvested corn grain for food, corn grain for biofuel, and corn stover, respectively, by multiplying their available grown yield amounts with harvesting decisions. Equation (5.25) states that the summation of biomass types (switchgrass, corn grain, and corn stover)

multiplied with their conversion factors cannot exceed the available biofuel conversion capacity of the biorefinery. Equation (5.26) limits the budget allocation to different farm operations, seeding, production, harvesting, and transportation with the available budget. Equation (5.27) imposes non-negativity on switchgrass, harvested switchgrass, corn grain for the food market, corn grain for biofuel production, and corn stover, respectively. Equation (5.28) defines seeding decisions as binary variables. Finally, equation (5.29) sets the value for harvesting decisions between 0 and 1.

5.3.2 Decomposition Algorithm

In order to solve the proposed stochastic MIP model, we customize the Benders decomposition for our specific problem [17], [18]. In particular, we decompose the problem into a master problem comprising only the first-stage variables and related constraints, and a subproblem involving second-stage decisions. First-stage variables refer to decision variables that must be decided at the beginning of a period before the realization of random events, namely yield amounts. Thus, seeding decisions that answer the land-allocation problem are first-stage variables. Second-stage variables refer to decision variables to be decided at the end of a time period after the uncertain event parameter is observed. In the second stage, after the yield uncertainty is revealed, the operational problem, including decisions of the production amounts, harvesting, and budget allocation, is solved.

5.3.2.1 Master (Land Allocation) Problem

Based on the decomposition, the BFP master problem (land-allocation) includes the deterministic part of the whole model and maximizes the master benefit (MB). The master

problem includes Z, which represent the benefits from the subproblem. The MP formulation is given as

$$Maximize\ MB = \alpha\big(-(E_b + P_{b1})\big) + \beta(-TCE_1 - TNP) + Z \tag{5.30}$$

$$E_b = \sum_i \sum_j \sum_k TEC_{ijk} S_{ijk} \tag{5.31}$$

$$P_{b1} = \sum_i \sum_j \big(\sum_k (\epsilon_k + RC_{ij}) S_{ijk}\big) \tag{5.32}$$

$$TCE_1 = \sum_i \sum_j \sum_k \sigma_k S_{ijk} \tag{5.33}$$

$$TNP = \eta \sum_i \sum_j \sum_k S_{ijk}\, fe_k (1 - \mu_k)\psi \tag{5.34}$$

$$\sum_k S_{ijk} \leq 1 \quad \forall\, i, j \tag{5.35}$$

$$S_{ij2} \leq 0 \quad \forall\, (i,j) \in GR\ or\ MR \tag{5.36}$$

$$\sum_{(i,j)\in CR} S_{ij1} \leq (1 - \lambda)|CR| \quad \forall\, t \tag{5.37}$$

Constraints for optimality and feasibility:

$$W(S_{ijk}, \hat{G}^l_{ijk}) \geq 0 \quad \forall l \in \Omega^{feas} \tag{5.38}$$

$$Z \leq W(S_{ijk}, \bar{G}^l_{ijk}) \quad \forall l \in \Omega^{opt} \tag{5.39}$$

Constraints on decision variables:

$$S_{ijk} \in \{0, 1\} \quad \forall\, i, j, k \tag{5.40}$$

$$Z \geq 0 \tag{5.41}$$

where $\hat{G}^l_{ijk}$ and $\bar{G}^l_{ijk}$ represent extreme rays and optimal solution values of the dual SP, respectively, $W(.)$ is a function used to define the lth feasibility or optimality cut, and Ω^{feas} and Ω^{opt} represent the set of feasibility and optimality inequalities, respectively.

5.3.2.2 Primal (Operational) Subproblem

The primal subproblem includes constraints with linear and binary variables from the entire model. Note that the primal SP maximizes the primal benefit (PB), which is represented by Z in the MP. Given a solution from the MP, $\underline{S}_{ijk}$, the primal SP formulation is given as

$$Maximize\ PB = \alpha\big(TR - (P_{b2} + H_b + T_b)\big) + \beta(TSE + TCS - TCE) \tag{5.42}$$

$$TR = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(p_{1s}^t \bar{N}_{ijs}^t + p_{2s}^t \tilde{Y}_{ijs}^t + p_{3s}^t \bar{Y}_{ijs}^t + p_{4s}^t Y_{ijs}^t\right) \tag{5.43}$$

$$P_{b2} = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(\gamma_1 \bar{N}_{ijs}^t + \gamma_2 \tilde{Y}_{ijs}^t + \gamma_3 \bar{Y}_{ijs}^t + \gamma_4 Y_{ijs}^t\right) \tag{5.44}$$

$$H_b = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(\sum_v \delta_v X_{ijvs}^t + \theta_1 \bar{N}_{ijs}^t + \theta_2 \tilde{Y}_{ijs}^t + \theta_3 \bar{Y}_{ijs}^t + \theta_4 Y_{ijs}^t\right) \tag{5.45}$$

$$T_b = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(\sum_v F_v X_{ijvs}^t + D_{ij}\left(V_1 \bar{N}_{ijs}^t + V_2 \tilde{Y}_{ijs}^t + V_3 \bar{Y}_{ijs}^t + V_4 Y_{ijs}^t\right)\right) \tag{5.46}$$

$$TSE = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(SE_{ij1}\left(\frac{N_{ijs}^t - \phi \bar{N}_{ijs}^t}{A_{ij1s}}\right) + SE_{ij2}\left(\frac{\tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t}{A_{ij2s}} - \phi \frac{Y_{ijs}^t}{A_{ij4s}}\right)\right) \tag{5.47}$$

$$TCS = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(CS_{ij1}\left(\frac{N_{ijs}^t - \xi \bar{N}_{ijs}^t}{A_{ij1}}\right) + CS_{ij2}\left(\frac{\tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t}{A_{ij2s}} - \xi \frac{Y_{ijs}^t}{A_{ij4s}}\right)\right) \tag{5.48}$$

$$TCE_2 = \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(\sum_v \rho_v X_{ijvs}^t + \omega_1 \bar{N}_{ijs}^t + \omega_2 \tilde{Y}_{ijs}^t + \omega_3 \bar{Y}_{ijs}^t + \omega_4 Y_{ijs}^t\right)$$

$$+ \sum_i \sum_j \sum_t \sum_s \varepsilon_s \left(D_{ij} \tau \left(\bar{N}_{ijs}^t + \tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t + Y_{ijs}^t\right)\right) \tag{5.49}$$

$$N_{ijs}^t = A_{ij1s} \pi_t \underline{S}_{ij1} \quad \forall\ i, j, t, s \tag{5.50}$$

$$\tilde{Y}_{ijs}^t + \bar{Y}_{ijs}^t = A_{ij2s} \underline{S}_{ij2} \quad \forall\ i, j, t, s \tag{5.51}$$

$$Y_{ijs}^t \le A_{ij4s} \underline{S}_{ij2} \quad \forall\ i, j, t, s \tag{5.52}$$

$$X_{ij1s}^t \le \underline{S}_{ij1} \quad \forall\ i, j, t, s \tag{5.53}$$

$$X_{ij2s}^t + X_{ij3s}^t = \underline{S}_{ij2}^1 \quad \forall\ i, j, t, s \tag{5.54}$$

$$X_{ij4s}^t \le \underline{S}_{ij2} \quad \forall\ i, j, t, s \tag{5.55}$$

$$\bar{N}_{ijs}^t - A_{ij1s} \pi_t X_{ij1s}^t \le 0 \quad \forall\ i, j, t, s \tag{5.56}$$

$$\bar{N}_{ijs}^{t} - N_{ijs}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.57}$$

$$\tilde{Y}_{ijs}^{t} - A_{ij2s}X_{ij2s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.58}$$

$$\bar{Y}_{ijs}^{t} - A_{ij3s}X_{ij3s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.59}$$

$$Y_{ijs}^{t} - A_{ij4s}X_{ij4s}^{t} \leq 0 \quad \forall\, i,j,t,s \tag{5.60}$$

$$\sum_i \sum_j \left(e_1\bar{N}_{ijs}^{t} + e_3\bar{Y}_{ijs}^{t} + e_4Y_{ijs}^{t}\right) \leq \Delta C_t \quad \forall\, t,s \tag{5.61}$$

$$P_{b2} + H_b + T_b \leq (B - E_b + P_{b2}) \tag{5.62}$$

$$0 \leq X_{ij1s}^{t} \leq 1 \quad \forall\, i,j,t,s \tag{5.63}$$

$$N_{ijs}^{t}, \bar{N}_{ijs}^{t}, \tilde{Y}_{ijs}^{t}, \bar{Y}_{ijs}^{t}, Y_{ijs}^{t} \geq 0 \quad \forall\, i,j,t,s \tag{5.64}$$

5.3.2.3 Dual Subproblem

For the decomposition algorithm, we first define dual variables associated with constraints of the primal SP formulation. The dual SP involves minimization of the dual benefit, which is equal to the primal benefit in the case of optimality. Given a solution from the MP, $\underline{S}_{ijk}$, and letting G_{ijk} define the set of dual variables, the dual SP is formulated as

$$\begin{aligned} Minimize\ W(\underline{S}_{ijk}, G_{ijk}) = {} & \sum_{ijts}\left(\left(A_{ij1s}\pi_t\underline{S}_{ij1}\right)\Pi_{ijts}^{1} + \left(A_{ij2s}\underline{S}_{ij2}\right)\Pi_{ijts}^{2} + \left(A_{ij4s}\underline{S}_{ij2}\right)\Pi_{ijts}^{3}\right) \\ & + \sum_{ijts}\left(\underline{S}_{ij2}\Upsilon_{ijts}^{1} + \underline{S}_{ij2}\Upsilon_{ijts}^{2} + \underline{S}_{ij2}\Upsilon_{ijts}^{3}\right) \\ & + \sum_{ts}\Delta C_t\,\varkappa_{ts} + \sum_s (B - P_{b1} - E_b)\text{Ϡ}_s + \sum_{ijvts} \text{Л}_{ijvs}^{t} \end{aligned} \tag{5.65}$$

Subject to

$$\Pi_{ijts}^{1} - \text{ϟ}_{ijts}^{2} \geq \beta\varepsilon_s\left(\frac{SE_{ij1}}{A_{ij1s}} + \frac{CS_{ij1}}{A_{ij1s}}\right) \quad \forall\, i,j,t,s \tag{5.66}$$

$$\begin{aligned} \text{ϟ}_{ijts}^{1} + \text{ϟ}_{ijts}^{2} + e_1\varkappa_{ts} + \left(\gamma_1 + \theta_1 + D_{ij}V_1\right)\text{Ϡ}_s \geq {} & \alpha\varepsilon_s\left(p_{1s}^{t} - \gamma_1 - \theta_1 - D_{ij}V_1\right) \\ & + \beta\varepsilon_s\left(-SE_{ij1}\frac{\phi}{A_{ij1s}} - CS_{ij1}\frac{\xi}{A_{ij1s}} - \omega_1 - D_{ij}\tau\right) \quad \forall\, i,j,t,s \end{aligned} \tag{5.67}$$

$$\Pi_{ijts}^{2} + \text{ϟ}_{ijts}^{3} + (\gamma_2 + \theta_2 + D_{ij}V_2)\text{Ϡ}_s \geq \alpha\varepsilon_s(p_{2s}^{t} - \gamma_2 - \theta_2 - D_{ij}V_2)$$

$$+\beta\varepsilon_s\left(\frac{SE_{ij2}}{A_{ij2s}} + \frac{CS_{ij2}}{A_{ij2s}} - \omega_2 - D_{ij}\tau\right) \quad \forall\, i,j,t,s \tag{5.68}$$

$$\Pi_{ijts}^{2} + \text{ϟ}_{ijts}^{4} + e_3\varkappa_{ts} + (\gamma_3 + \theta_3 + D_{ij}V_3)\text{Ϡ}_s \geq \alpha\varepsilon_s(p_{3s}^{t} - \gamma_3 - \theta_3 - D_{ij}V_3)$$

$$+\beta\varepsilon_s\left(\frac{SE_{ij2}}{A_{ij2s}} + \frac{CS_{ij2}}{A_{ij2s}} - \omega_3 - D_{ij}\tau\right) \quad \forall\, i,j,t,s \tag{5.69}$$

$$\Pi_{ijts}^{3} + \text{ϟ}_{ijts}^{5} + e_4\varkappa_{ts} + (\gamma_4 + \theta_4 + D_{ij}V_4)\text{Ϡ}_s \geq \alpha\varepsilon_s(p_{4s}^{t} - \gamma_4 - \theta_4 - D_{ij}V_4)$$

$$+\beta\varepsilon_s\left(-SE_{ij2}\frac{\phi}{A_{ij4s}} - CS_{ij2}\frac{\xi}{A_{ij4s}} - \omega_4 - D_{ij}\tau\right) \quad \forall\, i,j,t,s \tag{5.70}$$

$$\text{ϒ}_{ijts}^{1} - A_{ij1s}\pi_t\text{ϟ}_{ijts}^{1} + (\delta_1 + F_1)\text{Ϡ}_s + \text{ Л}_{ij1s}^{t} \geq \alpha\varepsilon_s(-\delta_1 - F_1) + \beta\varepsilon_s(-\rho_1) \quad \forall\, i,j,t,s \tag{5.71}$$

$$\text{ϒ}_{ijts}^{2} - A_{ij2}\text{ϟ}_{ijts}^{3} + (\delta_2 + F_2)\text{Ϡ}_s + \text{Л}_{ij2s}^{t} \geq \alpha\varepsilon_s(-\delta_2 - F_2) + \beta\varepsilon_s(-\rho_2) \quad \forall\, i,j,t,s \tag{5.72}$$

$$\text{ϒ}_{ijts}^{2} - A_{ij3}\text{ϟ}_{ijts}^{4} + (\delta_3 + F_3)\text{Ϡ}_s + \text{Л}_{ij3s}^{t} \geq \alpha\varepsilon_s(-\delta_3 - F_3) + \beta\varepsilon_s(-\rho_3) \quad \forall\, i,j,t,s \tag{5.73}$$

$$\text{ϒ}_{ijts}^{3} - A_{ij4}\text{ϟ}_{ijts}^{5} + (\delta_4 + F_4)\text{Ϡ}_s + \text{Л}_{ij4s}^{t} \geq \alpha\varepsilon_s(-\delta_4 - F_4) + \beta\varepsilon_s(-\rho_4) \quad \forall\, i,j,t,s \tag{5.74}$$

Constraints for variables:

$$\Pi_{ijts}^{1}, \Pi_{ijts}^{2}, \text{ϒ}_{ijts}^{2} \in R \tag{5.75}$$

$$\Pi_{ijts}^{3}, \text{ϒ}_{ijts}^{1}, \text{ϒ}_{ijts}^{3}, \text{ϟ}_{ijts}^{1}, \text{ϟ}_{ijts}^{2}, \text{ϟ}_{ijts}^{3}, \text{ϟ}_{ijts}^{4}, \text{ϟ}_{ijts}^{5}, \varkappa_{ts}, \text{Ϡ}_s, \text{Л}_{ijvs}^{t} \geq 0 \tag{5.76}$$

5.3.2.4 Cutting Planes

Algorithm steps of the Benders decomposition applied to the BFP problem are displayed in Figure 5.3. We first make settings in the decomposition algorithm by assigning 0 to the iteration counter, *n*, and infinity to *Z* and *tol*, which gives the difference between the optimal objective function value of the dual SP and Z^* (optimal value of *Z* in the MP). In each iteration, we first check whether the iteration counter is less than the maximum number of iterations allowed (max iteration). If this condition is not met, the best solution is displayed. Otherwise,

the dual SP is solved. If the dual SP is unbounded, a feasibility cut is added to the MP. If the dual SP is optimally solved, an optimality cut is added to the MP. Then the MP is solved. If *tol*, which is updated by the difference between Z^* and dual SP optimal objective function value ($W^*(\underline{S}_{ijk}, \bar{G}_{ijk})$), is within the predefined epsilon distance, then a solution is displayed. Otherwise, we continue iterations until either epsilon or the max iteration condition terminates the algorithm. Note that letting S^*_{ijk} define the optimal solution of the MP, in each iteration of the decomposition algorithm, we set $\underline{S}_{ijk}$ values in the dual problem to S^*_{ijk} values.

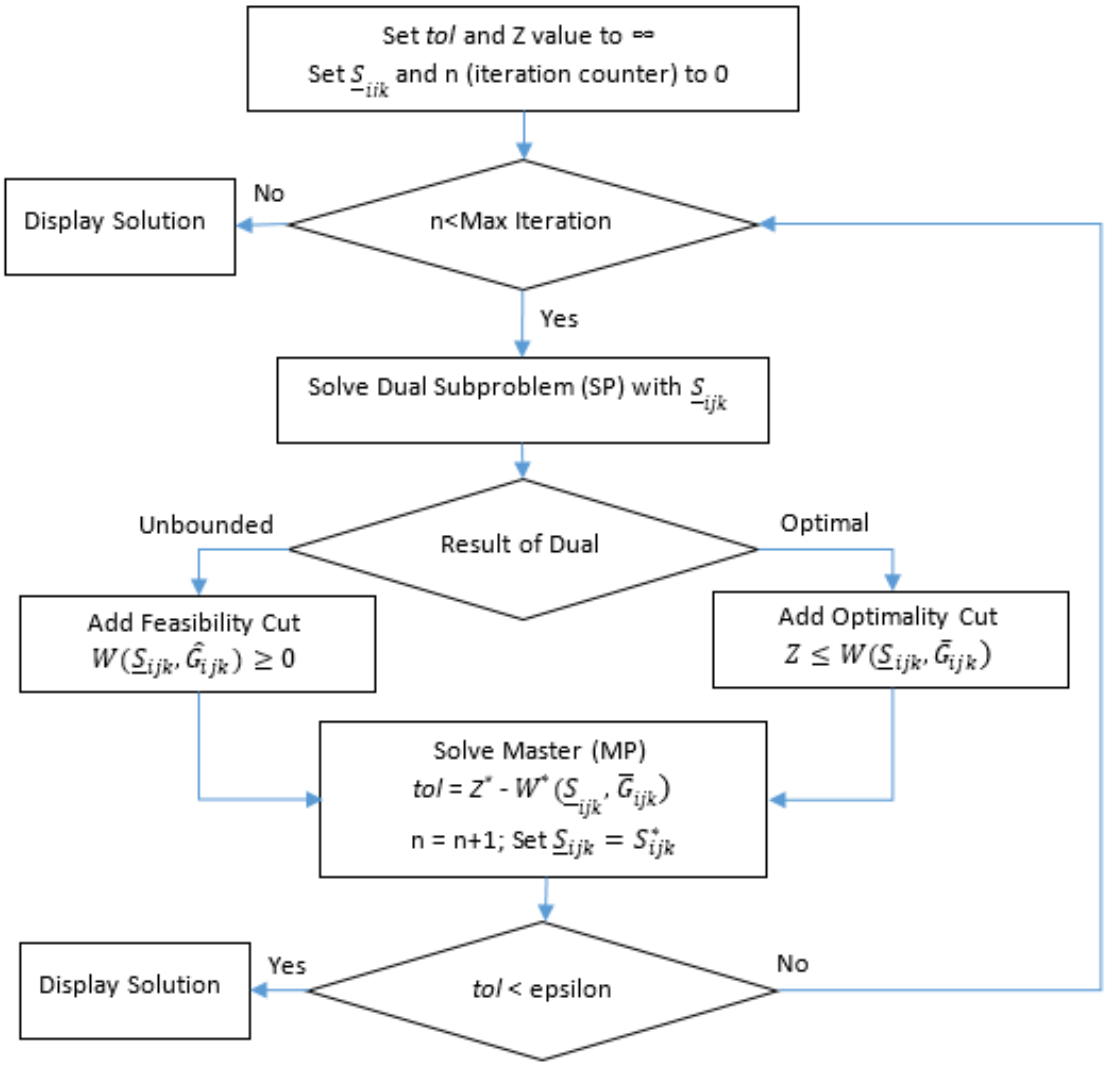

Figure 5.3 Flow chart of proposed decomposition algorithm and its steps.

In order to solve the MP, feedback from the dual SP in the form of a cutting plane is returned to the MP after each iteration in the decomposition algorithm. Feasibility and optimality cuts are generated based on the solution of the dual SP, and represented by inequalities (5.38) and (5.39), respectively. When the dual SP is unbounded, we obtain extreme dual rays ($\widehat{\Pi}^1_{ijts}$, $\widehat{\Pi}^2_{ijts}$, $\widehat{\Pi}^3_{ijts}$, $\widehat{\Upsilon}^1_{ijts}$, $\widehat{\Upsilon}^2_{ijts}$, $\widehat{\Upsilon}^3_{ijts}$, $\widehat{\varkappa}_{ts}$, $\widehat{\mathrm{X}}_s$, and $\widehat{\Lambda}^t_{ijvs}$) and add the following feasibility cut to Ω^{feas}

$$\sum_{ijts}\left(\left(A_{ij1s}\pi_t S_{ij1}\right)\widehat{\Pi}^1_{ijts} + \left(A_{ij2s}S_{ij2}\right)\widehat{\Pi}^2_{ijts} + \left(A_{ij4s}S_{ij2}\right)\widehat{\Pi}^3_{ijts}\right)$$
$$+S_{ij2}\widehat{\Upsilon}^1_{ijts} + S_{ij2}\widehat{\Upsilon}^2_{ijts} + S_{ij2}\widehat{\Upsilon}^3_{ijts}$$
$$+\sum_{ts}\Delta C_t\,\widehat{\varkappa}_{ts} + \sum_s (B - P_{b1} - E_b)\widehat{\mathrm{X}}_s + \sum_{ijvts}\widehat{\Lambda}^t_{ijvs} \geq 0 \qquad (5.77)$$

Otherwise, if the dual is optimal but Z^*, representing the subproblem value in the master problem, is not within the epsilon distance of the dual SP optimal value, then we obtain an optimal extreme point solution ($\overline{\Pi}^1_{ijts}$, $\overline{\Pi}^2_{ijts}$, $\overline{\Pi}^3_{ijts}$, $\overline{\Upsilon}^1_{ijts}$, $\overline{\Upsilon}^2_{ijts}$, $\overline{\Upsilon}^3_{ijts}$, $\overline{\varkappa}_{ts}$, $\overline{\mathrm{X}}_s$, and $\overline{\Lambda}^t_{ijvs}$) and add the following optimality cut to Ω^{opt}

$$Z \leq \sum_{ijts}\left(\left(A_{ij1s}\pi_t S_{ij1}\right)\overline{\Pi}^1_{ijts} + \left(A_{ij2s}S_{ij2}\right)\overline{\Pi}^2_{ijts} + \left(A_{ij4s}S_{ij2}\right)\overline{\Pi}^3_{ijts}\right)$$
$$+\sum_{ijts}\left(S_{ij2}\overline{\Upsilon}^1_{ijts} + S_{ij2}\overline{\Upsilon}^2_{ijts} + S_{ij2}\overline{\Upsilon}^3_{ijts}\right)$$
$$+\sum_{ts}\Delta C_t\,\overline{\varkappa}_{ts} + \sum_s (B - P_{b1} - E_b)\overline{\mathrm{X}}_s + \sum_{ijvts}\overline{\Lambda}^t_{ijvs} \qquad (5.78)$$

The introduction of these cutting planes into the master problem continues until the algorithm is terminated with a solution. Note that equations (5.77) and (5.78) represent the extended version of the constraints of the master problem given as equations (5.38) and (5.39), respectively.

5.4 Case Study Data

In this section, we present the data used for application of the proposed model in a biorefinery project at Hugoton, Kansas. The area surrounding the biorefinery has three different land types: cropland, grassland (pasture land), and marginal land (land potentially in CRP). The studied area is divided into 21 rows and 21 columns, where each zone is defined as the size of 260 ha (one square mile). Switchgrass is used for biofuel production, while corn is considered a source of both food and biofuel production. Switchgrass is cultivated on all land types, while corn is only considered on cropland. The planning horizon is taken as ten years since the biorefinery enters into a contract with farmers, and switchgrass has about ten years of life. The following subsections present the remaining part of the input data. Readers can refer to the study of Cobuloglu and Büyüktahtakın [15] for a detailed explanation of the data.

5.4.1 Yield Amount

Here we explain the calculation for stochastic yield amount of switchgrass and corn, which we expect to be affected in a similar way by weather conditions, e.g., greater precipitation would lead to a greater amount of corn and switchgrass yield. The corn yield and its price for 18 years are displayed in Figure 5.4 [19]. The yield amount of corn follows a normal distribution with parameters 8.49 for mean, 0.84 for standard deviation, 6.91 as the minimum value, and 10.68 as the maximum value. Based on the cumulative distribution of the given statistics of the distribution, the low-yield amount for corn grain is found to be less than or equal to 8.04 tonnes/ha with 30% probability. Similarly, the high-yield amount of corn grain can be greater than or equal to 8.93 tonnes/ha with 30% probability. Finally, the probability of observing a yield amount between the upper and lower bounds, which we take as the mean

value of 8.49 tonnes/ha, is 40%. Corn stover yield is taken as 1.1 times that of corn grain, based on the literature [15]. However, only half of that amount is harvestable, in order to meet minimum requirements for soil erosion protection. Thus, harvestable corn stover is considered to be 4.42 tonnes/ha, 4.67 tonnes/ha, and 4.91 tonnes/ha with 30%, 40%, and 30% probability, respectively. Test statistics for the amount of switchgrass are 14.57 for mean, 3.55 for standard deviation, 9.5 as the minimum value, and 20.5 as the maximum value [20]. Based on this data, the yield amount for switchgrass is defined as 12.71 tonnes/ha, 14.57 tonnes/ha, and 16.4 tonnes/ha with 30%, 40%, and 30% probability, respectively. As described in the problem definition section, we consider a total of 59,049 scenarios for a ten-year planning horizon.

Figure 5.4 Yield and price data of corn for eighteen years.

The mean values for yield amount of switchgrass, corn grain, and corn stover are provided in Table 5.1. Since switchgrass reaches its maximum potential yield at the third year, its yield amount changes until the third year. It also has changing productivity rates on different land types.

TABLE 5.1 YIELD TYPE, SEEDING LOCATION, AND CORRESPONDING YIELD AMOUNTS

Yield type	Land type	Yield (tonnes/ha)		
		t = 1	t = 2	t = 3–10
Switchgrass	Cropland	3.64	9.62	14.57
Switchgrass	Grassland	2.55	6.73	10.20
Switchgrass	Marginal land	1.82	4.81	7.29
Corn grain	Cropland	8.49	8.49	8.49
Corn stover	Cropland	9.34	9.34	9.34

5.4.2 Price

The price level of corn grain in the food market is another uncertain parameter in the proposed stochastic model. Since the price of corn grain depends on yield amount, a linear regression model, shown in Figure 5.5, is employed to define its level.

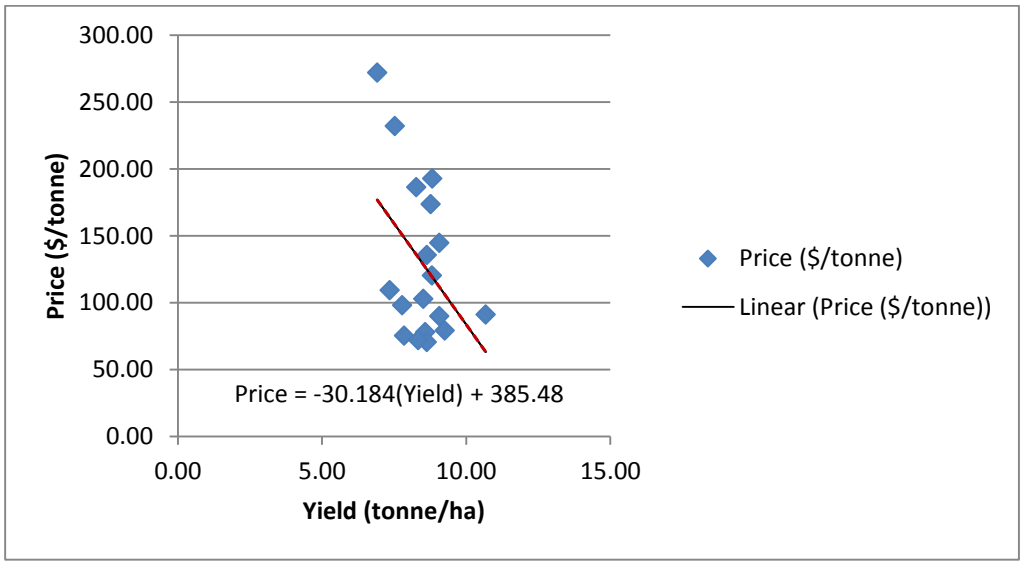

Figure 5.5 Correlation between corn grain yield and its price level.

Based on the data provided by the U.S. Department of Agriculture [21], the negative relation between corn price and corn yield is given as follows:

$$\text{Price} = -30.184\ (\text{Yield}) + 385.48$$

Using this formula, the price levels of corn grain in the food market are defined as 142.80, 129.22, and 115.94 $/tonne for yield amounts of 8.04 tonnes/ha, 8.49 tonnes/ha, and

8.93 tonnes/ha, respectively. Due to contracts between farmers and the biorefinery, constant biomass prices, namely 100 $/tonne, 129.22 $/tonne, and 50 $/tonne are used for switchgrass, corn grain, and corn stover, respectively.

5.4.3 Production, Harvesting, and Transportation Cost

The cost of different farm operations for switchgrass and corn cultivation are given in Table 5.2. We use airflow planting for switchgrass establishment, while reduced tillage is considered for corn seeding. An additional variable cost, the unloading and handling of biomass at the biorefinery, is taken as $1.88 per tonne of biomass.

TABLE 5.2 PRODUCTION, HARVESTING, AND TRANSPORTATION COSTS FOR SWITCHGRASS AND CORN

Yield type	Land type	**Seeding** ($/ha)	**Production**			**Harvesting**		**Transportation**	
			Rent ($/ha)	Fixed ($/ha)	Variable ($/tonne)	Fixed ($/ha)	Variable ($/tonne)	Fixed ($/ha)	Variable ($/tonne-km)
Switchgrass	Cropland	435.15	234.6	435.15	12	31.61	24.5	5.70	0.1367
Switchgrass	Grassland	445.77	23.7	445.77	12	31.61	24.5	5.70	0.1367
Switchgrass	Marginal	474.80	75.3	474.80	12	31.61	24.5	5.70	0.1367
Corn	Cropland	342.76	234.6	205.85	26	64.54	15.2	-	0.5
Corn stover	Cropland	-	-	-	22.33	14	9	5.70	0.1367

5.4.4 Soil Erosion and Carbon Sequestration

The economic value of savings from soil erosion and carbon sequestration is provided in Table 5.3. The soil erosion value, carbon sequestered, its CO_2 equivalence, and corresponding economic value are given for each land type.

5.4.5 CO_2 Emissions, Nitrogen Pollution, and Ethanol Conversion Rate

Readers can refer to the previous work of Cobuloglu and Büyüktahtakın [15] for data regarding CO_2 emissions, N pollution, and ethanol conversion rates for each biomass type.

TABLE 5.3 SAVINGS VIA SOIL EROSION PREVENTION AND CARBON SEQUESTRATION

Yield type	Land type	**Soil erosion** ($/ha-year)	**Carbon sequestration**		
			C (Mg/ha-year)	CO_2 equivalence (tonnes/ha-year)	Savings ($/ha-year)
Switchgrass	Cropland	61.18	4.42	16.22	324.4
Switchgrass	Grassland	9.89	3.2	1.17	23.5
Switchgrass	Marginal	19.85	0.32	11.74	234.8
Corn	Cropland	-36.9	0.368	1.35	27

5.5 Computational Results

In this section, we discuss the results of different mathematical solution approaches. The biofuel and food production problem is solved using CPLEX version 12.2 on a desktop computer with 3.40 GHz and 16 GB memory. The maximum number of iterations allowed for Benders decomposition is defined as 500. The epsilon value is set to 0.01 for the decomposition algorithm. The solution time for the stochastic model and Benders decomposition is set to one hour, since longer times experience a memory problem. Scenarios in the stochastic model are reduced to one, and yield amounts are set to mean values in order to obtain a deterministic model. Solution statistics for the deterministic model, stochastic model, and decomposition algorithm are presented in Table 5.4. The impact of varying the objective function weights and budget levels over the objective value (Obj Val), Gap, and CPU time are given for the deterministic, stochastic, and decomposition models, respectively.

It can be seen that the objective value of the deterministic model is less than the objective values of other models. This is because the stochastic model provides better strategies under uncertainty. On the other hand, the objective value of the decomposition model is greater than the stochastic model and the optimality gap in the decomposition is as small as 32% of the gap in the stochastic model in average. The difference in solution quality

between the deterministic and stochastic models indicates the necessity of decision making under uncertainty. These results also indicate that the development of a decomposition model for the given problem is of great importance in order to observe maximum benefits. However, solution time for the deterministic model is considerably less than solution time for the stochastic model and its decomposition. Note that a gap of 0.05% is set for the deterministic model in order not to encounter memory problems. On the other hand, the optimality gap of the stochastic model is between 1.6% and 2.3%, which reduces to 0.37% and 0.89% in the decomposition for the same cases with higher quality solutions. Another observation for the given experiments involves problem complexity. As the budget gets larger, the solution quality in the stochastic and decomposition approaches increases.

TABLE 5.4 COMPARISON OF SOLUTION APPROACHES

Objective weights (α; β)	Budget (M$)	Deterministic			Stochastic			Decomposition			
		Obj Val (M$)	Gap (%)	CPU time (sec)	Obj Val (M$)	Gap (%)	CPU (sec)	Obj Val (M$)	Gap (%)	CPU (sec)	Iterations
(1; 0)	500	206.9	0.05	354.2	221.3	2.19	3600	223.1	0.83	3600	131
(1; 0)	750	257.8	0.05	651.1	276.1	1.94	3600	278.3	0.66	3600	175
(1; 0)	1000	294.1	0.05	122.7	318.5	1.69	3600	320.9	0.39	3600	143
(0.5; 0.5)	500	135.3	0.05	105.1	145.8	2.29	3600	146.4	0.89	3600	166
(0.5; 0.5)	750	150.2	0.05	547.0	161.9	2.08	3600	162.2	0.77	3600	121
(0.5; 0.5)	1000	161.4	0.05	18.7	173.4	1.79	3600	174.8	0.48	3600	117
(0; 1)	500	112.2	0.05	26.7	119.9	1.96	3600	120.7	0.67	3600	101
(0; 1)	750	130.4	0.05	4.1	139.1	1.73	3600	140.4	0.43	3600	112
(0; 1)	1000	134.6	0.05	5.8	143.0	1.59	3600	144.1	0.37	3600	118

In another experiment, we compare the decomposition algorithm and the stochastic MIP model with respect to their solution speeds. In this experiment, we set a time limit of 7,200 CPU seconds and a gap of 0.10%. In order to observe the differences easily, the size of the region is reduced from a matrix that is 21 by 21 to a matrix that is 10 by 10. The solution statistics of the stochastic model and the decomposition for different objective weights and

budget levels are presented in Table 5.5. We observe that the decomposition algorithm reaches a solution within an hour for all instances. However, the solution time for the stochastic model is longer than that for the decomposition algorithm. When the budget is limited, the complexity of the problem increases. Under limited budget in profit prioritization (1; 0) and equal weight (0.5; 0.5) cases, the solution time of the decomposition approach is almost two times faster than the solution time of the stochastic MIP. Overall average solution speed for the nine presented cases indicates that decomposition method uses only 63.4% of the time required for a solution in the stochastic model.

TABLE 5.5 COMPARISON OF STOCHASTIC PROGRAMMING AND BENDERS DECOMPOSITION

Objective weights (α; β)	Budget (M$)	Stochastic			Decomposition			
		Obj Val (M$)	Gap (%)	CPU (sec)	Obj Val (M$)	Gap (%)	CPU (sec)	Iteration
(1; 0)	125	56.7	0.10	6128	56.7	0.10	3117	149
(1; 0)	187.5	70.6	0.10	4957	70.6	0.10	2810	182
(1; 0)	250	81.1	0.10	3421	81.1	0.10	2419	154
(0.5; 0.5)	125	37.5	0.10	6407	37.5	0.10	3136	177
(0.5; 0.5)	187.5	41.3	0.10	5168	41.3	0.10	2984	132
(0.5; 0.5)	250	44.5	0.10	3560	44.5	0.10	2576	133
(0; 1)	125	31.2	0.10	4189	31.2	0.10	2878	129
(0; 1)	187.5	36.3	0.10	3230	36.3	0.10	2722	146
(0; 1)	250	37.8	0.10	3020	37.8	0.10	2751	124
Overall average		-	-	4453	-	-	2821	-

5.5.1 Sensitivity Analysis

In this section, we discuss the impact of key parameters on the solution. We first analyze the impact of changing the food security factor on solutions of the deterministic, stochastic, and decomposition models. For this experiment, the budget is set to 750 M$, and priority is given to profit with the objective function weights (1; 0). Figures 5.6 and 5.7 display the impact of changing the food security factor on the economic values and environmental

impacts, respectively. Figure 5.6 indicates that the deterministic model estimates the economic values to be lower in all cases when compared with results of the stochastic and decomposition models. We also observe that decreasing food security leads to higher objective values in all models. This is because as we change the food security from 100% to 50%, more cropland becomes available for switchgrass cultivation. Switchgrass is more profitable on cropland than corn. Please note that, since we display the objective function value in Figure 5.6, the difference between the stochastic and deterministic models gives the value of the stochastic solution.

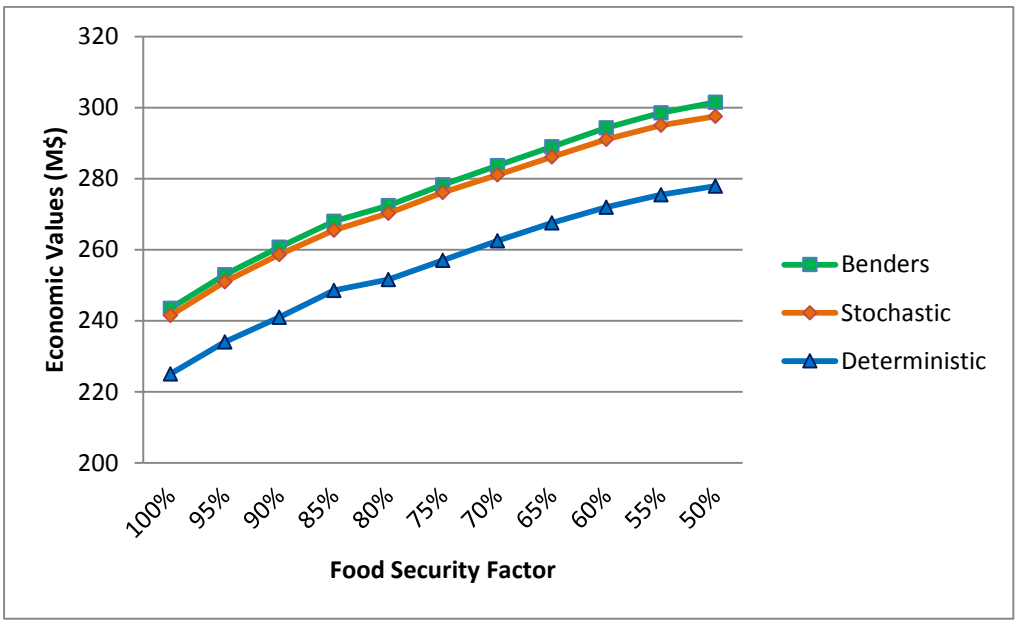

Figure 5.6 Economic values provided by different mathematical approaches when profit is maximized.

Figure 5.7 displays interesting insights relative to environmental impacts of changing the food security factor. Note that this figure provides environmental impacts when priority is given to profit in the objective function. As the food security factor increases, switchgrass production on cropland is limited, and the majority of cropland becomes available for only corn production. Since the models focuses on profit, when the food security factor is set to 100%, the overall

negative environmental impacts of corn become higher than the benefits provided by switchgrass production. We also observe that the total environmental impacts of corn and switchgrass are lower when estimated by the deterministic model. Thus, net environmental impacts become negative in the stochastic and decomposition models faster than in the deterministic model when food security factor is more than 80%.

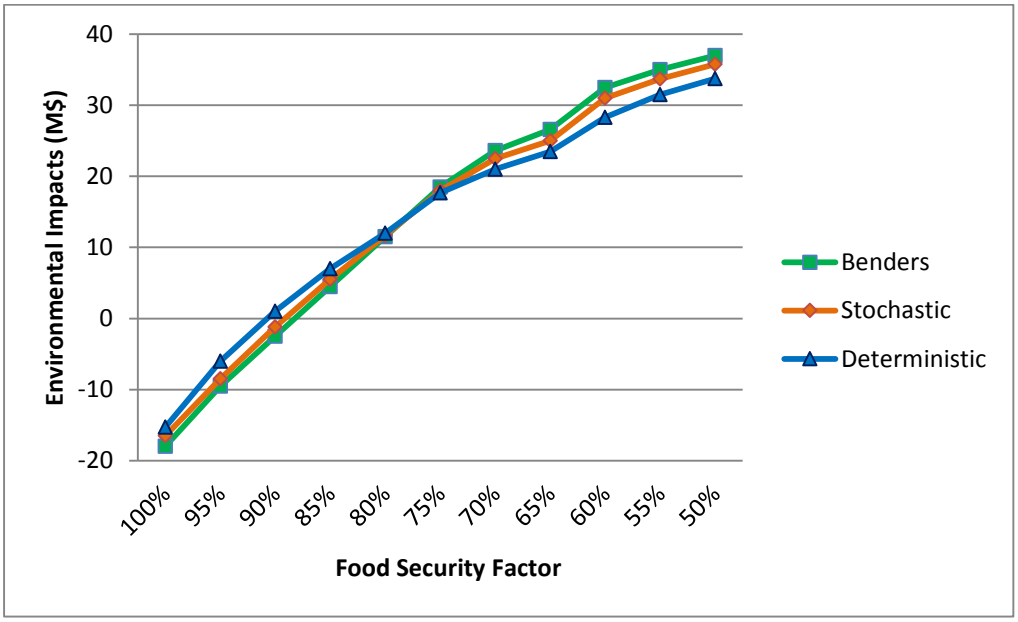

Figure 5.7 Environmental impacts provided by different mathematical approaches when profit is maximized.

We also compare results of the stochastic and deterministic models to analyze the value of stochastic solution under various budget cases. Figure 5.8 displays the value of stochastic solution when priority is given only to profit, while Figure 5.9 present results when priority is given only to the environment. We observe that as the budget increases, the VSS becomes significantly important. In other words, since a higher budget leads to higher land utilization, the difference between results of the stochastic and deterministic models increases in the

profit maximization. When there is ample budget for land utilization, the VSS reaches a saturation point and then stops.

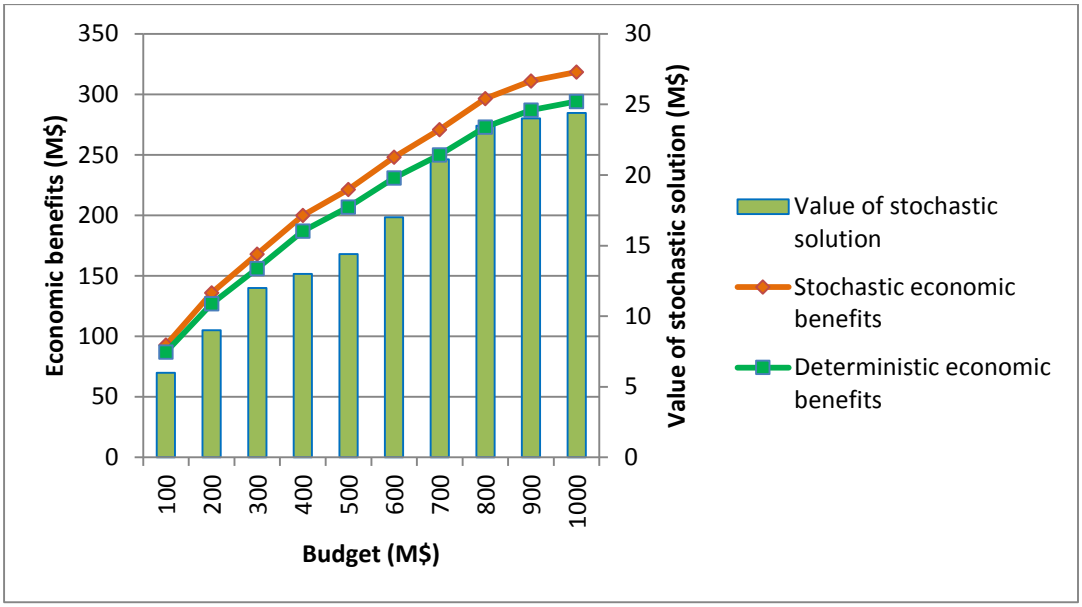

Figure 5.8 Comparison of stochastic and deterministic models under profit maximization.

Figure 5.9 displays the value of stochastic solution when priority is given only to environmental benefits in the objective function. When we compare results of profit maximization and environmental benefit maximization, we observe that the VSS in environmental benefit maximization is lower than the VSS in the profit maximization case, as expected. This is because the magnitude of economic outcomes are larger than the magnitude of environmental benefits. The difference between the deterministic and stochastic models is smaller than 2 M$ when we utilize the 100 M$ budget. On the other hand, the increment in the VSS becomes stable after 800 M$. That is because 800 M$ is enough to utilize all land types in the environmental benefits maximization case when compared to profit maximization.

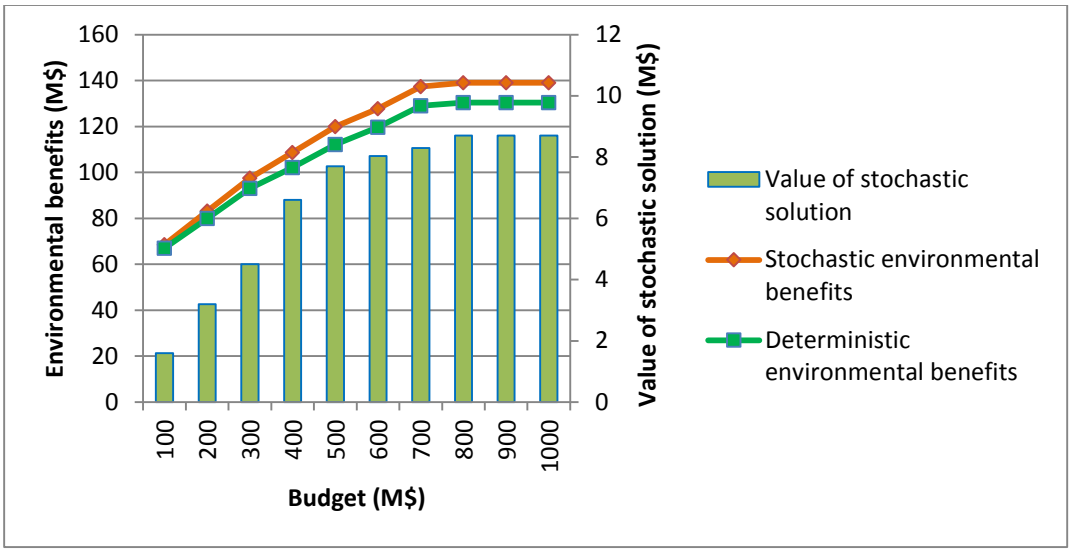

Figure 5.9 Comparison of stochastic and deterministic models under environmental benefits maximization.

5.6 Conclusion and Discussion

In this paper, we develop a two-stage stochastic MIP model for food and biofuel production at the farm level. In order to model uncertainty in the yield amount of crops and price level of corn in the market, we consider a scenario-based stochastic optimization approach. For that purpose, yield and price data provided by the USDA is analyzed. We define low-, medium-, and high-yield amounts for each crop type with corresponding probabilities. The associated price level for each yield is also integrated into the scenarios. We first solve the problem as a stochastic MIP model. In order to overcome complexities arising from the size of the model, we decompose the problem into a master problem (land allocation level) and a subproblem (operational level) and employ Benders cuts to find a solution.

Application of the model is demonstrated for a biorefinery project in Kansas. Deterministic, stochastic, and decomposition models are utilized for various cases. The objective function of the three models shows that both stochastic and decomposition models

outperform the deterministic model. The proposed decomposition model is also more efficient than the stochastic model in terms of solution quality. The sensitivity analysis provides important insights for food and biofuel production. Based on the food security factor, the limitation of energy crop production on cropland sacrifices the environmental benefits. As corn production increases on cropland, associated negative impacts also increase. We also observe that the deterministic model underestimates both economic and environmental benefits. Another analysis of the value of stochastic solution shows that obtaining stochastic information is significantly important when we seek to maximize profit. That is because the magnitude of economic impacts is higher than the values of environmental impacts in the objective function.

The proposed stochastic model can be utilized for various food and biofuel production problems in different regions. In the future, more uncertainties on the demand side could be involved in the decision-making process. However, that would decrease the solvability due to size of the problem. In order to overcome the potential complexity, a scenario reduction technique may be applied. In addition, more specialized cutting planes on the MP could be investigated for increasing the solution speed of the model. In case the probability distribution is difficult to obtain, then robust optimization models could be developed. The proposed model could also be adjusted for other biomass and food crops that have similar characteristics to corn and switchgrass.

5.7 References

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CHAPTER 6

CONCLUSION AND FUTURE RESEARCH

6.1 Summary of Contributions

In this dissertation, we have developed a number of mathematical approaches that optimize the decision-making process for stakeholders in the biomass and food production. In Chapter 1, we review and investigate the related literature in order to discover the gap where further research is needed. Most of these studies address biofuel supply chain where mathematical models are primarily developed for network design. The studies in biomass production focus on either cost of farm operations or environmental impacts. Thus, in Chapter 2, we provide a mixed-integer linear programming model that integrates economic and environmental impacts of one of the most favorable biomass types, switchgrass, when produced as a bioenergy crop. In Chapter 3, we include a very prevalent food crop, corn as a biomass alternative. In that chapter, we expand the scope of the problem by including the competition of energy and food crops along with more environmental impacts. In Chapter 4, we propose a stochastic multi-criteria decision-making tool to help farmers decide the most sustainable biomass crop type among different alternatives. Finally, in Chapter 5, we present a stochastic optimization model with uncertainties in yield amount and associated price level in order to provide decision makers better strategies in the long run.

One of the most important contributions of this dissertation regarding its intended applications is the conversion of various environmental impacts into economic values. Because most studies focus on carbon emissions, to the best of our knowledge, this is the first study incorporating soil erosion savings, nitrogen pollution and its impact on underground water,

carbon sequestration, sustainability of food supply, and biodiversity in a mathematical model. In order to provide highest accuracy in the results, spatial and temporal properties of these environmental impacts are reflected in the model by considering different land types. Biodiversity is defined as a constraint that provides birds with available habitat by limiting the number of harvested regions. In the stochastic AHP study, we provide a precise structure and complete list of the economic, environmental, and social criteria that are necessary for sustainable biomass crop selection by reviewing the literature and interviewing experts. It is also the first AHP-based MCDM tool developed for sustainable biomass crop selection. In contrast to other studies, this dissertation considers energy and food crops together in the decision-making process.

Contributions regarding the data section include providing concise information to researchers in biomass production. Most environmental impacts from switchgrass and corn production at the farm level have not been quantified and are not directly available from the literature. We first gather information from the USDA database, experts, and various ecological and agricultural journal papers. Then, we compute the economic values of the related environmental impacts by conducting a number of transformation and calculation. Therefore, this dissertation provides data precisely for researchers looking into a variety of environmental and economic input and output for switchgrass and corn biomass production.

In order to provide better insights for managers, various cases and sensitivity analysis have been employed at the results sections of each chapter. The effects of changing priorities, availability of cropland, budget amount, yield amount, and price levels on the model outputs are discussed in details. We also examine various N pollution levels and CRP incentives for

marginal land utilization. Since we consider both economic and environmental impacts, corresponding trade-offs between food and biomass production are analyzed in this study. In order to obtain better insight into crop selection in the AHP study, we analyze the impact of each aspect through sensitivity analyses. In the stochastic programming study, the computational efficiencies of deterministic, stochastic, and decomposition approaches are presented in the analysis section.

In terms of theoretical contributions, the nonlinear relation of revenue and yield quantity is approximated with a piecewise linear function. In the stochastic AHP study, vague and imprecise expert opinions have been converted into crisp numbers by utilizing a closed-form approximation of the median for beta distributions. In this dissertation, we provide the first stochastic programming study that models the competition of food and biofuel production at the farm level together. We also customize Benders decomposition algorithm for solving the food and biomass production problem more efficiently.

6.2 Future Research Directions

In the future, there are several directions in which to build upon the chapters in this dissertation. In its current form, this study provides operational and tactical strategies for biomass and food production at the farm level. The models could be further extended by their scope, application, and methodologies.

One possible extension for the scope of the problem is in supply chain management. In addition to decisions at the farm level, the model can provide decisions regarding biofuel logistics, such as amount of biofuel transportation and type of transportation modes between the biorefinery and end users. Such a study would be particularly helpful for the biorefinery.

With the integration of a supply chain perspective, biorefinery investment locations, technologies, and capacity could be decided by the model. This extension on the scope of the problem would provide more strategic-level insights for managers and biorefinery companies. In this case, the government could also reach global optimization for biofuel production policies. However, further extending the scope of the problem would increase the complexity due to a higher number of decisions and constraints in the model.

There are numerous application areas for the proposed decision-making models in this dissertation. As an alternative energy crop, Miscanthus, could be considered. Since wheat grain and wheat straw are used in food and biofuel production in a similar manner to that of corn grain and corn stover, wheat could be considered in the application. The model could be applied to larger landscapes. Instead of zones and sections, larger regions such as counties could be considered for more strategic-level decision making. The proposed models and approaches could be tested on case studies in other regions, states, or countries in order to see how they respond. This may require the addition of decision variables and parameters regarding the storage places to the models. Although we provide the social aspect in the AHP study, we have not considered this in the optimization models due to the difficulty of obtaining data. For that purpose, outputs of the AHP could be utilized as input for an optimization model. Thus, in addition to economic and environmental impacts, more effects on society could be considered in the mathematical models. Environmental impacts could also be extended by including the populations of other species in addition to bird species if adequate data is acquired. As an energy crop, switchgrass and Miscanthus may show invasive properties in different regions. Therefore, preventive decisions could be integrated into the model to

minimize risks associated with invasiveness. Finally, results of the SAHP model in biomass crop selection could be compared with results of other approaches, such as ANP, TOPSIS, or VIKOR. As biomass and biofuel production becomes more common, the criteria to be considered in the decision-making structure and the corresponding weights may be updated depending on the significance of the criteria. Finally, in order to convert imprecise expert evaluations into crisp values in the stochastic AHP model, the mod, mean, or median of beta distribution could be driven from random sampling in the future.

The proposed models could also be enhanced with other approaches in the future. First, in addition to uncertainties in the amount of yield and associated price, demand fluctuations could be included in the stochastic optimization model. However, this would lead to an increase in the number of the scenarios and size of the model. In that case, in order to tackle the problem complexity and increase the solution efficiency, more specific cuts could be generated for solving food and biomass production at the farm level. In case the probability of an uncertain parameter is difficult to obtain, robust optimization models could also be developed in order to define the range of uncertainty of a stochastic parameter.