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Designing a Dedicated Energy Crop Supply System in Tennessee: A Multiobjective Optimization Analysis

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A multiobjective optimization model integrating with high-resolution geographical data was applied to examine the optimal switchgrass supply system in Tennessee that considers both feedstock cost and greenhouse gas (GHG) emissions in the system. Results suggest that the type of land converted into switchgrass production is crucial to both plant gate cost and GHG emissions of feedstock. In addition, a tradeoff relationship between cost and GHG emissions for the switchgrass supply is primarily driven by the type of land converted. The imputed cost of lowering GHG emissions in the feedstock supply system was also calculated based on the derived tradeoff curve.

Key Words: bioenergy, land use change, multiobjective, switchgrass, tradeoff curve

JEL Classifications: C61, Q13, Q16

Biofuel production from lignocellulosic biomass (LCB) is being advocated as an alternative to fossil-based transportation fuels in the United States. LCB-based biofuel production has the potential to mitigate greenhouse gas (GHG) emissions from the transportation sector and to enhance rural economic activity through more intense use of agricultural lands (English et al., 2006). The Renewable Fuel Standard (RFS) established in 2005 and revised in the Energy Independence and Security Act 2007 mandates 21 billion gallons of advanced biofuel (other than ethanol derived from corn starch) available for transportation use by 2022 with 16 billion gallons to be produced from LCB feedstock (U.S. Congress, 2007). Based on the recently revised One Billion Ton Update study (U.S. Department of Energy, 2011), considerable LCB feedstock, including dedicated energy crops, will be required to fulfill this goal. Notwithstanding the potential availability of LCB feedstock to meet the mandate, the cost of LCB feedstock will be an important factor influencing the sustainability of an LCB-based biofuel industrial sector. Given that the quantity and quality

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of LCB feedstock influences the cost of biofuel production, an important research question is how the feedstock supply chain for biofuel production should be optimally configured.

The RFS also requires lifecycle GHG emissions of advanced biofuels to be 50% lower than fossil fuels. Rapid expansion of the biofuel sector and resulting biogenic GHG emissions from ethanol production and biomass power plants have prompted environmental groups to seek more stringent GHG regulations on bioenergy industry. With the increasing focus on allowable life cycle GHG emissions related to bioenergy production, it is important to consider the related GHG emissions from the potential production of LCB feedstock. Changes in GHG emissions caused by alterations in land use and feedstock production, storage, and transportation activities in the supply chain of a potential LCB feedstock may impact the sustainability of LCB-based bioenergy production. Thus, another important research question is how GHG emissions produced from supplying LCB feedstock is influenced by the optimal configuration of the feedstock supply chain.

Switchgrass is a perennial grass that is native to North America and has shown great potential as a dedicated energy crop for bioenergy production (Fike et al., 2006; Wright and Turhollow, 2010). The positive attributes of switchgrass as a dedicated energy crop include high potential biomass yields and low fertilizer and chemical requirements relative to row crops (Jensen et al., 2007). Switchgrass also has a deep fibrous root system that can mitigate soil erosion and sequester carbon in soils, thereby increasing productivity of soil (Mitchell, Vogel, and Sarath, 2008). Switchgrass grows well on the soils where other conventional crops cannot be produced (Lewandowski et al., 2003) and thus is well suited to the eroded soils of the southeastern United States. In addition, abundant sunshine and precipitation in the region are conducive to high switchgrass yields relative to other regions of the United States (English et al., 2006).

The cost of feedstock has been considered as an obstacle to the development of a LCB-based bioenergy industry, including switchgrass (U.S. Department of Energy, 2007). Switchgrass is bulky relative to its energy content, which makes it expensive to harvest, store, and transport (Sokhansanj, Kumar, and Turhollow, 2006). Switchgrass is harvested in a limited period of the year so the requirements for feedstock storage can be enormous and costly. Weathering and precipitation during storage of switchgrass cause losses of dry matter that increase the cost of feedstock at the plant gate (Mooney et al., 2012). The opportunity cost of converting cropland to switchgrass production will also influence the willingness of farmers to grow switchgrass (James, Swinton, and Thelen, 2010). Switchgrass production most likely competes for land with a low opportunity cost such as pasture and hay land (English et al., 2006). The aforementioned factors are highly spatial-dependent (Noon, Zhan, and Graham, 2002) and have a major influence on the delivered cost of switchgrass to a conversion facility and thus the profitability of switchgrass-based biofuel (Hess, Wright, and Kenney, 2007).

Activities in a switchgrass supply chain produce GHG emissions that are different from current agricultural activities in a region. Changes in land use alter GHG flux on soils because switchgrass sequesters soil carbon at a different rate than existing cropping activities (Elliott et al., 2014; Kwon et al., 2013). The application of fertilizer and herbicides, the use of farm machinery for switchgrass production, and the production of those chemicals and equipment create GHG emissions. Transportation of switchgrass to the conversion facility also generates GHG emissions. GHG emissions from changes in land use are potentially spatially oriented because soil types and soil quality vary considerably among regions (Qin, Zhuang, and Chen, 2011). The availability of land for switchgrass production and transportation infrastructure may also differ by region.

Given the importance of feedstock costs and GHG emissions in the development of a sustainable advanced biofuel industrial sector, information is needed about the potential tradeoff between the two performance criteria. Thus, the objective of this study is to evaluate the potential tradeoffs between the potentially competing objectives of minimizing feedstock costs and minimizing GHG emissions in the design of a switchgrass feedstock supply chain. We evaluate the key factors that influence feedstock cost and GHG emissions and the relationship of those two objectives in a switchgrass supply chain through a multiobjective optimization analysis. Certain factors such as the type of land (e.g., pasture and hay land or cropland) converted to switchgrass production may have a positive impact on one objective, e.g., minimizing cost (GHG emissions), in the feedstock supply chain while having a negative influence on the other objective, e.g., minimizing GHG emissions (cost), Thus, a tradeoff may exist between those two objectives. The potential tradeoff between feedstock cost and GHG emissions is evaluated using switchgrass feedstock in Tennessee as the case study. The tradeoff relationship can be used to calculate the imputed cost of abating GHG emissions in the switchgrass feedstock supply chain for bioenergy production. This study provides useful information to both the government and investors so that a more balanced and sustainable supply system of energy crops for the bioenergy sector can be developed.

Literature Review

The design of a sustainable LCB supply chain and efficient conversion technology has been a growing focus in the bioenergy literature given the desire of expediting the commercialization of bioenergy industry. A detailed review of LCB supply chain studies can be found in An, Wilhelm, and Searcy (2011) and Sharma et al. (2013). Mathematical programming is a widely used approach to evaluate the optimal location of the conversion facility and the optimal design of an LCB supply chain. Sharma et al. (2013) recently summarized 32 refereed journal papers applying mathematical programming to evaluate the optimal configuration of biomass/biofuel supply chains between 1997 and 2011. Among the 32 papers, more than 55% were published after 2008, suggesting a growing interest in optimization analyses of LCB feedstock and biofuel supply chains. The objectives of the mathematical programming models in many studies, including more recent studies after 2011, were single objective optimizations using economic criteria such as cost minimization, net present value maximization, or profit maximization (e.g., Dunnett, Adjiman, and Shah, 2007; Kondili, Pantelides, and Sargent, 1993; Mas et al., 2010; Maung and Gustafson, 2013), whereas a few studies considered dual economic and environmental criteria in the design of a feedstock supply chain. For example, You and Wang (2011) evaluated minimum economic cost and minimum GHG emission criteria to examine the optimal biofuel supply chain as a case study in Iowa and found that efficient conversion technology was the key for commercialized LCB-based biofuel production. Bernardi, Giarola, and Bezzo (2012) considered multiple objectives in a biofuel supply chain and observed that the negative predictive value for biofuel production was positively related to both carbon emissions and water consumption.

When assessing the economic and environmental performance of the LCB supply chain, spatial information was often important to the analysis (Archer and Johnson, 2012). For instance, high-resolution spatial data were crucial in studies that evaluated the location for conversion facility (e.g., Bowling, Ponce-Ortega, and El-Halwagi, 2011; Zhang, Johnson, and Sutherland, 2011). Unlike the capital and operation costs of conversion facility, cost of LCB feedstock is sensitive to spatial variation in the quantity and quality of lands between sites (Mooney et al., 2009; Noon, Zhan, and Graham, 2002). In addition, the attributes and the quality of the local transportation network affected the transportation cost and GHG emissions of a feedstock supply chain (Jäppinen, Korpinen, and Ranta, 2011; Yu et al., 2013). Most importantly, spatial factors such as the type of land converted to LCB feedstock production could have different implications to the economic and environmental performance of the feedstock supply chain. For example, the opportunity cost of converting hay and pasture land to switchgrass is much lower than diverting cropland to switchgrass production as a result of the lower net returns from pasture and hay production (James, Swinton, and Thelen, 2010). However, converting hay and pasture land to switchgrass production can result in a net increase in GHG emissions from the soils, whereas converting cropland to switchgrass land can sequestrate more carbon in soil (Kwon et al., 2013).

Integrating geographical information into a multiobjective optimization framework has a long history in the land use literature (Malczewski, 2006). Recently, multiobjective programming model studies using spatial data for the optimization of the LCB feedstock and biofuel supply chain have started to appear in the bioenergy literature. You et al. (2012) conducted a county-level, multiobjective study of LCB feedstock supply chains in Illinois and found a tradeoff between the economic and environmental performance of the biofuel supply chain. They also found that new jobs created were positively correlated with the economic cost of the supply chain. However, analysis of the potential tradeoff between feedstock cost and GHG emissions from converting pasture and hay land or cropland to LCB feedstock production is still lacking in the multiobjective optimization of the LCB supply chain literature. This study aims to add to the bioenergy literature by providing a case study of how the type of land (pasture and hay land versus cropland) converted to switchgrass production affects the tradeoff in feedstock costs and GHG emissions for a conversion facility in Tennessee.

Conceptual Framework

It is hypothesized that the conversion facility considers both economic and GHG emissions in the design of the switchgrass supply chain. The objective of the facility is to identify a most preferred solution that keeps cost and GHG emissions of the feedstock supply chain as low as possible given that the two attributes cannot be simultaneously optimized (Mavrotas, 2009). The multiobjective function is formulated as follows (Chankong and Haimes, 1983, p. 114):

$$(1) \qquad \min.\ [C_F(X), E_F(X)]$$

where C_F is total cost of switchgrass at the gate of facility F (\$), E_F is total GHG emissions calculated as carbon dioxide equivalents in metric tons (CO_2e Mg) produced in the switchgrass supply chain, and X is a set of decision variables. In contrast to a single optimal solution, the multiobjective optimization generates efficient, noninferior solutions that cannot improve one objective (e.g., cost minimization) without lowering the target of the other objective (e.g., GHG emissions minimization) (Zakariazadeh, Jadid, and Siano, 2014).

Switchgrass production can be converted from hay and pasture land and/or cropland. The share of hay and pasture land converted into switchgrass, R, will affect the optimization output because the land converted to switchgrass production from hay and pasture land or cropland has different impacts on opportunity costs and GHG emissions in the feedstock supply chain. Figure 1 shows the relationship among feedstock cost (C_F), GHG emissions (E_F), and the share of hay and pasture land in a region (R) in a switchgrass supply chain. Hay and pasture land has a lower profitability than cropland; thus, the cost of converting hay and pasture land is lower than the cost of converting cropland. When more hay and pasture land is converted (i.e., a higher value of R), total feedstock cost is lower. Thus, the negative relationship $\left(\text{i.e., } \frac{dC_F}{dR} < 0\right)$ between the feedstock cost and

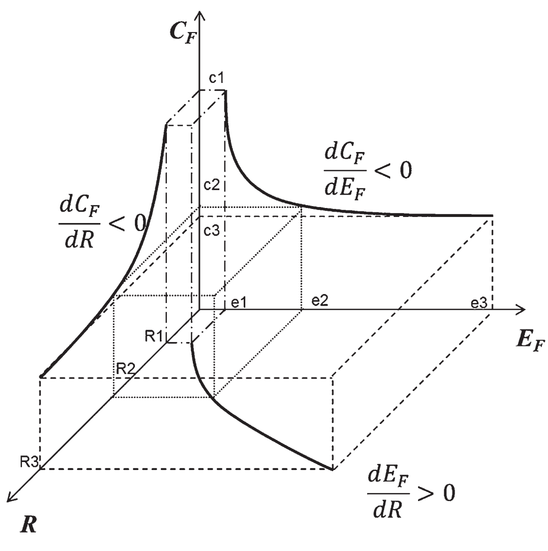


Figure 1. Relationship among Cost (C_F), Greenhouse Gas (GHG) Emissions (E_F), and the Share of Hay and Pasture Land Used (R) for the Switchgrass Supply System

the hay and pasture land ratio is found in Figure 1. In contrast, converting cropland to switchgrass production will increase soil carbon resulting from carbon sequestration of the grass. However, changing land use from hay and pasture to switchgrass releases stored carbon to the atmosphere because of land preparation and the different rate of carbon sequestration associated with the root fraction (Agren and Franklin, 2003; Kwon et al., 2013). Thus, the positive relationship exists between GHG emissions and the hay and pasture land ratio in Figure 1 $\left(\frac{dE_F}{dR} > 0\right)$. When the hay and pasture ratio changes from R1 to R2 to R3, the corresponding feedstock costs (c1, c2, and c3) and GHG emissions (e1, e2, and e3) are determined in the model. The resulting tradeoff relationship between feedstock cost and GHG emissions $\left(\frac{dC_F}{dE_F} < 0\right)$ is observed.

Methods and Data

Mathematical Model

A multiobjective model incorporating spatial characteristics was developed to determine the amount of land converted from current agricultural activities and feedstock draw area to meet the feedstock demand for the conversion facility. The potential tradeoff between the two objectives, i.e., cost minimization and GHG emissions minimization, was also evaluated. The cost considered in this study is the plant gate cost of switchgrass, including the farm gate cost and transportation cost. Because there is no market price for switchgrass, the farm gate cost of feedstock was calculated by considering the cost of switchgrass production, harvest, storage, and the opportunity cost of land conversion to switchgrass production. GHG emissions analyzed in this study include both direct and indirect emissions. Direct GHG emissions come from land use change for feedstock production, energy use for farming operations, and transportation. The estimated GHG emissions from the change in land coverage include the net change of both aboveground and underground in a steady-state status over 30 years after land conversion. Indirect GHG emissions in the feedstock supply chain refer to the production of seed, fertilizer, herbicides, farm machinery, and trucks used in agricultural production activities. The components used to calculate the economic cost and GHG emissions are summarized in Table 1. The model structure and constraints are found in the Appendix.

The conversion facility was assumed to be a medium size with a nameplate capacity of 189,271 kiloliters (kL) per year (Tembo, Epplin, and Huhnke, 2003). The facility was designed to be located in an industrial park in Tennessee so it can access the required infrastructure, e.g., power line, roads, water system, etc. It was assumed that the conversion technology used in the facility would convert a ton of switchgrass into 0.29 kL of biofuel (Wang, Saricks, and Santini, 1999). Given the conversion rate, the monthly feedstock demand from the conversion facility required approximately 55,000 dry Mg of switchgrass. Switchgrass was assumed to be harvested annually from November to February under the available working hours in each month that were determined based on historical weather records (Larson et al., 2010). Switchgrass was assumed to be harvested and packaged in large 1.2 × 1.2 × 2.4-m rectangular bales. Bales were stored at the edge of the field with storage dry matter losses increasing at a decreasing rate over time (Mooney et al., 2012). Semitruck trailers were used for switchgrass transportation from the field to the facility. The maximum travel distance from field to the conversion facility was set to 121 km, which was adjusted from the radius of 80 miles used in the literature (e.g., Epplin, 1996) based on the actual road network in the study area and the facility capacity. A dry matter loss rate of 2% was assumed during switchgrass transportation (Kumar and Sokhansanj, 2007).

Analytical Procedure

To solve a multiobjective optimization problem, the ε-constraint method and weighting method are the most commonly used approaches (Mavrotas, 2009). The ε-constraint method, which optimizes one objective using the other objective(s) as constraint(s), may outperform the

Table 1. Components for Cost and Greenhouse Gas (GHG) Emissions from Switchgrass Supply Chain

	Economic Cost		GHG Emissions	
	Farm Gate	Transport	Direct	Indirect
Land conversion	• Opportunity cost		• Land use change	
Production	• Establishment • Annual maintenance		• Fuel use	• Fertilizer production • Herbicide production • Seed production • Machinery production
Harvest	• Labor • Fuel • Machinery		• Fuel use	• Machinery production
Storage	• Labor • Fuel • Machinery • Materials		• Fuel use	• Machinery production
Transportation		• Labor • Fuel • Truck	• Fuel use	• Truck production

weighting method because it provides more comprehensive and robust solutions using a relative efficient solving process (Mavrotas, 2009). However, the ε-constraint method also has a potential issue on the efficiency of the solution, i.e., the solution may be weakly efficient. Thus, an augmented ε-constraint method developed by Mavrotas (2009) that overcomes the ambiguity in the solution from the conventional ε-constraint method was used in this study. The efficient solutions generated from the augmented ε-constraint method determine the tradeoffs of the two objectives considered, revealing how the performance of one objective (cost) changes with different preferences on the other objective (GHG emissions). The details of the method and its advantage over the conventional ε-constraint method are illustrated in Mavrotas (2009).

In this study, the feedstock supply chain cost was minimized subject to a range of GHG emission levels.[1] The range of the objective function $E_F(X)$ was divided into k identical intervals; thus, the optimization of (k + 1) grid point was solved and the tradeoff curve was generated. The optimization problem was formulated as follows (Zakariazadeh, Jadid, and Siano, 2014):

$$\text{(2)} \qquad \min.\ \left(C_F(X) - \varepsilon \times \frac{s}{r}\right)$$

$$\text{(3)} \qquad s.t.\ E_F(X) + s = e,$$

where ε is a small number (in this study ε was set to 10^{-3}), s is the nonnegative slack variable, and r is the range of the GHG emissions objective between the minimum GHG emissions level (e_0) to the unconstrained GHG emissions level (e_n). The constraint of GHG emissions e $\left[e = e_n - \left(\frac{e_n - e_0}{k}\right) \times h,\ h = 0,1,\ldots,k\right]$ is the hth range of $E_F(X)$. The slack variable was added in the objective function (equation [2]) to prevent the program from producing weak efficient solutions (Mavrotas, 2009, p. 460).

Figure 2 shows an example of the tradeoff curve generated for a conversion facility A through imposing a series of GHG emission constraints. With e_0 and e_n, the (n-1) emission constraints from e_0 to e_n break down the range of [e_0, e_n] into n equidistant parts. Given various constraint levels of GHG emissions, the corresponding optimal costs are then determined

[1] The optimization process can also be modeled by minimizing the GHG emissions using a range of feedstock cost levels and the tradeoff relationship between cost and GHG emissions in the switchgrass feedstock supply chain still remains.

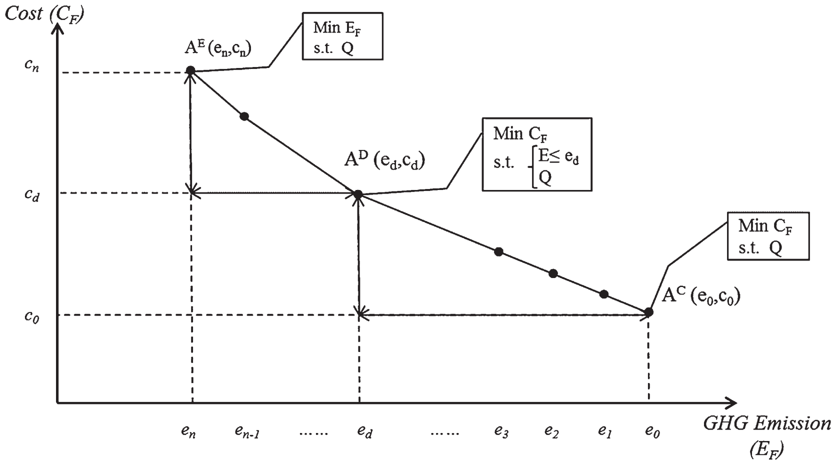


Figure 2. A Tradeoff Curve between Cost and Greenhouse Gas (GHG) Emissions in a Feedstock Supply System

using equations (2)–(3) to form the tradeoff curve for facility A. For example, the optimal cost c_d is determined by setting a specific GHG emission constraint e_d, which gives one solution point, A^D with (e_d,c_d). Point A^C in Figure 2 represents the solution for cost and GHG emissions under the unconstrained GHG emissions level (e_n). On the tradeoff curve in Figure 2, the relative changes of cost and GHG emissions show the imputed cost of reducing GHG emissions. For example, from solution point A^C to A^D, the imputed cost to reduce (e_0–e_d) CO_2e Mg of GHG emissions is \$(c_d–c_0), i.e., $\frac{c_d - c_0}{e_0 - e_d}$ (\$/CO_2e Mg), which is the slope of A^DA^C.

The conversion facility having the lowest feedstock cost in our study area was used to illustrate the potential tradeoff relationship between cost and GHG emissions in its switchgrass supply chain. The model first minimized the feedstock cost without imposing any constraint in GHG emissions as shown in equations (4)–(5) to generate the upper bound of GHG emissions level (e_n).

(4) min. $C_F\,(X)$,

(5) *s.t.* Q

where Q is the total amount of switchgrass to be produced for the conversion facility. To obtain the minimum GHG emissions level (i.e., e_0) in the feedstock supply chain for the facility, equations (6)–(7) were used:

(6) min. $E_F(X)$,

(7) *s.t.* Q

The feedstock cost for the minimized GHG emissions level was also an ex post estimate. Two targets of e_d were then imposed in this study to generate the tradeoff curve.

Data

More than 230 industrial parks in a database maintained by the Tennessee Valley Authority were considered as potential candidates for the conversion facility location in Tennessee (Smith, 2011). All of the industrial parks had access to water, power, and roads as well as sufficient room for feedstock storage. Existing cropland of corn, wheat, soybean, sorghum, cotton, and hay in the state and within 80 km of the state border was considered as the potential feedstock supply area (see Figure 3). Public land such as national parks was excluded from the study. Land area was decomposed into five square-mile hexagons (defined as land resource units). In addition, a street-level network from the U.S. Census of Bureau was applied to generate the routes from each land resource unit to the facility with the following hierarchy: 1) primary/ major roads; 2) secondary roads; 3) local and

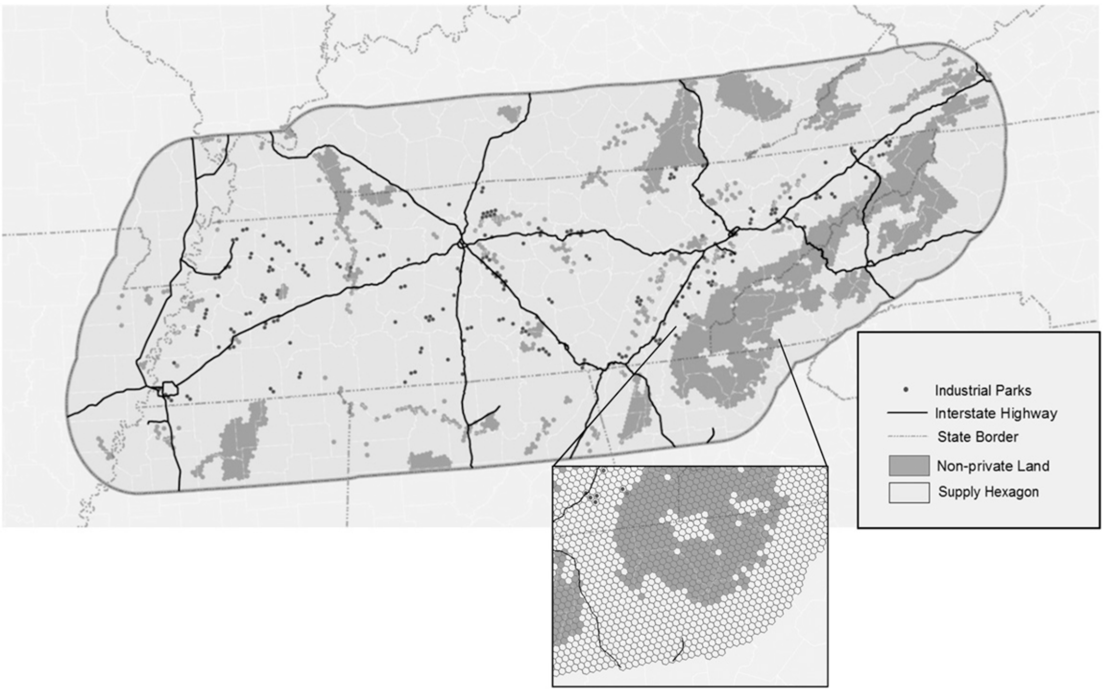


Figure 3. Feedstock Supply Region and Industrial Park Locations

rural roads; and 4) other roads (U.S. Census Bureau, Geography Division, Geographic Products Branch, 2012).

Crop yields were obtained from the SSURGO Database at the subcounty level (U.S. Department of Agriculture [USDA]. Nature Resources Conservation Service. Soil Survey Geograophical Database [SSURGO Database], 2012). Area in each land resource unit for each crop type was derived from the Cropland Layer Database (USDA, National Agricultural Statistics Service, 2011). The prices of crops were three-year average prices for 2010–2012 (USDA. National Agricultural Statistics Service). Production costs for crops were from the USDA (USDA, Economic Research Service, 2013b) and Policy Analysis System (POLYSYS) model (De La Torre Ugarte, Ray, and Tiller, 1998). Simulated switchgrass yields were obtained from the Oak Ridge Energy Crop County Level Database (Jager et al., 2010.) and were disaggregated to the land resource unit level using an index of soil quality. Production and harvest costs for switchgrass were from Larson et al. (2010) and the University of Tennessee, Department of Agricultural and Resource Economics (2009). The transportation cost of switchgrass included labor, energy consumption, semitruck maintenance, and loading/unloading. The energy, labor, and maintenance costs for operating equipment and capital costs were calculated based on the American Agricultural Economics Association Cost and Return Handbook (AAEA, 2000) and American Society of Agricultural Engineers standards (ASABE, 2006).

To estimate the GHG emissions from land use change, the DAYCENT model, a daily time-step version of the CENTURY (Parton, 1996) biogeochemical model was adopted to simulate the soil CO_2 and N_2O emission factors as a result of the conversion of different types of land into switchgrass production. Factors such as soil property, crop type, and weather were included in the DAYCENT model (Schimel et al., 2001). The annual weather data for Tennessee were acquired from the DAYMET model maintained by the Oak Ridge National Laboratory. The soil property data used in the DAYCENT were from the U.S. Geological Survey.

The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) Model 2013, which was developed and is maintained by the Argonne National Laboratory (Argonne National Laboratory, 2013), provided the emission factors for all the three GHG emissions from machinery combustion during LCB harvest. Diesel consumption was calculated from the time used during each operation (hours/acre) times the fuel use (gallon/hour) of the tractor. GHG emissions from switchgrass transportation were estimated using the Motor Vehicle Emissions Simulator (MOVES) by the U.S. Environment Protection Agency (2013). In addition to travel distance, local weather, travel speed, and the slopes of road were considered when estimating the truck emissions of switchgrass from farm gate to the conversion facility. The version used to estimate vehicle emissions was MOVES2010a. Indirect emissions from the production of agricultural machinery, fertilizer, herbicide, and seed were calculated based on the emission factors from GREET model.

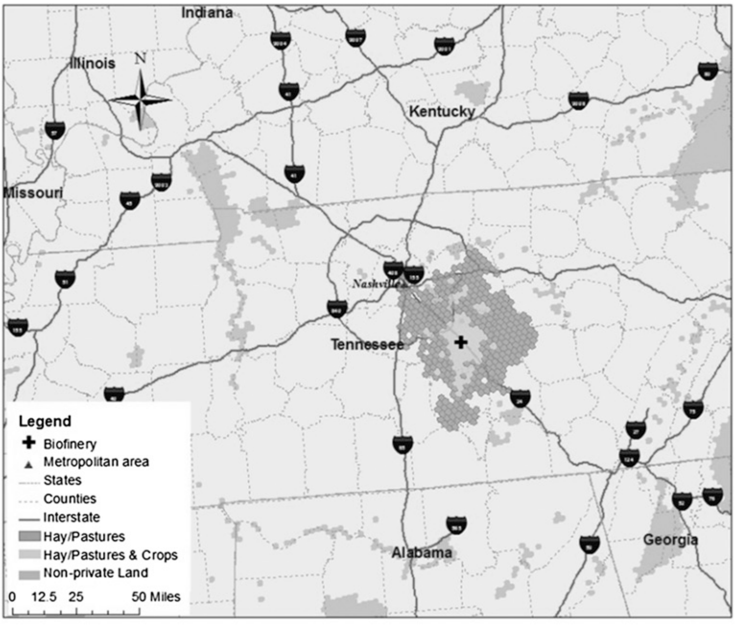
Empirical Results

The least feedstock cost conversion facility without imposing GHG emissions constraint was located in an industrial park adjacent to Interstate 24 in the southeast of Nashville (see Figure 4). The feedstock draw area for the minimum cost case (i.e., the minimum feedstock cost without imposing constraints on GHG emissions) in Figure 4A was more geographically compact than the minimum GHG emissions solution in Figure 4B. In the minimum cost case, switchgrass production was primarily produced on low opportunity cost hay and pasture land. When the objective is to minimize total GHG emissions as shown in equation (6), converting cropland becomes the first choice because of increased carbon sequestration. For the minimum GHG emissions solution in Figure 4B, all of the land used for switchgrass was converted from cropland. Feedstock draw area under GHG minimization was less dense geographically (Figure 4B) than under cost minimization (Figure 4A) because more hay and pasture land is available in east and middle Tennessee, whereas cropland is less available in the two regions relative to west Tennessee.

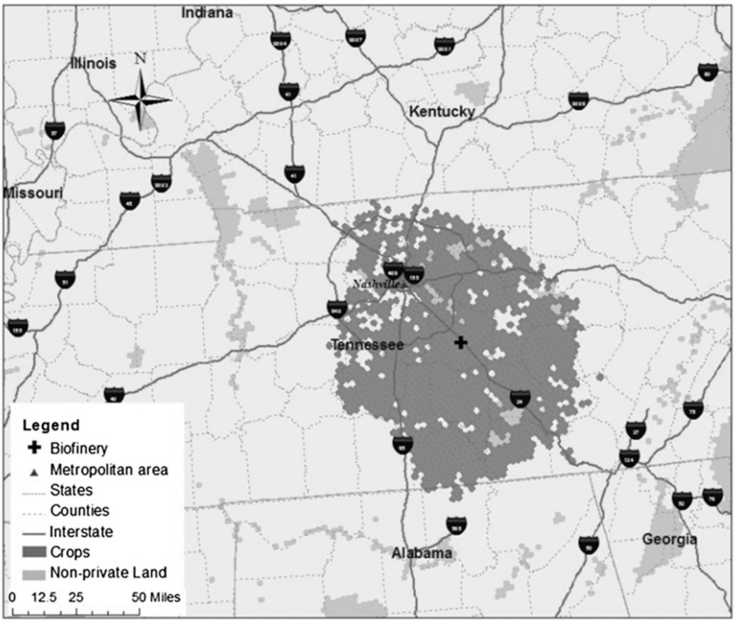
The output for the minimum cost and minimum GHG emissions solution points is summarized in Table 2. For the minimum cost case (the second column in Table 2), total GHG emissions produced in the switchgrass supply chain was 81.6 thousand Mg. The major source of GHG emissions was energy consumption for farming activities and totaled 36.7 thousand Mg followed by the conversion of hay and pasture land to switchgrass that released soil carbon by 25.1 thousand Mg. The production of seed, fertilizer, herbicide, farm machinery, and trucks yielded nearly 16,000 Mg in indirect GHG emissions. Switchgrass transportation between the farm gate and the conversion facility produced approximately 4,000 Mg of GHG emissions. Total feedstock cost including transportation and farm gate cost was \$46.0 million. Feedstock cost at the farm gate was \$35.4 million with an opportunity cost of \$1.6 million. Transportation of feedstock accounted for \$23% (\$10.6 million) of the total plant gate cost.

For the minimum GHG emissions point (the third column in Table 2), the switchgrass supply chain produced total GHG emissions of 34.5 thousand Mg. Given that all of the land used for switchgrass production was converted from cropland, more than 25,000 Mg of GHG emissions were sequestrated in soils. GHG emissions from transportation of feedstock were 7.2 thousand Mg higher than the transportation emissions in the minimum cost solution because of a larger feedstock supply area. Total feedstock cost for the minimum GHG emissions case was more than \$85 million. The opportunity cost of converting cropland to switchgrass (\$37.3 million) became the largest component of plant gate cost. The cost for switchgrass transportation was higher than the minimum cost solution because the feedstock supply area was more geographically dispersed.

Two additional grid points of GHG emissions (A^1, A^2) were included using equations (2) and (3) to develop a cost–GHG emissions tradeoff curve and are plotted in Figure 5. At



(a) Cost minimum solution



(b) GHG emissions minimum solution

Figure 4. Location of the Conversion Facility and Associated Feedstock Supply Region for Cost Minimum and Greenhouse Gas (GHG) Emission Minimum Solution Points

point A^1, total GHG emissions were constrained at 62.8 thousand Mg with the optimal feedstock cost of \$50.7 million. Total feedstock cost increased to \$60.2 million when limiting the level of GHG emissions of 43.9 thousand Mg at grid point of A^2. The share of hay and pasture land used for switchgrass production decreased from 98% to 65% to 11% to 0% from

Table 2. Summary for the Cost Minimum and Greenhouse Gas (GHG) Emissions Minimum Cases at the Selected Conversion Facility

	Cost Minimum	GHG Emissions Minimum
	GHG Emissions (1,000 Mg)	
Land conversion	25.1	–25.2
Energy use—farming	36.7	36.6
Energy use—transportation	3.9	7.2
Indirect sources	15.9	15.8
Total	81.6	34.5
	Cost ($ million)	
Cost at farm gate	35.4	71.2
Opportunity	1.6	37.3
Production	8.6	8.6
Harvest	22.4	22.4
Storage	2.8	2.9
Transportation	10.6	14.2
Total at plant gate	46.0	85.4
Hay and pasture land ratio	97.8%	0.0%

the four points (A^c, A^1, A^2, and A^e) on the tradeoff curve. The tradeoff curve in Figure 5 suggests that the imputed cost of mitigating GHG emissions in the feedstock supply chain can be traced out along the tradeoff curve. Lowering GHG emissions from the point of A^c (81.6 thousand Mg) to A^1 (62.8 thousand Mg) increased the total cost in the feedstock supply system by $4.8 million (approximately $250/$CO_2$e Mg), whereas the average imputed cost of mitigating the same amount of GHG emissions between point A^1 and A^2 doubled to $500/$CO_2$e Mg. Moreover, the average imputed cost for GHG emission reduction increased to nearly $2,700/$CO_2$e Mg from the solution point A^2 to the minimum emission case A^e. This output suggests that the point A^1 may be the most preferred solution for the conversion facility when designing the feedstock supply system and locate the feedstock producers. The imputed cost of emissions abatement information developed in this tradeoff analysis may

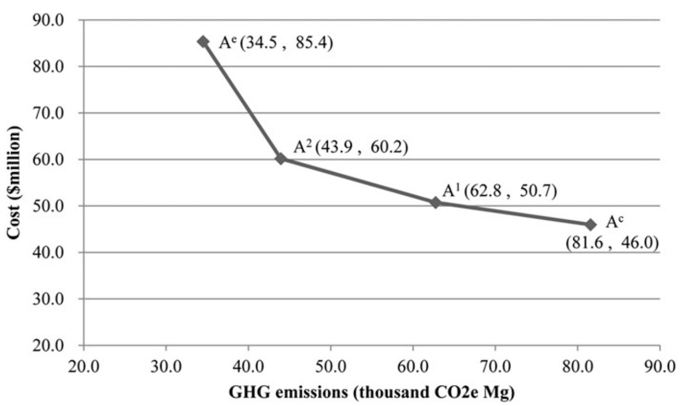


Figure 5. The Tradeoff Curve between Cost and Greenhouse Gas (GHG) Emissions of Switchgrass Supply Chain for the Least Cost Conversion Facility in Tennessee

be useful to policymakers and LCB-based energy investors seeking to develop a sustainable bioenergy sector in the region.

Conclusions

Expediting the development of alternative energy sources using lignocellulosic biomass feedstocks has been strongly promoted by state and federal government agencies over the past decade. However, technical barriers to the development of a cost-effective feedstock supply chain impede the sustainability of a bioenergy sector in the United States. Thus, the objective of this study was to identify the key factors to a sustainable LCB feedstock supply chain considering both economic and environmental performance. To achieve this objective, the potential tradeoff between cost and GHG emissions caused by type of land converted to switchgrass production was examined for a case study in Tennessee. This study applied a multiobjective mathematical model to minimize both cost and GHG emissions in a switchgrass supply chain.

Results show that both feedstock cost and GHG emissions from the switchgrass supply chain were heavily influenced by the type of land converted for switchgrass production. Also, the availability of the type of agricultural land to produce switchgrass, i.e., hay and pasture land or cropland, and the road network affected the location of conversion facility. The potential site with the least feedstock cost was located where low opportunity cost hay and pasture land is most geographically concentrated in Tennessee.

For this facility, the switchgrass supply chain produced the minimum cost output of 81.6 thousand Mg of CO_2e with the total feedstock cost of $46 million. The land for switchgrass production was primarily converted from hay and pasture land. In contrast, GHG emissions dropped to approximately 35,000 Mg but cost increased to more than $85 million when only cropland was converted to switchgrass. The tradeoff curve generated for the facility indicated that the imputed cost for GHG emissions abatement quickly increased along with the target (or constraint) of GHG emissions. This relationship implies that the location of switchgrass production and the resulting changes in crop production should be considered in targeting government incentives to encourage switchgrass-based biofuel production in the state and the southeastern region.

Finally, the tradeoff between cost and GHG emissions estimated in this study suggests that the selection of land for feedstock production can influence the economic and environmental performance of the feedstock supply chain. With the different ordering of the objective in this study (i.e., using GHG emissions as the main objective and constraining cost at multiple levels), the location of the conversion facility and feedstock draw area will change accordingly because cropland is concentrated in west Tennessee. However, the tradeoff relationship between cost and GHG emissions will remain. In addition, for other regions with different landscape of agricultural activities, the tradeoff curve between cost and GHG emissions in a feedstock supply chain can still be observed if the relative opportunity cost and soil carbon sequestration rate between the potential LCB feedstock and existing agricultural lands are found. For future research, the analysis can be extended to the whole supply chain system associated with different types of energy production (e.g., coal, natural gas) and the relationship between cost and net changes in GHG emissions among those energy products can be evaluated.

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Appendix

The cost of switchgrass at the conversion facility gate is defined as:

$$\text{(A-1)} \qquad C_F = C_{opportunity} + C_{production} + C_{harvest} + C_{storage} + C_{transportation}$$

where C_F is the total economic cost ($) of the switchgrass supply chain; and $C_{opportunity}$, $C_{production}$, $C_{harvest}$, $C_{storage}$, and $C_{transportation}$ are opportunity costs from land conversion, production cost, harvest cost, storage cost, and transportation cost of switchgrass, respectively. The definition of the parameters and variables used in the following equations are included in Table A1. The opportunity cost ($C_{opportunity}$) for switchgrass production equals the profit of previous crop type as presented in equation (A-2). If cropland revenue is less than the county-level land rent, the land rent for crop and pasture is used instead. The production cost for switchgrass production ($C_{production}$) includes the amortized establishment cost of the first year as well as an annual maintenance cost.

$$\text{(A-2)} \qquad C_{opportunity} = \begin{cases} \sum_{ip} \left(\dfrac{Price_{ip} * Yield_{ip} - PC_{ip}}{Yield_i^{swi}} * XC_{ip} \right), & if\ (Price_{ip} * Yield_{ip} - PC_{ip}) - LR_{ip} \geq 0 \\ \sum_{ip} \left(\dfrac{LR_{ip}}{Yield_i^{swi}} * XC_{ip} \right), & if\ (Price_{ip} * Yield_{ip} - PC_{ip}) - LR_{ip} < 0 \end{cases}$$

Table A1. Definitions of Subscripts, Parameters, and Variables

	Unit	Definition
Subscripts		
i		Locations of switchgrass production field
j		Location of the biorefinery
m		Month
p		Crops (hay and pasture, corn, soybean, wheat)
t		Storage protection method
k		Type of machinery (tractor, mower, loader, rake)
Parameters		
$\mathrm{Price}_{\mathrm{ip}}$	\$/unit	Traditional crop price
$\mathrm{Yield}_{\mathrm{ip}}$	ha/unit	Tradition crop yield
$\mathrm{PC}_{\mathrm{ip}}$	\$/ha	Production cost of traditional crop
$Yield_i^{swi}$	d Mg/ha	Yield for switchgrass in each hexagon
LR_{ip}	\$/ha	Land rent of traditional crop
Est	\$/ha	Establishment cost in the first year
AM	\$/ha	Annual maintenance cost
Sigma_i	\$/ha	Cost of harvesting switchgrass
γ_{it}	\$/d Mg	Cost of storing switchgrass
θ_i	\$/d Mg	Cost of transporting switchgrass from field to facility
$DMLT$	%	Dry matter loss during transportation
$\mathrm{lucE}_{\mathrm{p}}^{\mathrm{co2}}$	CO_2e Mg/ha	CO_2 emission from land conversion of crop to switchgrass
$\mathrm{lucE}_{\mathrm{p}}^{\mathrm{n2o}}$	CO_2e Mg/ha	N_2O emission from land conversion of crop to switchgrass
storE	CO_2e Mg/d Mg	GHG emissions from energy usage during storage
harE	CO_2e Mg/ha	GHG emissions from energy usage during harvest
proE	CO_2e Mg/ha	GHG emissions from energy usage during production
$\mathrm{transE}_{\mathrm{mip}}$	CO_2e Mg /truck	GHG emissions from energy usage during transportation
fertE	CO_2e Mg/d Mg	GHG emissions from fertilizer production
herbE	CO_2e Mg/d Mg	GHG emissions from herbicide production
seedE	CO_2e Mg/d Mg	GHG emissions from seed production
machE^k	CO_2e Mg/unit	GHG emissions from machinery production
$loadwt_{mi}$	d Mg/truck	Tonnage of switchgrass delivered per truck
aa_{ip}	ha	Cropland available in each hexagon for each crop
PAS_p	%	Maximum percent of land converted
$CapUnit$	kL/year	Annual capacity of a conversion facility
λ	kL/d Mg	Switchgrass–ethanol conversional rate
$rateava_m$	%	Ratio of working hours in each month to total
$avehour_m$	hour	Average working hours of machinery in each month
mtb_i	hour/ha	Machine time per acre for each machinery
$DMLS_{mt}$	%	Dry matter loss during storage
Dd_m	kL/month	Monthly demand for ethanol
Variables		
A_{ip}	ha	ha of switchgrass produced annually
AH_{mip}	ha	ha of switchgrass harvested monthly
XC_{ip}	d Mg	dry Mg of switchgrass produced annually
XH_{mip}	d Mg	dry Mg of switchgrass harvested monthly from November to February
XTN_{mip}	d Mg	dry Mg of switchgrass transported directly to the facility after harvest
NXS_{mipt}	d Mg	dry Mg of switchgrass newly stored monthly from November to February
XS_{mipt}	d Mg	dry Mg of switchgrass stored monthly from November to October
XTO_{mipt}	d Mg	dry Mg of switchgrass transported from storage to the facility
$Numb_m^k$	unit	Number of equipment used in harvest

Note: GHG, greenhouse gas.

$$C_{production} = \sum_{ip}\left(\frac{\text{Est} + \text{AM}}{Yield_i^{swi}} * XC_{ip}\right) \quad \text{(A-3)}$$

$$C_{harvest} = \sum_{ip}\left(\frac{\text{Sigma}_i}{Yield_i^{swi}} \times XC_{ip}\right) \quad \text{(A-4)}$$

$$C_{storage} = \sum_{mipt}\gamma_{it} * NXS_{mipt} \quad \text{(A-5)}$$

$$C_{transportation} = \sum_i \theta_i \times \frac{\sum_{mp} XTN_{mip} + \sum_{mpt} XTO_{mipt}}{1 - DMLT} \quad \text{(A-6)}$$

The sources of GHG emissions of the switchgrass supply chain are land use change (E_{luc}), energy consumption from switchgrass production, storage harvest (E_{energy}), transportation ($E_{transportation}$), and the production of seed, fertilizer, herbicide, and machinery (E_{ind}). Equations to calculate the GHG emissions from these sources are given in (A-7)−(A-11), and the definitions for parameters and subscripts are also in Table A1.

$$E_F = E_{luc} + E_{energy} + E_{transportation} + E_{ind} \quad \text{(A-7)}$$

$$E_{luc} = \sum_{mip}\left(lucE_p^{co2} + lucE_p^{n2o}\right) * AH_{mip} \quad \text{(A-8)}$$

$$E_{energy} = \sum_{mip} storE * XH_{mip} + \sum_{mipb}(proE + harE) * AH_{mip} \quad \text{(A-9)}$$

$$E_{transportation} = \sum_{mi} transE_{mip} * \frac{\sum_p XTN_{mip} + \sum_{pt} XTO_{mipt}}{loadwt_{mi} * (1 - DMLT)} \quad \text{(A-10)}$$

$$E_{ind} = \sum_{mip}(fertE + herbE + seedE) * AH_{mip} + \sum_m Numb_m^k * mach\text{E}^k \quad \text{(A-11)}$$

Several constraints about feedstock availability and inventory flow for the switchgrass supply chain are presented in equations (A-12)–(A-22). Land use constraints are specified in equations (A-12) and (A-13). Equation (A-14) indicates that no more switchgrass was harvested than produced. Equation (A-15) indicates that the amount of switchgrass harvested each month is constrained by the available working hours in each month ($rateava_m$). Equation (A-16) limits the harvest season of switchgrass from November to February. Equation (A-17) calculates machinery use during switchgrass harvest. Equation (A-18) shows that the newly stored switchgrass in each month, m, equals the amount of switchgrass harvested deducting the amount of switchgrass delivered to the conversion facility directly. During harvest season, accumulative switchgrass storage equals the amount stored in previous month plus the newly stored amount as presented in equation (A-19). During off-harvest season, accumulated switchgrass storage equals the amount stored in the previous month subtracting the amount of switchgrass delivered to the facility in the current month, as presented in equation (A-20). Equation (A-21) indicates that the temporal framework considered in the model is a single harvest year. Equation (A-22) indicates that the switchgrass delivered to the facility each month meets the demand.

$$A_{ip} \le PAS_p \times aa_{ip}, \quad \forall i, p \quad \text{(A-12)}$$

$$XC_{ip} \le Yield_i^{swi} \times A_{ip}, \quad \forall i, p \quad \text{(A-13)}$$

$$XC_{ip} - \sum_m XH_{mip} \ge 0, \quad \forall i, p \quad \text{(A-14)}$$

$$\sum_{i,p,} XH_{mip} = \frac{CapUnit}{\lambda} \times rateava_m, \quad Dec \le m \le Feb \,\&\, \forall m \quad \text{(A-15)}$$

$$XH_{mip} = 0, \quad March \le m \le Oct\, \forall m, i, p \quad \text{(A-16)}$$

$$Numb_m^k \times avehour_m - \sum_{i,p}(mtb_i^k \times AH_{mip}) \ge 0, \quad \forall m \quad \text{(A-17)}$$

$$\sum_t^2 NXS_{mipt} = XH_{mi} - \frac{XTN_{mip}}{1 - DMLT}, \quad Nov \le m \le Feb \,\&\, \forall m, i, p \quad \text{(A-18)}$$

$$XS_{(m+1)ipt} = (1 - DMLS_{mt}) \times XS_{mipt} + NXS_{(m+1)ipt}, \quad Nov \le m \le Feb \,\&\, \forall m, i, p, t \quad \text{(A-19)}$$

$$XS_{(m+1)ipt} = (1 - DMLS_{mt}) \times XS_{mipt} - \frac{XTO_{(m+1)ipt}}{1 - DMLT}, \quad Mar \le m \le Oct\, \forall\, m, i, p, t \quad \text{(A-20)}$$

$$XS_{mipt} = 0, \quad m = Oct \,\&\, \forall m, i, p, t \quad \text{(A-21)}$$

$$\lambda\left(\sum_{i,p} XTN_{mip} + \sum_{i,p,t} XTO_{mipt}\right) = Dd_m, \quad \forall m \quad \text{(A-22)}$$