Farmers' Switchgrass Adoption Decision Under A Single-Procurer Market: An Agent Based Simulation Approach

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Abstract

Recently, a number of pilot and demonstration scale advanced biofuel facilities have been established, but commercial scale facilities are yet to become operational. To make informed decisions about this emerging industry, potential biorefinery entrepreneurs and regional policy makers need analysis of how farmers are willing to adopt these feedstocks and how will they switch land into bio-feedstock use to ensure a stable feedstock supply. This paper develops an agent-based simulation model to study farmers' switchgrass adoption decisions over time within a specific agricultural region. We explicitly examine the effect of various contractual terms across market scenarios and consider the potential for contractual hold-ups. Results show that a contract with a payment of $175/acre plus $50/ton could make both biorefinery and farmer profitable during the simulation period. It is also shown that alfalfa, but not annual crops will be the mostly affected crop (replaced) by the introduction of switchgrass in the region of North Michigan.

Key Words: agent based simulation, contract hold-up, ethanol price, switchgrass.

JEL Codes: L10, L11, L14

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-- An Agent Based Simulation Approach

1. Introduction

The Energy Independence and Security Act of 2007 [1] (EISA), expansion of the Renewable Fuel Standard (RFS), mandates the production of 36 billion gallons of biofuels per year by 2022 including 21 billion gallons of cellulosic and advanced biofuels (increased from 2 billion gallon per year in the year of 2007), in addition to 15 billion gallons of conventional (corn) ethanol (refer to figure 1, panel a). Studies of biomass potential by the USDOE indicated that over a billion tons of biomass feedstocks may be available in the US (Perlack et al. 2005). Furthermore, Epplin.,et al (2007) estimates that a billion tons of cellulosic biomass, which might be converted to 90 gallons of biofuel under standard conversion technology, could be used to produce ethanol comprising approximately 26% of the BTUs of the 2005 U.S. net crude oil imports, alleviating the U.S's dependence on foreign oil (Demirbas, 2009).

Recently, a number of pilot and demonstration scale advanced biofuel facilities (e.g. API in Michigan, Genera in Tennessee and Buckeye Technologies in Florida) have been established, but commercial scale facilities are yet to become operational. To make informed decisions about this emerging critical industry, potential biorefinery entrepreneurs and regional policy makers need significant analysis and information on how farmers are willing to adopt these feedstocks and how will they switch land into energy crop production to ensure a stable feedstock supply. The commonly cited reasons that impede farmers' switchgrass adoption includes price uncertainty due to the lack of a mature market, high conversion and sunk costs, long-term commitment, and low yields in

[1] See http://www1.eere.energy.gov/femp/regulations/eisa.html

the establishment years. Researchers computed that for switchgrass, the fraction of farmers willing to adopt switchgrass varies between 30~70% in different regions and even within regions (Jensen et al., 2007; Wen et al., 2009; Rossi & Hinrichs, 2011**).** Hipple & Duffy (2002) also observed a significant “wait-and-see” behavior among farmers that further warrants a detailed investigation of the effect of adaptive behavior on swichgrass adoption.

Many of the impediments mentioned above could be alleviated by establishing contracts between farmers and biorefinery (Alexander et al., 2012). However, when only a single outlet (a single biorefinery) exists in the market, farmers have also expressed their concern about being held-up by the biorefinery (Jensen et al., 2007). In reality, contracts are commonly used in existing biorefineries to procure switchgrass from farmers (e.g. Genera biorefinery[2]) and regions are limited to a single biorefinery in the market.

In this paper, we develop an agent-based modeling approach to simulate the decisions of farmers to convert land to switchgrass use where a single biorefinery contracts with farmers to procure switchgrass. Agent-based simulation is a bottom-up modeling approach that allows the researchers to specify different attributes and behavioral decision rules for different agents or actors in the model (i.e. capture agent heterogeneity) and then study the interaction of these agents and the consequences of the interactions (Heckbert, Baynes & Reeson, 2010). Our model, therefore, captures the effect of interactions between farmers (i.e. social learning processes) and the interaction between farmers and biorefinery (i.e. contractual issues) on farmer decision-making. Furthermore,

[2] Genera is a partner of UT Bioenergy Initiative and it currently uses a contract of per acre payment plus per ton payment to procure switchgrass (year1: $450/acre; year2: $250/acre + $40/ton; year3: $150/acre+$50/ton)

our approach 1) builds a baseline cropping scenario without switchgrass to validate the model using historical crop planting data, 2) calculates a feasible switchgrass contract price range that is profitable for both farmers and biorefinery, and 3) attempts to quantify the qualitative contract hold-up framework proposed by Klein (1996) and apply it to the context of a biorefinery-farmer biofeedstock procurement model.

The paper is structured as follows: section 2 briefly reviews other current land use studies and contracting issues and their findings; section 3 builds the agent based model to be implemented under the single-procurer contract scenario; section 4 presents the data, model initialization and base-line scenario validation; then section 5 discusses the simulation results and finally, section 6 concludes.

2. Previous Studies

2.1 Agricultural Land Use and Energy Crop Adoption Decisions

Previous studies of agricultural land use have simulated energy cropy adoption decisions. Egbendewe-Mondzozo *et al.* (2011) simulated biomass supply in southwestern Michigan using detailed production data and showed that the minimum biomass:corn price ratio ranged from 0.15 to 0.18, dependent on the type of energy crops. Larson, English & Lamber (2007) simulated biomass-crop land use change in Tennessee's biomass initiative region over different market scenarios (e.g. spot market tonnage contract, per acre contract). Their results showed that spot market prices were not high enough to induce biomass production. Song, Zhao & Swinton (2011) adopted a stochastic process model showing that uncertainty and sunk costs influence farmers' option value of converting land to switchgrass use. Each of the above studies used optimization-based models rooted in economic theory. A central feature of these types of models is that they model decision-making in a representative farm. This approach has the drawback that it underrepresents farm-level heterogeneity and differences in farmer-level behavior. For example, farms may be quite heterogeneous in terms of their agronomic conditions and farmer propensity/ability to learn. The simplification of using a "representative" farm ignores the learning process and is also likely to overestimate or underestimate the real occurrence if aggregated to the region level.

Agricultural land use studies have also used agent-based modeling methods to simulated energy crop adoption decisions. In particular, this approach has been used where there is a high-degree heterogeneity among farmers and the environment, and high frequency of interaction among farmers and between farmers and environment (Shastri et al, 2011; Kelly & Evans, 2011). Kelly & Evans (2011) modeled the impact of farmers' preferences on their land use pattern in Indiana Creek Township. Scheffran, *et al.* (2007) modeled the spatial dynamics of biofuel crop growth in Illinois by emphasizing the effect of the introduction of biomass on the price evolution for both regular crops and biofeedstocks. Although these studies emphasize things that are representative in the farm level heterogeneity and farmers' learning (self-learning and learning from others), the most common feature of agent-based land use models are rule-based but ignores the various resource constraints that may limit farmers' ability to change land use pattern. On the contrary, mathematical programming based multi-agent system (MP-MAS) (Schreinemachers, Berger & Aune, 2007) uses optimization methods in agent based models and thus incorporates farm planning feasibility into the model. However, most MP-MAS models are quite stylized and the learning process is rigid and ignores the social learning process (using self-learning instead). It should also be noted that most agent-based energy crop adoption simulations assume a spot market. For the very few studies that use contracts (e.g. Alexander, *et al.*, 2013), it is also assumed a mature market exists and contract hold-up issues is not taken into consideration, which is shown to be one of the very important considerations by farmers.

2.2. Risk in Farming and Contract Hold-up

Farmers face several different types of risk, including production risk (e.g. yield risk, input price risk), marketing risk (e.g. output price risk) and financial risk (e.g. high leverage). Contracts are commonly used to mitigate some of these risks by imposing different compensation mechanisms (Alexander et al, 2012**)** and contracting periods (Jensen et al., 2007; Rossi & Hinrichs, 2011**)**.

When using contracts, farmers also face additional types of risk associated with contractual holdup by procurers. Here, farmer payments might be delayed or be canceled due to various reasons (e.g. quality satisfaction, procurer bankruptcy, procurer market power, high spot market price) (Klein, 1996; Gow, Streeter & Swinnen, 2000). The hold-up problem is especially eminent for perennial switchgrass when there is only one buyer (i.e. biorefinery) in the market. In this case, land devoted to perennial switchgrass may be classified as a relation-specific asset and provides an opportunity for an opportunistic procurer to extract further rents from the farmer through the threat of contractual holdup (Gow, Streeter & Swinnen, 2000; Hipple & Duffy, 2002).

3. The Agent Based Model

3.1 Agent Based Model Decision Tree

In agent-based models, the model behavior is guided by a defined decision-making procedure for each agent. Figure 1 presents a flowchart of the decision-making process for each category of agent (i.e. farmers and biorefineries). The solid lines in Figure 1 mean that the former action will influence the next action in the current year (e.g. the switchgrass acres under contract and biorefinery's expected ethanol price in this year will influence its hold up decision in the current year), while the dashed lines in the figure mean that the former action will influence the next action in the next year (e.g. if the contract is held up this year by biorefinery at the end of this year, farmers will have less cash available for the next year when he begins to do the farm planning).

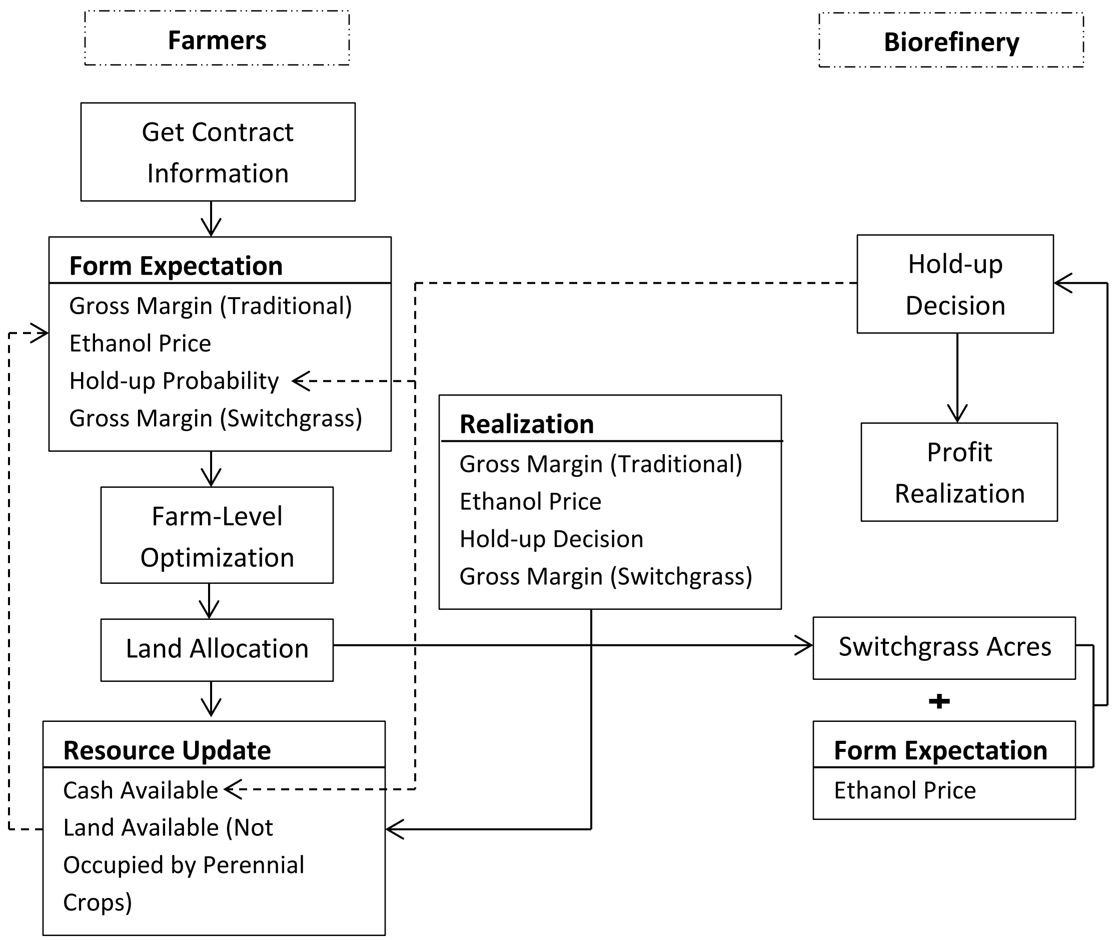

Figure 1 Agent Based Model Decision Tree

At the beginning of each year, farmers will get to know the compensation mechanism in the contract and form their expectations on crop gross margins (both traditional crops and switchgrass) and ethanol price. Along with the biorefinery past hold-up behavior (illustrated in more detail below), the latter will be used to determine the farmers' expectations of the probability that the biorefinery will hold-up the contract. Based on the expectations, farmers will carry out a linear programming optimization that incorporates risk and decide the land allocation for each year. Then biorefinery will be informed how many acres have been allocated to switchgrass use. It will utilize this information and the expectation on the ethanol price to decide whether to hold-up a contract with the farmer or not. Finally, based on biorefinery's hold-up decision, biorefinery's and farmer's profit is realized and the available resources are updated for farmers. The model repeats this behavior for the simulation period (1 year = 1 time step).

3.2 The Contract

We consider a contract that is composed of a fixed per acre payment (A) and quantity/yield bonus ($\emptyset$). The contract is assumed to be static over the 10-year simulation period. While previous studies have solely used per ton or per acre contract compensation schemes (Larson et al, 2007; Zhou, 2013), we choose a per acre payment coupled with per ton payment contract. This is done several reasons, including: (1) a pure acre contract will transfer all the price and yield risk to biorefinery (Larson, English & Lamber, 2007); (2) a pure tonnage contract exposes farmers to high yield risk and since farmers typically will have a high level of perceived yield uncertainty during the first several years and will receive no income in the first year, adoption rates during that period will be reduced (Jensen et al., 2007; Alexander, 2012).

3.3 The Biorefinery's Decision Model

Define $q(h,t)$and $q(\tilde{h},t)$ as the expected utility biorefinery could get by holding up or not holding up the contract at stage 0. The values of $q(\tilde{h},t)$ and $q(h,t)$ are set according to:

$$q(\tilde{h},t) = Eprofit_{\tilde{h}} = (EP_{et} - c) * y_{swt} * rate - \sum_i (A + \emptyset Y_{iPIt})$$

$$q(h,t) = Eprofit_h - Dis_H = (EP_{et} - c) * y_{swt} * rate - \sum_i (A + \emptyset Y_{iPIt}) * \alpha - EDis_H$$

Here y_{swt} is the total amount of switchgrass procured, EP_{et} is the expected price of ethanol at year t stage 0, which also conforms to Bayesian learning process similar with that defined in the last section for farmers, *rate* is the conversion rate from switchgrass to ethanol and α is the percent payment if contract hold-up occurs. For simplicity, we just hold $\alpha = 0.8$ (a sensitivity analysis is done with this parameter later) during the simulation. $EDis_H$ is the expected potential future profit loss of the currently contracted land for contract hold up. As this county is defined as only one depot of a biorefinery that procures from 10 counties, the fixed cost of operating the biorefinery is not included. Instead, the fixed cost is converted to the per gallon cost included in c taken from Haque & Epplin (2010).

The utility of holding up a contract for the biorefinery will always be higher than not holding up contract if the expected future profit loss ($EDis_H$) is 0. However, due to various reasons such as reputation damage (Klein, 1996), $EDis_H$will most commonly deviate from 0 under most circumstances. It is difficult to quantify the whole effect of future loss because it’s difficult to forecast the potential loss of lands that are currently not in switchgrass use. As a substitute, it is reasonable to predict a coarse expectation of the profit loss due to loss of lands that are currently in switchgrass land use. Therefore, $EDis_H$ is quantified as:

$$EDis_H = \omega_1 * CA * \left((EP_e - c) * \bar{Y} * rate - (A + \emptyset\bar{Y})\right)$$

ω_1 is the loss coefficient in the range of [0, 1] and is constant through the simulation, CA is the current acres of switchgrass under contract and $\bar{Y}$ is the average yield of switchgrass of the year.

3.4 The Farmers' Decision Model

3.4.1 The Optimization Model

Farmers are assumed to be partially rational individuals who maximize their expected utilities at the beginning of each year based on their current knowledge of crop yield, price and risk. In addition, the farmers' decision problem is always inter-temporal and the analysis should consider for farmers' time preference.

While the Mean-Variance formation of farm risk programming is prevalent (Hazell, P. B., & Norton, R. D.,1986; Larson, English & Lamber, 2007), it is impractical here as the non-convex quadratic programming library in Java[3]and many other agent-based modelling toolkits. Thus a multi-period linear programming using MOTAD (Minimization of Total Absolute Deviation) model is used as defined by Hazell (1971)[4]:

$$\underset{x_1 \cdots x_n,\, d_1 \cdots d_k}{\boldsymbol{Max}} \sum_t \left(\frac{1}{1+\delta}\right)^{t-1} EU_t(\boldsymbol{X})$$

$$= \underset{x_1 \cdots x_n,\, d_1 \cdots d_k}{\boldsymbol{Max}} \sum_t \left(\frac{1}{1+\delta}\right)^{t-1} \left\{ \sum_{i=1}^{n} \sum_{w=1}^{s} EM_{iwt} X_{iwt} - \frac{\lambda}{2} \sum_{j=1}^{k} d_{kt}^{-} \right\} \quad (1)$$

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[3] We use Repast Simphony toolkit to build the agent based model, where Java is the language for the toolkit

[4] For a detailed description of MOTAD model, please refer to Hazell (1971).

$$s.t.\ \sum_{i=1}^{n}\sum_{w=i}^{s} a_{mist}\, X_{ist}$$

$$\leq b_{mit}\ (for\ all\ m - number\ of\ constraints;\ all\ t - periods)$$

$$\sum_{i=1}^{n}\sum_{w=1}^{s} (M_{kiw} - \bar{M}_{iw}) X_{ist} + d_{kt}^{-} \geq 0\ (for\ all\ k\ and\ t)$$

$$x_{iwt},\ d_{kt}^{-}\ \geq 0\ (for\ all\ i, k\ and\ t)$$

Here k denotes the number of historical periods we use to calculate historical gross margin deviations from the mean, s denotes the number of different soil types. In this application, the period's numbers are set to 5 (k = 1, 2, 3, 4 and 5). M_{ki} is the kth historical gross margin for crop i on the most commonly seen soil type in the region (productivity index equal to 10), d_{kt}^{-} is the absolute value of negative deviation of the kth gross margin occurrence from the mean gross margin.

The sum of d_{kt}^{-}, together with the second constraint, approximate the variance component of the utility function described in equation (1). For simplicity and tractability, it is also assumed here that farmer's subjective standard deviation of gross margin distribution calculated by the historical years doesn't change for traditional crops. The only thing that changes is the expected gross margin for each crop.

Finally, the realized gross margin for traditional crop i (that is, excluding switchgrass) in time t could be expressed as:

$$M_{iPIt} = (P_{it} - C_{vYield})\, Y_{iPIt} - C_{vAcre}$$

PI is the soil productivity index. Here we assume production fixed and variable costs could be decomposed into yield-related variable cost (C_{vYield}) and acre-related variable cost (C_{vAcre}). We also assume that crop yield changes linearly with regard to soil productivity index:

$$Y_{iPIt} = Y_{i10t}\left(1 + \alpha_i * \frac{PI - 10}{10}\right)$$

For traditional crops, we assume that Y_{i10t} are continuous, but for switchgrass, we assume that Y_{i10t} has only two states: high yield and low yield year. Notice that 10 is the dominant PI in the region. α_i is a coefficient representing the crop yield's sensitivity to PI. Therefore, if we know M_{i10t}, we could also know:

$$M_{iPIt} = (M_{i10t} + C_{vAcre})\left(1 + \alpha_i * \frac{PI - 10}{10}\right) - C_{vAcre}$$

3.4.2 The Learning Model

We assume that the gross margin of traditional crops (corn, soybean, wheat and alfalfa) for farmer i follows a normal distribution:

$$M_{i10} \sim N(\mu, \sigma^2) \text{ or } M_{i10} = \mu + \varepsilon_{it}$$

$$E(\varepsilon_{it}) = 0, \qquad V_{\varepsilon_{it}} = \sigma^2$$

σ^2 is assumed known to farmers based on the historical data used to calculate the historical deviations in the second constraint of the optimization problem, while μ is unknown and conform to a normal prior distribution $\mu \sim N(m, s^2)$ (Feder & O'Mara, 1982). At the end of the year, crops realize their true gross margin and farmers will form a posterior distribution of μ, utilizing the observed gross margin realizations. More realistically, if we assume that the observed gross margin from other farmers may subject to some error, φ, which comes from some farm-specific attributes or communication information distortion and that $\varphi \sim N\left(0, \sigma_\varphi^2\right)$, which is known to all farmers (Ma & Shi, 2011), then the posterior could be expressed as follows (y_s is the realized own gross margin, while $\bar{y}_o$ is the mean of observed others', and n is the number of observations from other farmers):

$$m' = \frac{y_s \frac{1}{\sigma^2} + \bar{y}_o \frac{n}{\sigma^2 + \sigma_\varphi^2} + \frac{m}{s^2}}{\frac{1}{s^2} + \frac{Me}{\sigma^2} + \frac{n}{\sigma^2 + \sigma_\varphi^2}}, \qquad (s^2)' = \frac{1}{\frac{1}{s^2} + \frac{Me}{\sigma^2} + \frac{n}{\sigma^2 + \sigma_\varphi^2}}$$

Here *Me* = 1 if the farmer grew the crop in the last year and equals to 0 if not.

As no official record of historical switchgrass yield and gross margin exists, this paper considers two switchgrass yield scenarios according to Kells & Swinton (2014), one high yield (4.7 tons/acre) and one low yield (4.1 tons/acre) which are randomly assigned to different simulation years. In addition, a farmers' expected gross margin is also determined by their expectation of whether the biorefinery will hold up the contract. Farmers' learning on switchgrass yield and contract hold up follows a Bayesian procedure for binomial variables. Let's denote the probability of the occurrence of high yield by τ. Set the prior of Bayesian method to $\tau \sim \text{beta}(\alpha, \beta)$. The posterior becomes:

$$\alpha^* = \alpha + s_t, \quad \beta^* = \beta + n_t - s_t$$

Here n_t denotes the number of observations and s_t the number of realizations of the defined occurrence. Then the new mean and variance of τ are updated as:

$$E(\tau) = \frac{\alpha^*}{\alpha^* + \beta^*}$$

$$Var(\tau) = \frac{\alpha^* * \beta^*}{(\alpha^* + \beta^*)^2(\alpha^* + \beta^* + 1)}$$

Define farmers expected biorefinery's contract hold-up probability is Epro. It could be expressed as:

$$Epro = \Delta_1 proHis + \Delta_2 proCal$$

$proHis$ is calculated from biorefinery hold-up history using Bayesian updating on binomial variables defined above. $proCal$ is the expected hold-up possibility in this year calculated by farmers following rational expectations. Δ_1 and Δ_2 are the weights assigned to each part ($\Delta_1 + \Delta_2 = 1$), representing farmers' perceived reliability of past experience and current calculation. $proCal$ could be calculated using $q(\tilde{h}, t)$ and $q(h, t)$ function defined in biorefinery's learning section as:

$$proCal = Pr\left(Eq(\tilde{h}, t) < \mathrm{E}q(h, t)\right)$$

$$= Pr\left(w_1 * CA * \left((P_e - c)\bar{Y} * rate - (A_1 + theta_1\bar{Y})\right) < CA(1 - \alpha)(A_1 + theta_1\bar{Y})\right)$$

$$= Pro\left(P_e < \frac{(1 - \alpha + w_1)(A_1 + theta_1\bar{Y})}{w_1 * \bar{Y} * rate} + c\right)$$

Given that the ethanol price follows a normal distribution and farmers will update their beliefs on the mean and variance of ethanol price, the value of $proCal$ is straightforward to calculate.

3.4.3 Additional Farmer Decision Constraints

In order to prevent the occurrence of unrealistic land allocation results, additional crop rational constraints (e.g. maximum proportion of a crop to total crop acres) are imposed on the farm optimization problem following Hazell & Norton (2006) and Anderson (2010). In their model, Kelley & Evans (2011) also include farmers' preference for trees and agricultural crops, which plays a similar role in the objective function with crop rational constraints.

The rational constraints imposed here include the maximum proportion of perennial grasses/annual crops that could be grown on the unused land and the proportion of each annual crop acres (corn, soybean and wheat) to the total annual crop acres. These constraints are chosen based on historical data and/or the calibration process. That is, the set of proportions are chosen so that the simulated crop acre patterns best fit for the observed historical pattern[5]. As perennial alfalfa grass is the major crop in this region historically, it is reasonable to argue that people have different preference for perennial crops and annual crops thus a method of setting limits conditional on the proportion of perennial grass acres is proposed. Table 1 below shows the calibrated crop rational constraint parameters combination.

Table 1 Crop Maximum Limit Imposed for Farmers

Crop Type	Parameters	Conditions	Value	Value Source	Limit
Perennial	Alfalfa/AL**	AtT*>=0.2	0.2	Calibration	Max
		AtT*<0.2	0.4	Calibration	Max
Annual	Corn/TAC***	N/A	0.44	Historical Data	Max
Annual	Soybean/TAC***	N/A	0.4	Historical Data	Max
Annual	Wheat/TAC***	N/A	0.3	Historical Data	Max
Total Annual	Annual/AL**	AtT*>=0.2	0.9	Calibration	Max
		AtT*<0.2	0.7	Calibration	Max

* AtT: proportion of alfalfa to total farmland
** TAC: Total Annual Cropland
*** AL: Available Cropland (Excluding those freed by perennial grass)

Furthermore, once the production period for perennial grass ends, these lands can be allocated to either annual and perennial crops. That is, the maximum proportion values for row 1 and row 5 become:

$$\frac{alfaOut + 0.2(or\ 0.4) * TAC}{alfaOut + TAC} \text{ and } \frac{alfaOut + 0.7(or\ 0.9) * TAC}{alfaOut + TAC}$$

3.4.4 Treatment of Switchgrass Adoption as Technology Diffusion

As a relatively new crop to be introduced in the area, switchgrass is analogous to a new technology, whose diffusion will empirically follow an "S" shape path such that the

[5] As switchgrass is historically not presented, it is not included in the calibration process. As a result, no switchgrass maximum proportion is included in the first several years. Switchgrass proportion is set manually based on current literatures after the tick when switchgrass is included in the model.

diffusion rate is slow at the beginning as only bold farmers will be willing to try, but then accelerates due to social learning and finally becomes stable (Berger, 2001; Alexander *et al.*, 2013).

Therefore, following the method used in Alexander *et al.* (2013), we first define each farmers' "willingness to consider" planting switchgrass. Farms who are willing to consider the adoption will include switchgrass in the optimization model and subsequently update their beliefs proposed above. Farmers who are not willing to consider switchgrass at the initialization phase will look at their neighbor's adoption decision. If the percentage of neighbors who have already adopted switchgrass exceeds the farmers' threshold, then the farmer becomes willing to consider planting switchgrass. This approach is also consistent with the use of "social" and "factual" farmers in Shastri et al. (2011). Farmers' thresholds are assigned randomly following a normal distribution.

4. Data, Initialization and Baseline validation

4.1 Study Area

The study area for this study is Alpena County, located at North Michigan Lower Peninsula (also the north tier of Michigan). The region was chosen as a biorefinery has recently located to this area. The major crops in this county are Alfalfa, Corn, Winter Wheat and Soybeans. According to NASS Census Statistics 2007[6], there are 573 farms with an average size of 150 acres/farm, covering 85,947 acres of land in total (with 46,450 acres harvested cropland, an approximate of 59577 acres planted cropland). The harvested area for Hay, Corn, Winter Wheat and Soybeans are 25,265 acres (with Alfalfa Hay for 17,858 acres, taking a share of 71%), 7810 acres, 3695 acres and 2802 acres,

[6] See http://www.nass.usda.gov/Data_and_Statistics/ for detailed information and census statistics

respectively[7]. The major crops mentioned account for up to 85% (it ranges from 87% ~ 92% during 2008~2012) of the total harvested cropland.

4.2 Farm endowment data and land ownership data

We use source data sources in this model. The first data source is USDA NASS agricultural census data 2007, which contains the average farm characteristics across Alpena County (e.g. farm size, crop composition, net farm income and the mapping from farm size to many other variables). We also utilized NASS survey data for the historical average crop price and yield of the county.

The second data source is 2008 farmland ownership data recorded in spatial explicit Common Land Units (CLU)[8] provided by the Farm Market Id Company.. There are a total of 4808 CLUs in Alpena County recorded by the company, among which 3481 CLUs have a farmer name (property right) in record, and the percentage of acres covered by CLUs with farmers' name reaches 62% of all the farmlands. This data source also includes 178 farmers' records (30% of the total farms in the county) on farmstead location and gross farm income for the previous year.

4.3 Simulation of Future Traditional Crop Price and Yields

Crop price is adopted from the USDA prediction for the next decade. The method to simulate future crop yield is adopted from Richardson, Klose & Gray (2000), which uses a method of simulating multivariate Empirical (MVE) probability distribution. The multivariate empirical probability distribution is drawn from historical years (1998~2012)

[7] This data only exist for census years, available every fifth year (e.g. 2002, 2007), the CDL data is quite inaccurate in Alfalfa Acres after comparing it with the census data 2007.

[8] According to USDA FSA, A Common Land Unit (CLU) is the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer in agricultural land associated with USDA farm programs. The CLUs in Alpena County cover almost all the farm lands in the area.

for the four traditional crops. During the simulation, the inter-temporal and intra-temporal relationships among the four crop yields are captured by inter and intra temporal matrix derived from historical data. Figure 2, Figure 3 and Figure 4 show the final real and simulated yields and prices.

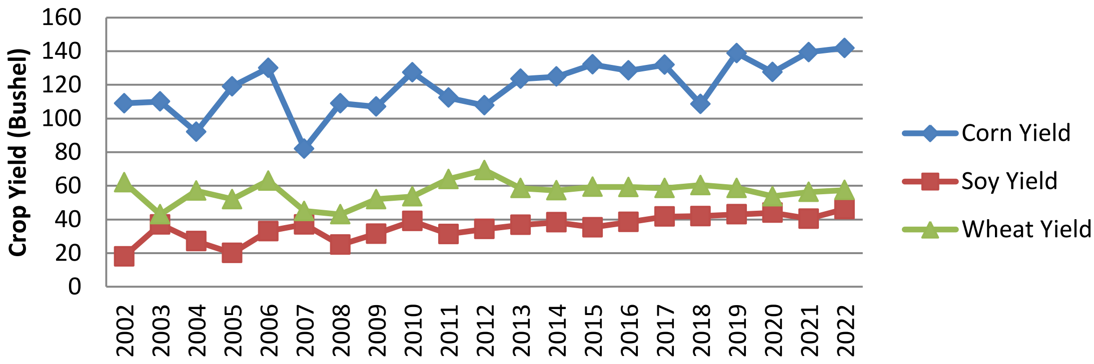


Figure 2 Real (2002~2012) and Simulated (2013~2022) Crop Yield (Bushel/Acre)

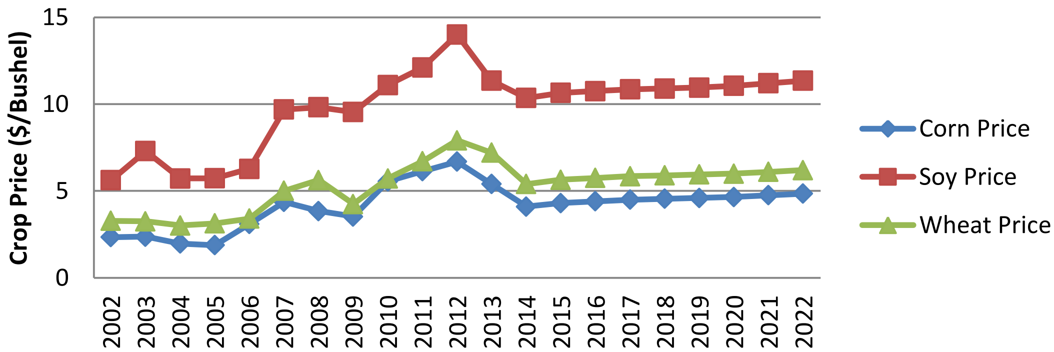


Figure 3 Real (2002~2012) and Simulated (2013~2022) Crop Price ($/Bushel)

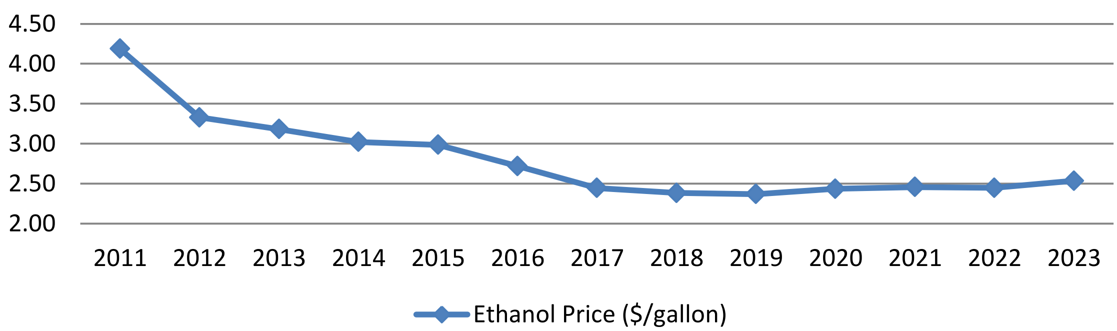


Figure 4 EIA Predicted Ethanol Price during Simulation Period

4.4 Model Initialization

The model is firstly initialized with 273 farmers with attributes for total farm acres, cropland acres (spatial explicit) and net cash income of the last year (used as cash to buy inputs) according to the CLU data. Census data is used later for those farmers who are not in the CLU dataset (additiona 300 farmers)[9]. According to the census data, the total farmland in the region is 59,577 acres. Table 1 summarizes some of the census and generated total farm characters.

Table 2 Total Farm Acres and Farm Cropland Acres

Farm Category by Size		Total Farm Acres		Farm Cropland Acres	
Farm Size (Acres)	**Farm Number**	**Census (Acres)**	**Generated (Acres)**	**Census (Acres)**	**Generated (Acres)**
1 ~ 9	16	82	86	21	21
10 ~ 49	195	5593	5648	2044	2041
50 ~ 69	43	2515	2511	1240	1244
70 ~ 99	96	7663	7667	3132	3130
100 ~ 139	63	7418	7415	3739	3736
140 ~ 179	44	6946	6931	2977	2980
180 ~ 219	28	5454	5453	2951	2952
220 ~ 259	10	2339	2328	1933	1935
260 ~ 499	41	14314	14301	10628	10629
500 ~ 999	29	20982	20968	18870	18870
1000 ~ 1999	8	12641	12639	12042	12039
Sum	**573**	**85947**	**85947**	**59577**	**59577**

Farm size is also chosen as the reference for farm income for those farmers not recorded by CLU data under the assumption that the larger the farm is, the higher income the income it generates. Generated net income distribution for 2007 is shown in Table 3.

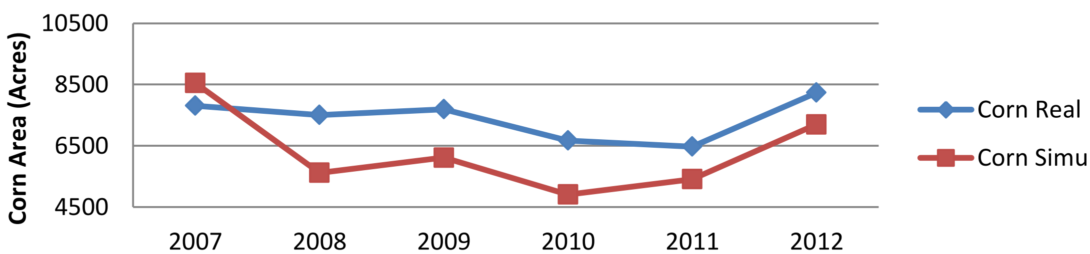
[9] Farmers not in CLU dataset occupy less than 40% of the total cropland.

Table 3 2007 Farm Income Distribution

Farm Size (Acres)	Generated Data Distribution		
	Min ($)	Mean ($)	Max ($)
1 ~ 9	3549	5532	7266
10 ~ 49	7611	9803	12109
50 ~ 69	12390	14593	16615
70 ~ 99	16711	19066	21221
100 ~ 139	21522	23399	25658
140 ~ 179	25807	28158	30279
180 ~ 219	30692	32797	34769
220 ~ 259	35142	37387	38936
260 ~ 499	39480	41580	43954
500 ~ 999	44346	46239	48142
1000 ~ 1999	44092	45776	47835
NASS census (No stratification)	3020		48550

4.5 Baseline Validation

As historical data from 2007 to 2012 regarding the total corn, soybeans and wheat planted acres[10] is available, the simulation is set to start from 2007 using the calibrated parameters and the simulation results are compared to the real data to see whether the simulation produces a similar crop acres pattern to the real world empirical data. Note that during this period, switchgrass is not included in the model as there is historically no switchgrass grown in this region.



[10] Alfalfa acres are not reported in the yearly statistic book, and CDL data that comes from satellite map has a low reliability of distinguishing between grass crops and non-crop pasture. Therefore, historical alfalfa acre is not included in the validation process, but the simulated amount will be included in the later ABM simulation experiment. Another reason for not including alfalfa acres into the validation is that alfalfa is a perennial grass thus we do not know how many acres have been already allocated to alfalfa and how many acres is about to turn out of alfalfa use in one year.

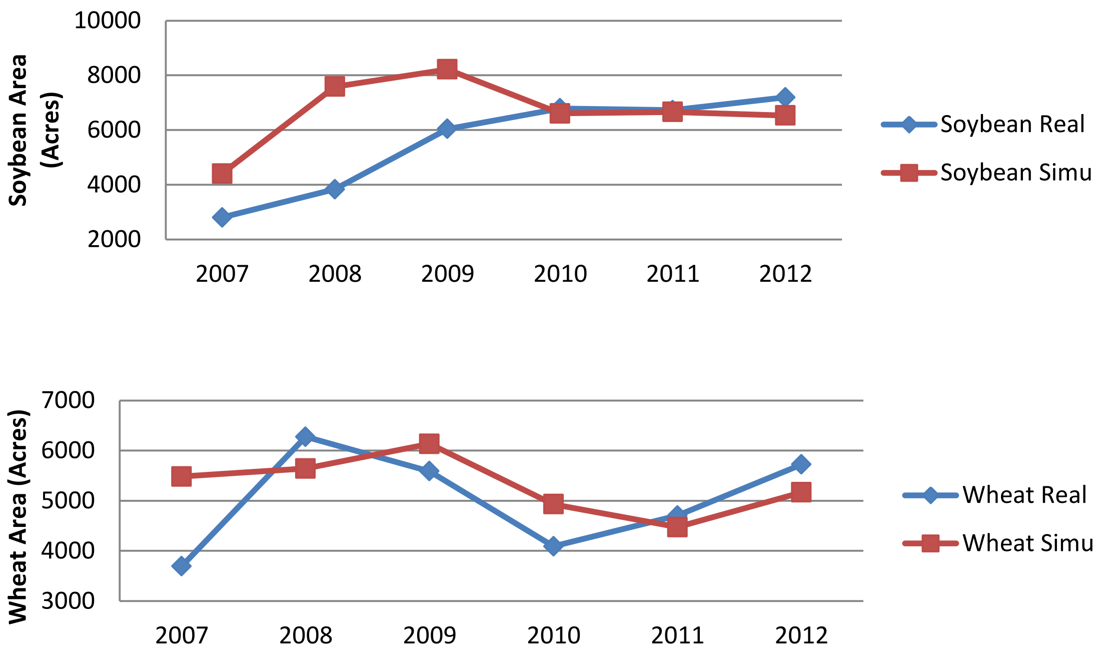


Figure 5 Annual Crops Real Data and Simulated Data 2007 to 2012

As Figure 5 illustrates, simulated land use results are similar historical data. Although the simulated acres during the first several years are somewhat lower or higher than the historical data for different crops, they start to converge to each other during the last few years. It is reasonable because at the beginning of the simulation, the crop acres for each crop are zero. For a perennial crop like alfalfa this is not true. However, after several years' of learning and planting in the simulation, the starting point effect gradually disappears. Since the overall trends and the last few years' simulated acres are similar with the historical data, the calibrated model is validated.

5. Simulation Results

The simulation is run such that during the simulation period 2007 to 2012, only traditional crops exist to give the model a time period to evolve. Then after the year of 2013, switchgrass is introduced and the simulation runs for a 10-year period.

5.1 Model Parameters

Before running the simulation, the parameters shown in the above sections are parameterized (see Table 4 below). From previous literature (Jensen et al., 2007, Alexander et al, 2012**)**, one of the most serious problems for setting up a biorefinery is that farmers are afraid that the refinery will not pay them on a timely basis due to monopsony power. We, therefore, set farmers' perceived probability of contractual hold-up by biorefineries ($E_0(p)$) according to a uniform distribution from 0.5 to 0.7. At the same time, as a new crop, the perceived yield by farmers at first is low, and therefore, a low range (0.3 to 0.5) is randomly assigned to each farmer on the possibility of high switchgrass yield in the following year. In addition, as the switchgrass upper limit is set arbitrarily, a sensitivity analysis regarding this parameter will be conducted at the end of this section. In addition, as farmers are often assumed to be not as rational as the biorefinery when calculate the biorefinery's hold-up possibility, farmers give more weight on past biorefinery hold-up fractions rather than their own calculation.

Table 4 Key Model Parameters

Whose	**Parameter**	**Meaning**	**Value**
Farmer	sw	Switchgrass upper limit	0.3
	$E_0(p)$	Initial hold-up perceived probability	U(0.5, 0.7)
	$E_0(p_{YH})$	Initial perceived probability of high yield	U(0.3, 0.5)
	Y_H	High yield of switchgrass	4.7
	Y_L	Low yield of switchgrass	4.1
	Δ_1	Weight on past experience	0.7
	Δ_2	Weight on calculated probability	0.3
Refinery	A	Fixed payment per acre	100, 125,150,175,200
	$\emptyset$	Payment per ton	50
	α	Percent paid if hold up contract	0.8
	w1	Expected future loss coefficient is holding up	0.2

As illustrated by Zhou (2013), the contract price for switchgrass in Tennessee needs to go up to $475/acre under acreage contract or $77/ton under tonnage contract. In contrast, we choose a fixed payment per acre plus payment per ton contract, which is the most preferable contract by Michigan Farmers[11]. It is also the current contract form provided by the University of Tennessee Biofuel Initiative. However, when choosing the value for per acre fixed payment and per ton payment, we do take the payment suggested by Zhou (2013) into consideration given the average yield of around 4.5 tons/acre. By choosing a different per acre payment, it is possible to get a feasible estimation of the payment schedule under which both the biorefinery and farmers would be profitable facing biorefinery's possible hold up potential. For the expected future loss coefficient if the biorefinery holds up the contract, the value is set to be low as it is the only outlet for farmers to sell their switchgrass.

5.2 Results and Discussion

5.2.1 Comparison of Contracts with Different Per Acre Payment

For biorefineries, there is a trade-off. On the one hand, they want more land dedicated into switchgrass such that they could procure more switchgrass every year; on the other hand, if they want more switchgrass, they have to pay more to farmers, which might result in unprofitable results even though the amount of land devoted to switchgrass is high. Therefore, the biorefinery should balance these two factors to determine the price level. Here we hold the per-ton payment constant ($50/ton) and test different per acre payments to compare potential different contract configuration results. In Table 5 below, we provide the end of simulation period crop acres and biorefinery net present values to compare the results of different contract configurations.

[11] We Conducted a focus group talking during May 2013 and got this results, which is not published yet

Table 5 Comparison of Different Contract Configurations' Results

Per Acre Payment ($)	End Simulation Bio-NPV (million $)	End of Simulation Crop Acres				
		Switchgrass (Acres)	Corn (Acres)	Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
100	-0.024	1941	8202	9185	5971	25682
125	0.725	11341	8760	10489	6905	19981
150	1.605	22992	8728	10214	6484	9638
175	2.062	32577	7600	8961	5674	3307
200	0.563	38343	7018	7855	4615	314

The results are the average values for each variable at each tick for 10 simulation runs. We do this mainly to mitigate the random effect induced by the random assignment of risk aversion coefficient to farmers and random assignment of switchgrass yield to different simulation years.

According to the table above, the biorefinery's net present value (NPV) reaches the highest point ($2.062 million) when the per-acre payment is $175/acre plus the per ton payment of $50/ton. At this payment level, 32,577 acres of switchgrass are also grown at the end of the simulation. When payment is below this amount, although the profit is high for each purchased ton of switchgrass from biorefinery's point of view, there will be fewer farmers growing switchgrass as they might think it not profitable. Therefore, we will use this contract ($175/acre + $50/ton) in the latter analysis. Compared to the $472/acre payment calculated by Zhou (2013) and $250/acre + $40/ton that is currently used in the University of Tennessee Biofuel Initiative, the amount we got is lower assuming an average yield of 4.5 tons/acre ($375/acre). That could be attributed to the lower yield level of traditional crops and in Michigan compared with that in Tennessee, which overweigh the effect of perceived hold-up probability.

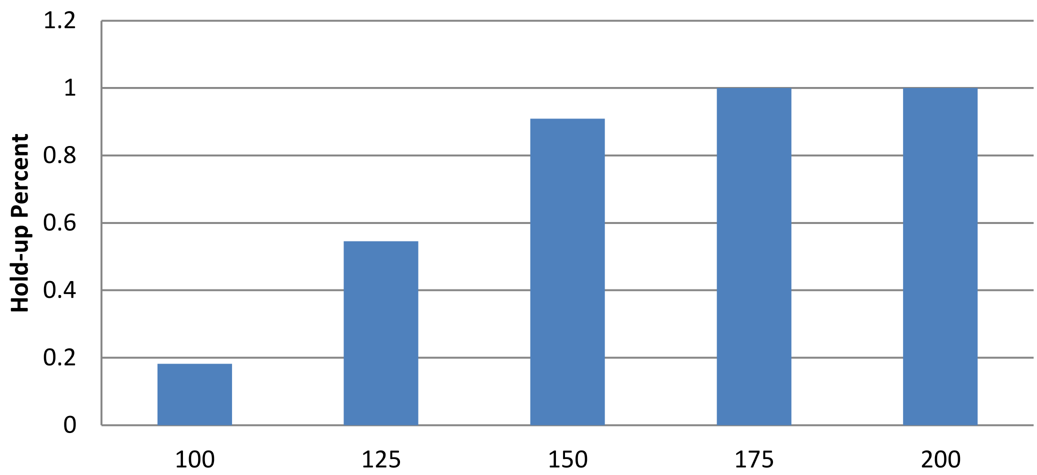


Figure 6 Percentage of Contract Hold-up Occurrence to Total Simulated Years

The percentage of contract hold-up occurrence to the total simulated years increases as the per acre payment increases while holding the per ton payment constant. Especially for per acre payments of $175/ton and $200/ton, the refinery will hold up the contract at each simulation year. This is because $175/acre and $200/acre payment is so high such that even though farmers are aware that the biorefinery will hold up contract for sure, they will still be profitable to grow switchgrass. In this case, the “real” contract price becomes the hold-up contract price, given the assumption that the percent payment if the contract is held up stays constant. The difference between the “nominal” and “real” contract price could be regarded as farmers’ risk premium of being held up. But as shown above, the $175/acre plus $50/ton contract is most profitable for biorefinery seeing from the net present value, we choose this contract to conduct additional analysis below.

5.2.2 Contract with $175 Per-Acre Plus $50 Per-Ton Payment

The two figures below show (1) the traditional crops and switchgrass grown, (2) switchgrass grower number and (3) biorefinery’s realized capacity at each simulation year for under the contract with $175 per acre plus $50 per ton payment.

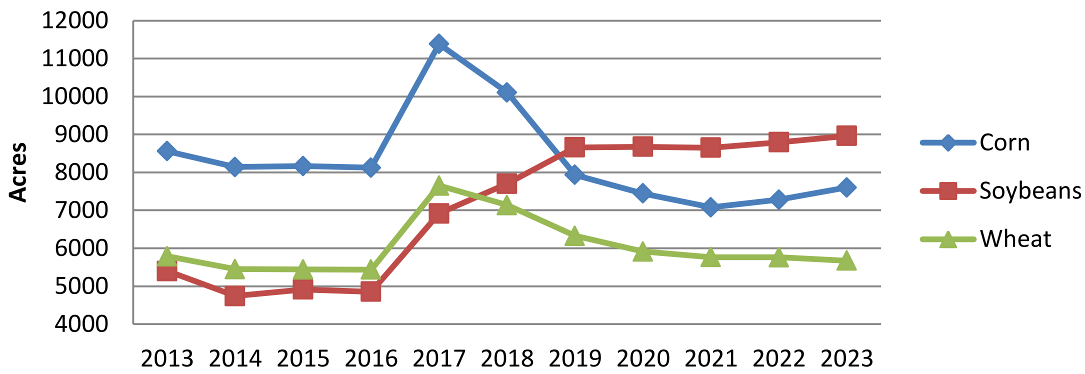


Figure 7 Corn, Soybeans and Wheat Acre Changes during Simulation Run

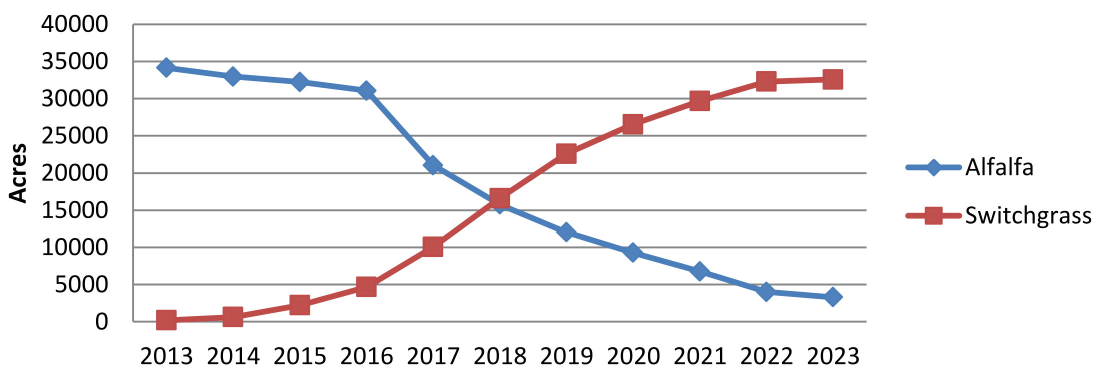


Figure 8 Alfalfa and Switchgrass Acre Changes during Simulation Run

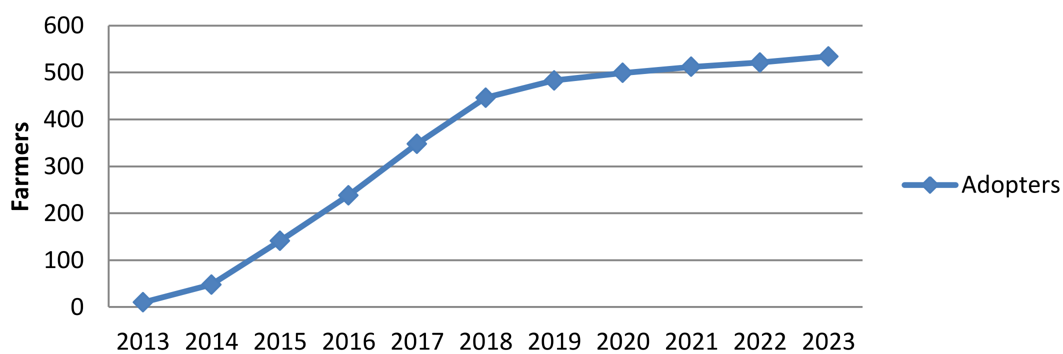


Figure 9 Switchgrass Adopters in the Simulation

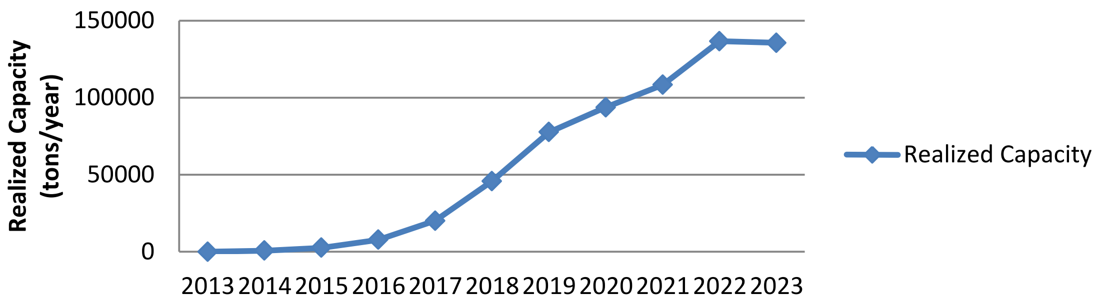


Figure 10 Realized Switchgrass Capacity in each Simulation Year

The results show that the total adopter number and switchgrass acres follow S-shape curves, which is consistent with many diffusion studies. The traditional crop that is mostly affected by switchgrass production is alfalfa. This is because after 2012, the gross margin for alfalfa follows a decreasing trend[12] while that for annual crops is increasing due to the increasing yield and mildly increasing crop price. The results show that if switchgrass is to be introduced in this county, the competition between land use in switchgrass and food crops may not be high. As the agronomic condition here is similar to those in other North Michigan Counties, the results here might also be generalized to the range of North Michigan.

Though under this configuration, the payment is high if not holding up the contract and thus biorefinery is expected to have a high probability of contract hold up, farmers could still be profitable under the assumption that the percent payment if contract is held up is held constant at 0.8 during the simulation. With a lower payment that is equivalent to the payment if contract is not held up, biorefinery has a lower propensity to hold up contract, but since it is shown in literatures (Hipple & Duffy, 2002; Jensen et al, 2017) that farmers' initial perceived contract hold-up possibility is high, farmers will

[12] The data is simulated data, the trend of which follows the historical alfalfa yield trend – a decreasing tread

need to have some time to adjust their perceived contract hold-up probability downward. Therefore, less land will be converted to switchgrass during at the early stage.

5.2.3 Sensitivity Analysis

Switchgrass Upper Limit

The sensitivity analysis is conducted for switchgrass upper limit (the max percent that switchgrass could occupy the unused land) as it is imposed arbitrarily in this model and are not subject to any calibration process as no switchgrass is grown in the county historically. The sensitivity analysis results for the limit that take the value of 0.1, 0.3, 0.5 and 1.0 when holding the $175/acre + $50/ton contract are presented in Table 6:

Table 6 Sensitivity Analysis for Switchgrass Limit under the Specified Contract

Switchgrass Limit (Percent)	End Simulation Bio-NPV (million $)	End of Simulation Crop Acres				
		Switchgrass (Acres)	Corn (Acres)	Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
0.1	0.856	25265	8374	9851	6274	8007
0.3	**2.062**	**32577**	**7600**	**8961**	**5674**	**3307**
0.5	1.900	30512	8283	9728	6129	3520
1	1.900	29766	8441	9965	6299	3694

From Table 6, it is shown that when switchgrass upper limit equals to 0.3, 0.5 and 0.9, the results (net present value and switchgrass acres) are similar. But for an upper limit of 0.1, the end of simulation switchgrass acres and biorefinery's end of simulation net present value are much smaller. This is because under the current payment scheme, switchgrass gross margin and annual crop gross margin stays with a relative stable ratio (remember that annual crop is more sensitive to soil productivity index. Therefore, they are more profitable in good soils). This makes farmers implicitly limit their switchgrass to around 0.3 percent of the new cropland, even though we explicitly loosen the constraint to higher than 0.3.

Percent Payment if Holding Up the Contract

In this part, we hold the contract price ($175/acre + $50/ton) and switchgrass upper limit (0.3), varying the level of percent payment is contract is held up from 0.6 to 0.9 and study the sensitivity of model result to this parameter. Table 7 shows the result

Table 7 Sensitivity Analysis for Percent Payment if Contract is Held Up

Percent Payment	End Simulation Bio-NPV (million $)	End of Simulation Crop Acres				
		Switchgrass (Acres)	Corn (Acres)	Soybeans (Acres)	Wheat (Acres)	Alfalfa (Acres)
0.6	0.642	5117	8992	9786	6415	25006
0.8	**2.062**	**32577**	**7600**	**8961**	**5674**	**3307**
0.9	-3.376	39967	6230	7211	4431	232

The sensitivity analysis shows that the result is quite sensitive to the assumption of percent payment is contract is held up. It is reasonable as the less paid by biorefinery, the less expected gross margin is for farmers to grow switchgrass. Thus, a future work should try to make the biorefinery choose percent payment at each time period, without setting is manually. But we believe the current approach does shed light upon the interaction effects between biorefinery and farmers.

6. Conclusions

In this paper, we studied farmers' switchgrass adoption decisions over time within the context of a single biorefinery using a contract to procure switchgrass from farmers and with the potential for contractual hold up by the refinery. The results show that the introduction of switchgrass has the potential to alter the county's crop patterns to a large extent. Under proper contract compensation mechanisms, both farmers and biorefinery could be profitable. We found that a proper contract payment could be $175/acre plus $50/ton payment.

It is also shown that alfalfa, but not annual crops will be the mostly affected crop (replaced) by the introduction of switchgrass in the region of North Michigan. This shows that the introduction of switchgrass might have more obvious influence on livestock enterprise but not on annual crop enterprise. As we don’t include livestock in the model because it is a minor business in this county region, we couldn’t generalize the results to southern part of Michigan where livestock rising is a considerable part of the economy there.

One of the drawbacks of the paper is that we hold the percent payment if contract is held up constant. In reality, biorefinery may adjust this number up and down based on their expected profit. But Modelling the optimal choice of payment percentage will future complicate the model and the lower the payment percent is, the higher future loss might be, though they might not change in a proportional way. So we believe that the current framework does could capture a great portion of contract hold-up essence. The consideration of that issue is left for future researches. Another interesting future research point is, when there are multiple outlets for switchgrass, will the procures tend to hold-up contract as frequently as under the single procure case and will the switchgrass acres increases compared to the current scenario.

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