Production and Spatial Distribution of Switchgrass and Miscanthus in the United States under Uncertainty and Sunk Cost

Jerome Dumortier, Nathan Kauffman, and Dermot J. Hayes

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The views expressed are those of the authors and do not necessarily reflect the positions of the Federal Reserve Bank of Kansas City or the Federal Reserve System.

Abstract

The U.S. cellulosic biofuel mandate has not been enforced in recent years. Uncertainty surrounding the enforcement of the mandate in addition to high production and harvest cost have contributed to a delay in the widespread planting of bioenergy crops such as switchgrass and miscanthus. Previous literature has shown that under uncertainty and sunk cost, an investment threshold is further increased due to the value associated from holding the investment option. In this paper, we extend the previous literature by applying a real option switching model to bioenergy crop production. First, we calculate the county-level break-even price which triggers a switching away from traditional field crops (corn, soybeans, and wheat) to bioenergy crops under various scenarios differing by commodity prices, production cost and biomass price expectations. We show that the resulting break-even prices at the county-level can be substantially higher than previously estimated due to the inclusion of the option value. In a second step, we identify counties that are most likely to grow switchgrass or miscanthus by simulating a stochastic biomass price over time. Our results highlight two issues: First, switchgrass or miscanthus are not grown in the Midwest under any scenario. Under low agricultural residue removal rates, biomass crops are mostly grown in the Southeast. Second, under the assumption of a high removal rates, bioenergy crops are not grown anywhere in the U.S. since the cellulosic biofuel mandate can be covered by agricultural residues.

1 Introduction

The Renewable Fuel Standard (RFS) mandates the production of 60 billion liters (L) of cellulosic ethanol by 2022 (EISA, 2007). Over the past years, the U.S. Environmental Protection Agency (EPA) has waived the cellulosic biofuel mandate because of insufficient capacity (Meyer and Thompson, 2012). Reasons for the absence of cellulosic ethanol production are largely attributed to high production and harvest costs associated with agricultural residues and bioenergy crops such as switchgrass and miscanthus (Babcock et al., 2011; Khanna et al., 2011). In addition, there are several characteristics to bioenergy crop production that add to the low adoption rate. First, prices and economic returns of field crops (e.g., corn, soybean, wheat) and bioenergy crops are stochastic and unknown at the time of planting. This uncertainty together with sunk cost from changing practices creates a barrier for farmers to adopt bioenergy crops because they hold a valuable option to wait and gather more information (Dixit and Pindyck, 1994). This characteristic has been shown to warrant the use of real option models to assess the switching decision from field crops to bioenergy crops (Song et al., 2011). Under a real option framework, the investment threshold increases compared to

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the traditional net present value analysis which results in a lower adoption rate. Second, switchgrass and miscanthus do not realize their full yield potential in the first year, i.e., there is a multi-year establishment period with little to no revenue from bioenergy crops (Jain et al., 2010). During this period, the farmer would have earned revenue if she/he had stayed in field crop production. Most analysis annualize the opportunity cost in the establishment period over the lifetime of the crop which is usually assumed to be 10 to 15 years depending on the bioenergy crop (Perrin et al., 2008; Khanna et al., 2008; Brechbill et al., 2011; Haque et al., 2014; Dumortier, 2016). In addition, the same annualization is done for the first year establishment costs. In reality, we have to recognize that the timing of the outlays at the beginning of the period may influence the farmer's decision to grow bioenergy crops. Third, the standard real option switching framework models an investor who switches between projects that are each governed by a different stochastic process (Alvarez and Stenbacka, 2004; Décamps et al., 2006). This may not be true for biomass production resulting from either agricultural residues or bioenergy crops. Assuming that the return uncertainty in bioenergy crop production is associated with the biomass price, then the farmer could already be exposed to the stochastic biomass price if agricultural residues are collected. That is, the return from bioenergy crops would have to overcome the return from field crops, the return from agricultural residues, the establishment cost, and the option value. And fourth, farmers switching to bioenergy crops reduce the supply of field crops and thus, increase the switching threshold for the remaining farmers as a consequence of increasing prices.

In this paper, we use a real options framework to model the switching decisions of farmers from field crops to bioenergy crops. The model is set in a perfectly competitive market for agriculture with price and return uncertainty as well as sunk costs associated with switching between activities. Real option analysis has been used in previous land-use literature to analyze the switching decision to peach production (Price and Wetzstein, 1999), forests (Schatzki, 2003; Dumortier, 2013), Conservation Reserve Program (Isik and Yang, 2004), or switchgrass (Song et al., 2011). We extend the previous literature in two ways by (1) calculating and including the option value in the break-even price of bioenergy crops and (2) simulating the land allocation in the U.S. at the county level.

In a first step, we set up a real option framework to examine the decision of a farmer to switch from field crops to bioenergy crops under uncertainty and sunk cost. The farmer can be in either of two regimes: agriculture or bioenergy. While in agriculture, the farmer may or may not collect agricultural residues which influences the decision to switch to bioenergy crops. Agricultural returns and the biomass price are the two sources of uncertainty in our model. Our approach follows closely Dumortier (2013) with the net return process for agricultural production following a mean reversion process (MRP). Economic theory requires net returns to approach a long-run equilibrium and cannot increase indefinitely because this would violate the zero-economic profit condition in the long-run and thus, a mean reverting process is more likely for agriculture. Odening et al. (2007) as well as Schatzki (2003) argue that a mean reverting process is more consistent with economic theory in the presence of competitive markets independent of whether the price process passes a unit-root test or not. For the biomass price, we differentiate between a mean reverting process and a Geometric Brownian Motion (GBM) process. We do this because an exponential increase in the biomass price is possible in the short- and medium-run. In the long-run, we would expect a mean reverting process as well. Tsekrekos (2010) notes that a mean reverting process produces two opposing effects: (1) It reduces the long-run variances and thus makes investment more likely and (2) it also eliminates extreme values which makes investment less likely. Song et al. (2011) demonstrated that the amount of switchgrass production is also dependent whether a one-way (i.e., irreversible) switching model is used as opposed to a two-way model. If the biomass price falls below a certain threshold, farmers might find it optimal to switch back to field crop production.

Our empirical model is at the county level and focuses on three major field crops (i.e., corn, soybeans, and wheat) and two bioenergy crops (i.e., switchgrass and miscanthus). We concentrate on those three field crops as potential acreage for bioenergy crops because they represented almost 67.5% of total field crop area in the U.S. in 2015. In addition to low and high production cost estimates, we have switchgrass and miscanthus yield data for each county. We will run scenarios that differ in terms of commodity prices, bioenergy crop, production cost, agricultural residues, irreversibility, and biomass price evolution. Running a multitude of scenarios allows us to put upper and lower bounds on land-use allocation and serves as a sensitivity analysis for our assessment.

Our results indicate that the probability of cellulosic ethanol production form bioenergy crops under the current mandate is low in large parts in the United States especially the Midwest. Areas most likely switching to bioenergy crop production are in the Southeast. In addition to the high production cost, the presence of agricultural residues, return uncertainty and sunk cost contribute to a high threshold for farmers to engage in bioenergy crop production. Given the existing mandates and the policy discussion of potential future use of bioenergy crops, it is important to understand the barriers of biomass production. This can inform policy makers on what influences the adoption rate and where policies might need to be implemented to increase adoption of bioenergy crops.

2 Model

At time t, the representative landowner in county i can be in either of two regimes k: agriculture (A) or bioenergy (G). Returns in both regimes are stochastic and the problem of the landowner is to determine the optimal regime given the current state and the expected evolution of the stochastic variables. While in agriculture, the farmer also has to decide how much of the available land to allocate to crop j. The following subsections set up the model for agricultural and bioenergy crop returns, the real option analysis, and the simulation procedure under a competitive market. Our setup is similar to regime switching model found in Nøstbakken (2006), Song et al. (2011), or Dumortier (2013).

2.1 Agricultural Returns

All farmers in regime A face a constant elasticity demand function that can be written similar to Dumortier (2016):

$$Q_j = \sum_{m=1}^{M} \left[\upsilon_{jm} \prod_{j=1}^{J} p_j^{\theta_{jm}} \right] + e \tag{1}$$

where Q_j is the quantity demanded for field crop j given prices p_j. For each crop, there are three demand sectors m: consumer/food, feed, and export. The demand parameters υ_{jm} and θ_{jm} represent the constants and the cross/own-price elasticities, respectively. There is a constant demand for corn ethanol that is represented by e. Given prices p_j, the return from agriculture in county i is written as

$$\pi_i^A(a_{ij}) = \max_{a_{ij}} \sum_{j=1}^{J} \left(p_j y_{ij} - \alpha_{ij} \right) a_{ij} - \sum_{j=1}^{J} \frac{\beta_{ij}}{2} a_{ij}^2 \tag{2}$$

where y_{ij} and a_{ij} denote the county specific crop yield and area, respectively. The county and crop specific cost parameters are α_{ij} and β_{ij}. Note that the return from agriculture exhibits increasing marginal cost. This captures either the decrease of yields because marginal land with lower average yields is brought into production or the requirement of more fertilizer use for the same reason (Mallory et al., 2011). In addition, increasing marginal cost guarantee a solution during the numerical maximization procedure. In addition to non-negativity constraints, equation (2) is subject to a binding land constraint because there is a maximum area available for crop production in each county. Setting up the Lagrangian and deriving the first-order conditions is straightforward.

Agriculture is a perfectly competitive market and hence, all agents are price takers and do not take the effect of their acreage decision on output prices into account. In aggregate however, the dynamics of the agricultural returns in each county are endogenous to the model. If farmers decide to move from agriculture to bioenergy, less cropland is available for production, thus increasing returns for the remaining farmers and vice versa. Let N_t be the set of farmers that is engaged in agricultural production at time t. Given N_t, the first order conditions associated with equation (2), the land and non-negativity constraints as well as the demand function in equation (1), we can fully characterize the profit maximizing agricultural production in county i. Denote the profit maximizing per hectare return for county i as $R_i(N_t)$. That is, given the set of counties that are producing field crops, we can calculate the per-hectare return $R_i(N_t)$ which represents the value function for equation (2).

We introduce uncertainty to agriculture in a multiplicative way, i.e., a random disturbance affecting the per-hectare return $R_i(N_t)$. Modelling a separate stochastic process for prices and costs would increase the state space and thus, the computational time, exponentially. Denote the disturbance term for agriculture with ϵ_t which summarizes the uncertainty associated with yield, price, and cost fluctuations. Let ϵ_t follow a mean-reverting process because of the perfectly competitive nature associated with agricultural production:

$$d\epsilon_t = \eta(\bar{\epsilon} - \epsilon_t)dt + \sigma_\epsilon \epsilon_t dz_\epsilon \tag{3}$$

with $\bar{\epsilon} = 1$, η as the mean-reversion speed, σ_ϵ as the standard deviation parameter, and dz_ϵ as the increment of a Wiener process. Let the stochastic per hectare county return from agriculture be $B_{it} = R_i(N_t)\epsilon_t$, i.e., the disturbance influences the net return from agriculture in a multiplicative way. We assume that long-run mean return for county i, i.e., $\bar{B}_i$, is determined by the set of landowners in agricultural production N_t. The long-run mean return changes over time depending on the set of farmers engaged in agricultural production. Using Itô's Lemma and given equation (3), it can be shown that the per-hectare return from agriculture in county i can be written as

$$dB_{it} = \eta_B(\bar{B}_{it} - B_{it})dt + \sigma_B B_{it} dz_B \tag{4}$$

The parameter η_B is the mean reversion speed to the long-run equilibrium return in agriculture which is denoted $\bar{B}_{it}$. The variance in agricultural production is denoted σ_B and dz_B is the increment of a Wiener process. The uncertainty in the net returns for agriculture is the same for all spatial units. We justify this assumption by the fact that all landowners face the same output prices, which are correlated with yield disturbances. Idiosyncratic shocks in the competitive equilibrium framework are possible as shown by Zhao (2003) but would increase the computational time significantly by requiring simulation of a covariance matrix for all counties at each time step.

2.2 Bioenergy Returns

We differentiate between dedicated bioenergy crops b and agricultural residues h as a source for biomass. Let P_t be the price per dry-ton of biomass. The profit from either b or h can be written as $\pi_i^q(P_t) = (P_t - c_i^q)\gamma_i^q$ where $q \in \{b, h\}$, c_i^q is the cost per ton (\$ t^{-1}), and γ_i^q is the yield (t ha^{-1}). Implicit in this formulation are several assumptions. First, the cost per ton is held constant over the projection period. Second, due to the linearity in returns, once a landowner decides to abandon agricultural production, all the land will be put in bioenergy crop production. A commonly used feature in real option land-use change models is that return per hectare is modeled instead of the price (Schatzki, 2003; Isik and Yang, 2004; Song et al., 2011). In the case of bioenergy crop production, the return could be negative initially if $P_t < c_i^q$ and thus, it is more realistic to model price instead of returns. This has the disadvantage that the partial differential equations that need to be solved in the subsequent real option framework are not homogenous of degree 1 anymore, i.e., the transformation into a simpler ordinary differential equation is not possible.

Unlike for agricultural returns which are assumed to follow a mean-reverting process, the biomass price will be modeled as a stochastic variables that evolves either according to a Geometric Brownian Motion, i.e.,

$$dP_t = \mu_P P_t dt + \sigma_P P_t dz_P \tag{5}$$

or a mean-reverting process, i.e.,

$$dP_t = \eta_P(\bar{P} - P_t)dt + \sigma_P P_t dz_P \tag{6}$$

The drift term and the variance of the biomass price are μ_P and σ_P, respectively. We assume that the correlation between the processes is $E(dz_A dz_P) = 0$, i.e., the shocks influencing the biomass price are independent of the disturbances influencing the agricultural net return. We uphold this assumption because it reduces the computational time. We will provide a qualitative sensitivity analysis about this assumption in the discussion section of this paper.

2.3 Real Option Analysis

Given the stochastic return processes for agriculture in equation (4) and the biomass price in either equation (5) or (6), the farmer has to decide which regime is optimal given the current state variables B_t and P_t as well as the expected evolution of the those variables. The farmer has the possibility to switch from a regime which yields one stochastic return (e.g., agricultural returns) to a new regime which results in a flow of profits with different stochastic properties (e.g., biomass price) (Alvarez and Stenbacka, 2004; Décamps et al., 2006). Given the initial values of the state variables at $t = 0$ as B_0 and P_0, the maximization problem is written as (Brekke and Øksendal, 1994; Vath and Pham, 2007):

$$J(B_t, P_t) = \sup_{\tau} E\left[\int_0^{\infty} e^{-rt} f^k(B_t, P_t)dt - \sum_{n=1}^{\infty} e^{-r\tau_n} I^{k_{n-1},k_n}\right] \tag{7}$$

where r represents the discount rate, $f^k(B_t, P_t)$ is the return from being in regime k given the state variables B_t and P_t, and C^{k_{n-1},k_n} represents the switching cost going from one regime to the other, i.e., (A, G) or (G, A). The decision variable is τ_n which represents the switching times between regimes. The switching time τ_n cannot be found explicitly but is determined by the impulses B_t and P_t received by the land owner.

In the case of one-way switching, i.e., the farmer cannot switch back to agriculture once the decision was made to invest in bioenergy crop production, the equation simplifies to (Tegene et al., 1999; Behan et al., 2006):

$$J(B_t, P_t) = \sup_{\tau} E\left[\int_0^{\tau} e^{-rt} f^A(P_t)dt + \int_{\tau}^{\infty} e^{-rt} f^G(B_t, P_t)dt - e^{-r\tau} I^{A,G}\right] \tag{8}$$

and $I^{A,G}$ is the cost of switching from agricultural production to bioenergy crops.

In the following section, we drop the county subscript i for notational convenience. At time t, the landowner in agriculture chooses between between staying in agriculture or switching to bioenergy crops (Song et al., 2011; Schatzki, 2003), i.e., solves the dynamic stochastic programming problem:

$$V^A(B_t, P_t) = \max\left\{B_t + (P_t - c^r)\gamma^r + e^{-rdt}E\left[V^A(B_{t+dt}, P_{t+dt}), V^G(B_t, P_t) - I^{A,G}\right]\right\} \tag{9}$$

where $V^A(\cdot)$ denotes the value from being in agriculture. Equation (9) assumes that the farmer who is currently in agriculture is also collecting agricultural residues. Hence, the instantaneous return from field crops, i.e., B_t is complemented by the returns from agricultural residues, i.e., $(P_t - c^r)\gamma^r$. If the farmer is not collecting residues, then $(P_t - c^r)\gamma^r = 0$. The expression $V^A(B_{t+dt}, P_{t+dt})$ represents the value from staying in agriculture and $V^G(P_t) - I^{A,G}$ is the value from switching to biomass crops. The expression is similar for the value while being in bioenergy crop production:

$$V^G(B_t, P_t) = \max\left\{(P_t - c^h)\gamma^h + e^{-rdt}E\left[V^G(B_{t+dt}, P_{t+dt}), V^A(B_t, P_t) - I^{G,A}\right]\right\} \tag{10}$$

Let $\pi^A = B_t + (P_t - c^r)\gamma^r$ and $\pi^G = (P_t - c^h)\gamma^h$, then Brekke and Øksendal (1994) show that the Hamilton-Jacobi-Bellman for equation (9) and (10) results in:

$$rV^k(B_t, P_t) \geq \pi^k + \eta_B(\bar{B} - B_t)V^k_B + \mu_P P_t V^k_P + \frac{1}{2}\sigma^2_B V^k_{BB} + \frac{1}{2}\sigma^2_P V^k_{PP} \tag{11}$$

where V^k represents the value function from being either in agriculture or bioenergy. This is the general case for a farmer that collects agricultural residues and receives $(P_t - c^r)\gamma^r$ in return. For a farmer not collection agricultural residues, we have $(P_t - c^r)\gamma^r = 0$. In addition, the following conditions must hold:

$$\begin{aligned} V^A(B_t, P_t) &\geq V^G(B_t, P_t) - I^{A,G} \\ V^G(B_t, P_t) &\geq V^A(B_t, P_t) - I^{G,A} \end{aligned} \tag{12}$$

In addition to the conditions in equations (11) and (12), the standard value matching and smooth pasting conditions apply. Assuming the optimal boundary to enter bioenergy production to be $P^\star(B_t)$, then the necessary value matching conditions is $V^A(B_t, P^\star(B_t)) = V^G(B_t, P^\star(B_t)) - I^{A,G}$ (Balikcioglu et al., 2011). The corresponding value matching condition to exit bioenergy production for the optimal boundary of $P^*(B_t)$ is $V^G(B_t, P^*(B_t)) = V^A(B_t, P^*(B_t)) - I^{G,A}$. The smooth-pasting conditions are when switching from agriculture to bioenergy are $V^A_B(B_t, P^\star(B_t)) = V^G_B(B_t, P^\star(B_t))$ and $V^G_P B_t, P^\star(B_t) = V^A_P(B_t, P^\star(B_t))$. Similarly, the smooth-pasting conditions are when switching from agriculture to bioenergy are $V^A_B(B_t, P^*(B_t)) = V^G_B(B_t, P^*(B_t))$ and $V^G_P B_t, P^*(B_t) = V^A_P(B_t, P^*(B_t))$.

The landowner determines whether to switch or not by either equation (11) or (12) holding with equality. Both equations holding with equality defines the border of the switching region. If equation (11) holds with equality, then the landowner stays in agriculture because the rate of return is equal to the current return and the expected capital appreciation. The option value is determined by the expected capital appreciation because it determines the expected future evolution of the current use. In addition to equation (11) holding with equality, equation (12) holding with inequality means that the value from staying in agriculture is bigger than the value from the bioenergy crops minus the switching cost. A switch from agriculture to bioenergy crops is triggered when the current return plus the expected rate of capital appreciation is smaller than the rate of return from staying and if the value function from being in agriculture is equal to the value function from bioenergy crops minus the switching cost (Fackler, 2004; Nøstbakken, 2006; Song et al., 2011; Balikcioglu et al., 2011).

No explicit solution exists for our model formulation and thus, we rely on the collocation method discussed and implemented in Miranda and Fackler (2002) and Fackler (2004) to solve equations (11) and

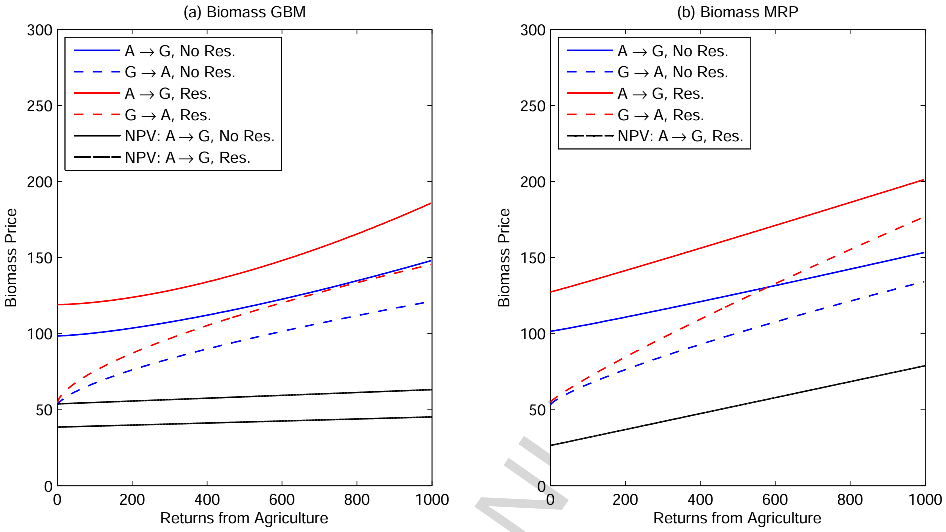


Figure 1: Illustration of real option framework. The biomass price threshold for a two-way switching model under the net present value (NPV) and the real option model (with and without the presence of agricultural residues) is illustrated in under a biomass prices evolving under a GBM (Panel (a)) and a MRP (Panel (b)) process.

(12) numerically. The basic idea behind the collocation method is to approximate the unknown value function by a function which is composed of known functions. In our case, we approximate the value function $V^k(B,P) \approx \phi(B,P)\theta^k$ where $\phi(B,P)$ represents a set of n base functions and θ^k represents a vector of n approximating coefficients. Each regime has a set of base functions and approximating coefficients. Note that the base functions are predetermined and known and that the numerical solution consists of finding the approximating coefficients. Applying the collocation method consists of solving the problem for a fixed number of points in the state space. In our case, we solve the problem on the interval [0,10] for agriculture (i.e., we assume that the maximum net return from agriculture is 1000 dollars) and [0,3] for the price of biomass, i.e., the state space of the allowance price is assumed to be bounded at \$300. The number of nodes is 40 and 25, respectively. During the simulation process, the agricultural net return is set to the upper bound in the unlikely event that the shocks exceed the state space. The simulation of the model is conducted in discrete time (Song et al., 2011; Chladná, 2007). Figure 1 illustrates the concept of the real option model. Panel (a) represents the two-way switching threshold from agriculture to biomass crops under a biomass price that evolves according to a Geometric Brownian Motion. The switching threshold under the real option model is significantly higher than under the net present value analysis. For example, if the current long-run return from agriculture is \$400 ha^{-1}, then the biomass price needs to be approximately \$40 t^{-1} and \$50 t^{-1} under the NPV analysis (without and with collection of residues, respectively) but needs to be approximately \$110 and \$130 under the real option analysis (without and with collection of residues, respectively). Panel (b) of Figure 1 illustrates the same concepts under a mean-reverting biomass price.

Note that $\bar{B}_i(q_t)$ represents the mean net return if no switching of landowners occurs, i.e., a fixed level of production. If switching occurs from other landowners, agriculture production decreases, and thus, prices and net return increase for landowners that stayed in agriculture leading to $\bar{B}_i(q_t)$ being updated to account

	υ_{jm}	Corn	Soybean	Wheat
Base price ($ bu^{-1})		3.60	8.98	4.93
Base price ($ t^{-1})		141.59	329.98	181.08
Food/Consumer Demand				
Corn	114.01	-0.230	-	-
Soybeans	626.79	-	-0.434	-
Wheat	54.70	-	-	-0.075
Feed Demand				
Corn	53.02	-0.201	-	-
Exports				
Corn	549.94	-0.570	-	0.120
Soybeans	1347.55	0.030	-0.63	0.020
Wheat	5725.74	0.170	0.040	-1.230

Table 1: Prices and price elasticities for food, feed, and export.

for the new production level. Previous research has shown that the under prefect competition, the investor, i.e., the landowner in our case, can be myopic and does not need to take into account the future switching of landowners (Leahy, 1993; Grenadier, 2002; Zhao, 2003). In our simulation model, the net returns from being in agriculture will be updated at each time step based on the rational expectations of the farmer with respect to future net returns.

3 Data and Model Parametrization

There are four components to our model that need to parameterized: (1) crop demand, (2) production of bioenergy crops, (3) production of corn, soybean, and wheat, and (4) stochastic process governing agriculture and bioenergy crop production. The supplemental material provided included all the data used for our analysis.

To determine the crop demand, prices and demand parameters used in equation (1) are calibrated to the 2022 long-run equilibrium as reported in FAPRI (2016). Note that the long-run equilibrium represents a steady-state which we use as starting point for our simulation model. Commodity prices are average prices over the period 2015 to 2022. All elasticities are from FAPRI (2011) with the exception of food/consumer demand for corn and export demand for soybeans which are taken from Chen (2010). The demand for ethanol e is set to 141.22 (in million metric tons). The base prices are deflated to 2012 Dollars using the Producer Price Index (Table 1).

The cost of production for switchgrass and miscanthus can be subdivided into the establishment period and the production period (Table 2). The switchgrass studies summarized in Perrin et al. (2008) range from \$260.71 - \$499.11 ha^{-1} year^{-1} for the establishment year and from \$146.79 -\$574.19 ha $^{-1}$ year^{-1} for the production period (in 2012 \$). Khanna et al. (2008) report per hectare cost for miscanthus of \$380.95, \$192.18, and \$103.66 in year 1, year 2, and years 3-10, respectively. For miscanthus, costs are reported as \$862.82, \$79.25, and \$79.24 (3-20 years). Our cost estimates are based on Jain et al. (2010) and Dumortier (2016) and are summarized in table 2. The county-specific yields for switchgrass and miscanthus are obtained from (Miguez et al., 2012). Their work covers both crops and thus, the simulation methods to obtain the yield estimates are consistent between the two bioenergy crops.

The production of biomass from agricultural residues entails the cost of nutrient replacement and harvesting. Dumortier (2016) estimate the cost to be \$28.72 and \$20.05 per ton of corn stover and wheat straw removed, respectively. The harvesting operations for agricultural residues include raking and bailing. Our approach is consistent with (Jain et al., 2010) and (Dumortier, 2016). The county specific sustainable removal coefficients for agricultural residues are obtained from Perlack and Stokes (2011). If crop residues are removed, reduced tillage or no-tillage is necessary to maintain soil health. Perlack and Stokes (2011) reports two sets of removal coefficients, i.e., low and high. The lower removal coefficients are associated with reduced tillage and the high removal coefficients require a switch to no-till. In this analysis, we assume no reduction of crop yields if residues are removed and that the loss in nutrients is compensated by the farmer. For agricultural residues as well as bioenergy crops, we assume a yield and storage loss of 6% and 20%, respectively (Khanna et al., 2008; Haque and Epplin, 2012; Perrin et al., 2012).

For the production of field crops, we follow the approach by Dumortier (2016) to determine the county level production of corn, soybean, and wheat. The 2022 county-level yield is taken from the projections of the Food and Agricultural Research Policy Institute Farm Cost and Return Tool (FAPRI CART). We use the average area harvested for corn, soybeans, and wheat over the period 2008-2012. The National Agricultural Statistics Service (NASS) provides county-level data on area harvested. The area available in each county is taken from the NASS. Area and yield are set to zero in counties where crop production occurred for less than two years in that time period. The production cost for the three crops are obtained from the Cost and Return database of the USDA.

The stochastic processes and real option parametrization In this analysis, we assume $\mu_G = 0.03$ (Song et al., 2011), $\sigma_A = 0.25$ (Dumortier, 2013), and $\eta = 0.6$ (Dumortier, 2013). We set $\sigma_G = 0.1$ because the values used in Song et al. (2011) are for the returns and not the price (Figure 2). Also, the values of Song et al. (2011) lead to significant return fluctuations. We assume a discount rate of 8% (Song et al., 2011). Dumortier (2013) provides a sensitivity analysis with respect to the discount rate showing that an increase in the discount rate leads to a higher switching threshold. Note that for mathematical reasons, the discount rate needs to be higher than the expected return from bioenergy crop production because otherwise, the expected return from bioenergy crops would go to infinity. The switching cost are taken from Song et al. (2011) and adjusted to inflation to 2012 prices. This leads to a switching cost from bioenergy crops to conventional crop production to 124.65 \$ ha^{-1}. The switching cost to bioenergy crops are listed in table 2.

Scenarios are run differentiating by (1) switchgrass and miscanthus, (2) low and high production costs, (3) presence and absence of agricultural residues, (4) one-way versus two-way switching, (5) biomass prices following a geometric Brownian motion and a mean-reverting process, and (6) low versus high agricultural residue removal rates. We will also analyze the effects of high commodity prices that were reported in

	Switchgrass		Miscanthus	
	Low Cost	High Cost	Low Cost	High Cost
Establishment Cost (\$ ha^{-1})	335	820	2993	3148
Production Cost (\$ ha^{-1})	87	182	72	147
Production Cost (\$ t^{-1})	26	29	15	16
$\bar{P}$	110	145	75	100

Table 2: Production cost for switchgrass and miscanthus (excluding harvest operation) in 2012 \$.

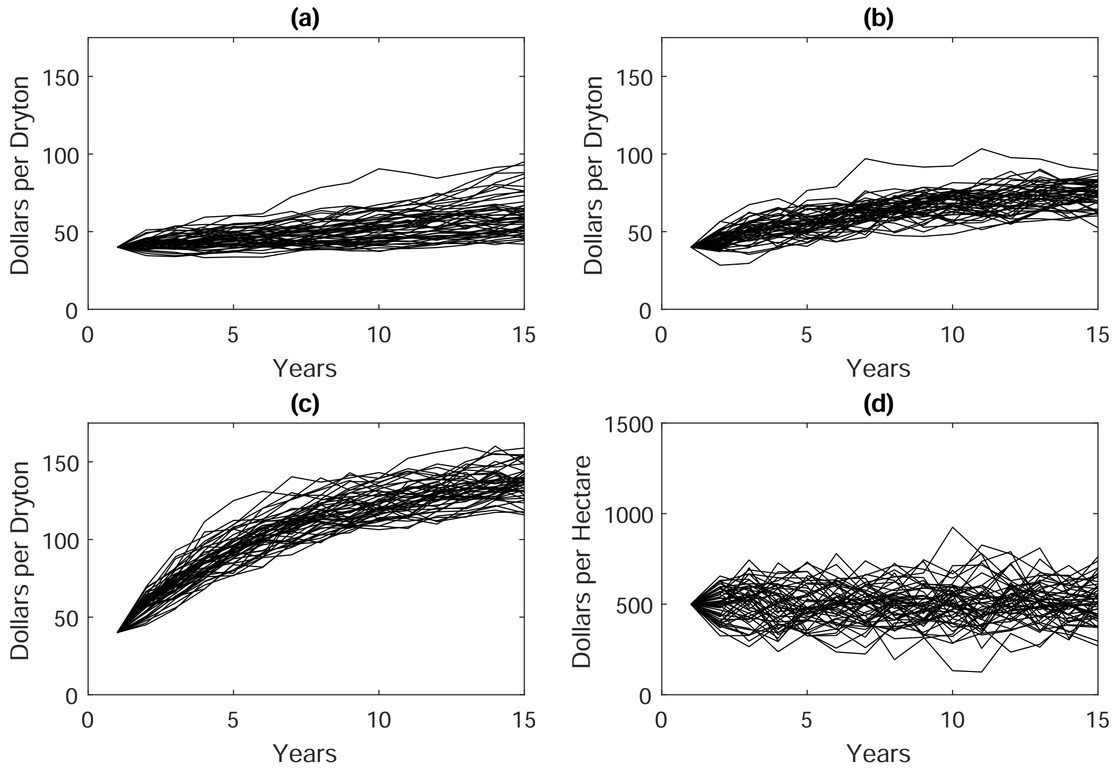


Figure 2: Price Simulation

FAPRI (2013). We focus on the eight scenarios that are the most realistic in terms of economic reality. One-way switching to bioenergy crops as well as an exponentially increasing biomass price in the long-run are doubtful and thus, we focus on a biomass price that is reverting to a long-run mean and the entry threshold when reversion back to traditional crops is possible. Those results will be presented for switchgrass and miscanthus under low and high production costs as well as with and without the presence of agricultural residues. We simulate 1,000 exogenous biomass price paths and determine the land-use allocation of farmers at each time-step. The results are reported for the first year the mandate of 60 billion L is reached.

4 Results

For each county growing either corn, soybeans, and wheat as well as having the potential to grow either switchgrass or miscanthus, we calculate the break-even price of biomass in \$ t^{-1} that is necessary to trigger a switch to the respective biomass crop. For the simulation model that determines the land allocation to switchgrass and miscanthus, we focus on the same scenarios as with the break-even price analysis with the exception that the decision to use agricultural residues is endogenous to the model.

4.1 Break-even Prices

Figures 3 and 4 summarize the county-level break-even prices for switchgrass and miscanthus under low residue removal rates.[1] The maps show that in the presence of agricultural residue collection, the break-even price for switchgrass is over 300 \$ t^{-1} for a significant part of the Midwest. This is significantly higher

[1]The maps for the high sustainable residue removal rates are very similar and we refer to the supplemental materials for detailed county-level break-even prices for that case.

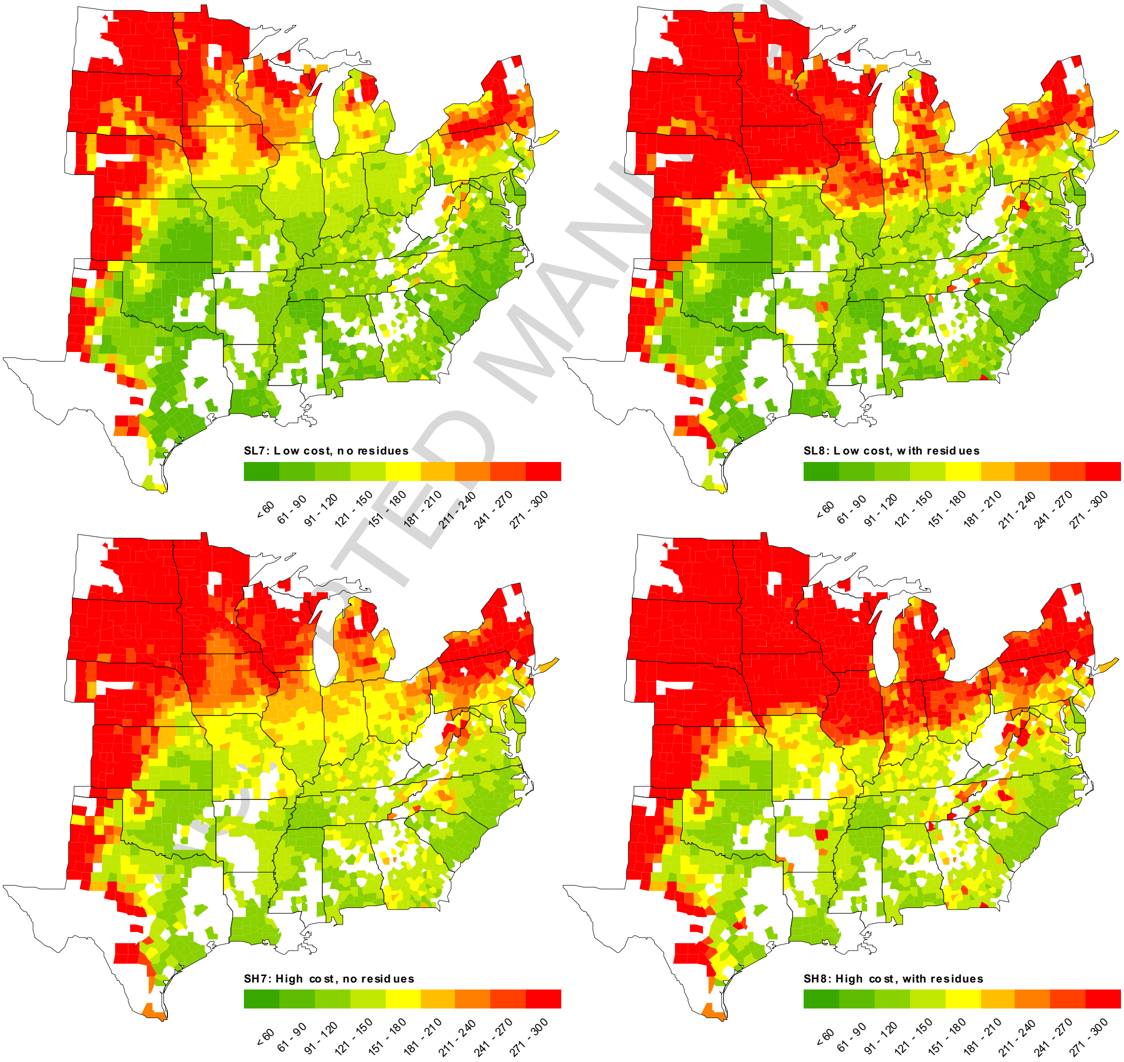


Figure 3: Break-even prices in \$ ha^{-1} for switchgrass. The biomass price threshold for a two-way switching under low production cost without residues (SL7) and with residues (SL8) as well us under high production cost without (SH7) and with (SL8) agricultural residues.

than the estimates by Jain et al. (2010) who find values ranging from 88-178 \$ t^{-1} for eight Midwestern states. For Illinois, Indiana, and Iowa, the break-even prices calculated by Jain et al. (2010) range from 103-178 \$ t^{-1}. The difference in the investment threshold compared to our study is due to the option value depicted in figure 1. Note that for computational purposes, our state space for the biomass price has an upper limit of 300 \$ t^{-1}, i.e., break-even prices above this value are censored to 300 \$ t^{-1}. The analysis indicates that for switchgrass, break-even prices are significant for the northern Great Plains and large parts of the corn and soybean regions in the United States. The switchgrass yield in the northern Great Plains is too low

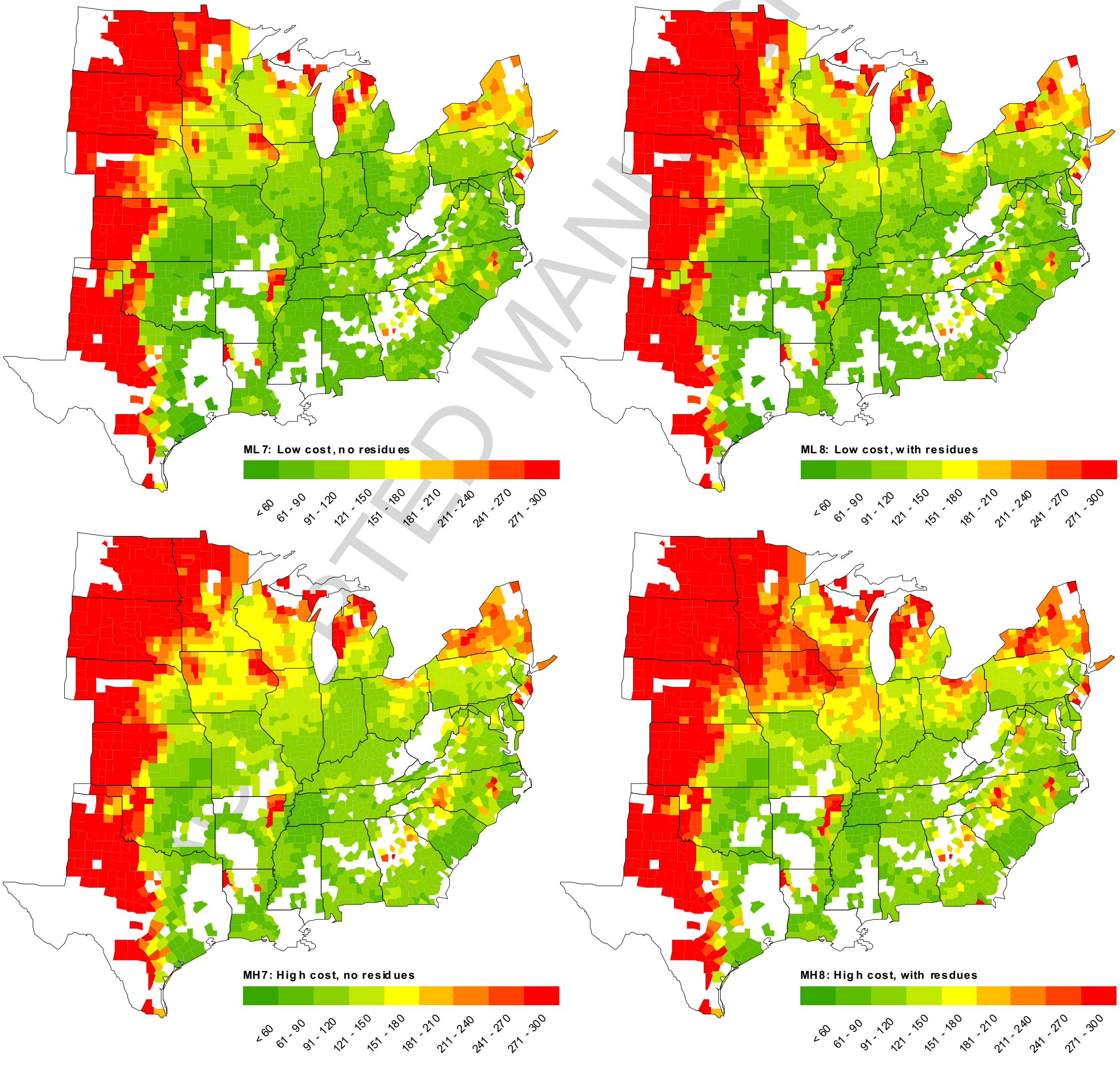


Figure 4: Break-even prices in \$ ha^{-1} for miscanthus. The biomass price threshold for a two-way switching under low production cost without residues (ML7) and with residues (ML8) as well us under high production cost without (MH7) and with (ML8) agricultural residues.

to be profitable to change to switchgrass despite the low yields with respect to the crops included. For the Midwest, switchgrass yields are high and so are corn and soybean yields. As aforementioned, farmers in the Midwest deciding to produce biomass can do so by collecting agricultural crop residues that do not entail the upfront switching cost of the establishment period. In addition, while collecting agricultural residues, farmers are already exposed to the stochastic biomass price.

For miscanthus, the break-even prices are generally lower which is due to the higher yields compared to switchgrass. Jain et al. (2010) find values ranging from 69-234 \$ t^{-1} for miscanthus. For Illinois, Indiana, and Iowa, the values range from 65-120 \$ t^{-1}. Especially under the low production costs, the break-even price is below 180 \$ t^{-1} for the majority of Midwestern counties. Similar to switchgrass, the break-even prices in the northern Great Plains are very high due to the low yields of miscanthus in that area and the significant establishment costs. As opposed to switchgrass, break-even prices in the southern Great Plains are generally higher but lower in the Midwest. Despite the high establishment costs for miscanthus, the yield differential compared to switchgrass is sufficient for a lower investment threshold. Figure 5 and 6 summarize the median (across counties) break-even prices by counties for the reduced tillage and no tillage scenarios. Under the reduced tillage scenarios and and with residue collection, Iowa, Minnesota, Nebraska, North Dakota, and South Dakota all have median break-even prices of 300 \$ t^{-1} or more. In the case of no tillage, Illinois, Indiana, Michigan, and Wisconsin are added as states with a median break-even price of 300 \$ t^{-1} or more. Since the sustainable residue removal coefficient is higher under the no tillage scenarios, the return that is obtained by the farmer is higher since the harvest cost of residues is partially a fixed per hectare and independent of the yield. This increases the break-even price for most counties.

4.2 Land Conversion over the Simulation Period

The previous section quantifies the biomass price that needs to be reached in order for farmers to grow bioenergy crops. The more interesting question is to determine how much land gets allocated to bioenergy crops given the current mandate of 60 billion liters. The calculate the probability of land conversion for each county, we simulate 1000 biomass price paths and at each time step, farmers decide whether a switch to either switchgrass or miscanthus is profitable given the returns from agriculture and the current biomass price. Given the farmers that remain in agricultural production, the new long-run return from remaining in agriculture is calculated similar to Leahy (1993); Zhao (2003); Chladná (2007); Dumortier (2013). At each step, we calculate the amount of cellulosic ethanol that is produced and if it surpasses 60 billion liters, the model stops. The mean probability is reported after 1000 runs.

Figures 7 and 8 show the results from switchgrass and miscanthus for the case of low agricultural residue removal rates. Landowners in the Corn Belt are very unlikely to change production practices to either switchgrass or miscanthus because net returns from agricultural production are too high and a switch to bioenergy crops is not profitable. The probability of growing switchgrass is zero for the majority of counties in Illinois, Indiana, Ohio, and Pennsylvania except in the southern parts of those states where there is a small probability of growing switchgrass. This can be contrasted to miscanthus that has a higher probability in those states but little potential in the southern Great Plains. This is consistent with the high break-even prices in those parts of the country. Figure 9 reports the expected area dedicated to bioenergy crops as a function of the cellulosic biofuel mandate. Two trends are noteworthy: First, the area dedicated to switchgrass responds much more elastic than for miscanthus, i.e., a small change in the mandate leads to a larger expansion of area for switchgrass than miscanthus. Second, under low agricultural residue removal rates, not enough biomass from agricultural residues can be collected to cover the mandate. That is, for a cellulosic ethanol production over 20 billion gallons, bioenergy crops need to be grown. The more interesting case from a policy perspective is the case of high agricultural residue removal rate (no tillage). In this case, no switchgrass or miscanthus is grown in the U.S. to meet the mandate of 60 billion L. This is illustrated in Figure 9 that shows that the expected area dedicated to bioenergy crops is zero for mandates below 70 billion L. Note that the case of no tillage and the resulting high residue removal rate is an extreme case by that assuming even a removal rate between the lower and upper limits presented in this paper makes the growth of switchgrass or miscanthus unlikely.

Figure 10 summarizes the effects of higher commodity prices as reported in FAPRI (2013). The prices

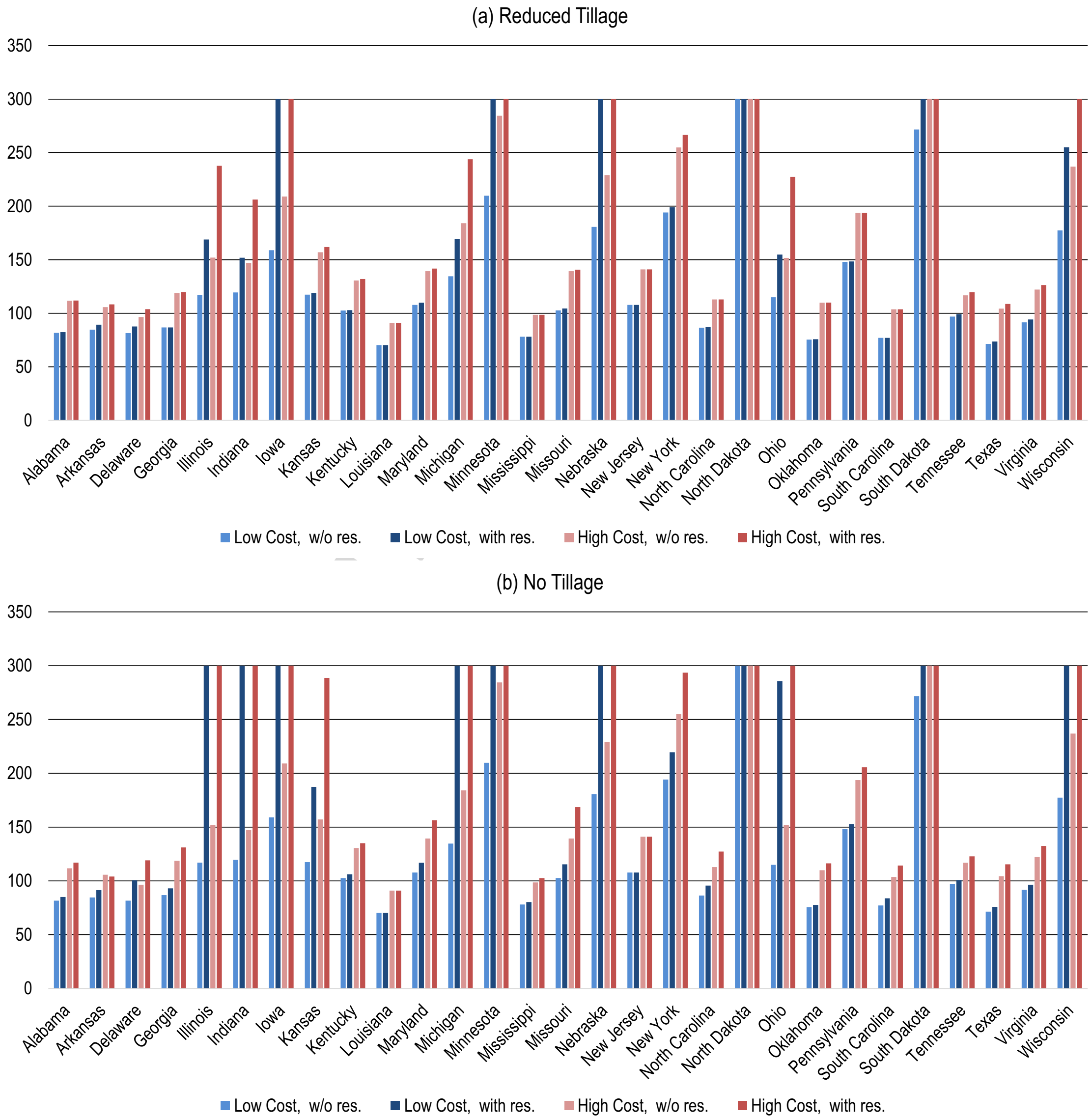


Figure 5: Median break-even prices in \$ ha^{-1} for switchgrass (reduced-tillage). The biomass price threshold for a two-way switching under low production cost without residues (ML7) and with residues (ML8) as well us under high production cost without (MH7) and with (ML8) agricultural residues.

for corn, soybeans, and wheat where 24%, 21%, and 20% higher than the prices used in this analysis. The median increase in the threshold ranges between 5% and 15%. Note that some states, e.g., North and South Dakota, whose break-even threshold is already high are unaffected by the higher commodity prices. The same is true for some scenarios for Iowa, Minnesota, Nebraska, and Wisconsin. It is noteworthy that the break-even prices changes but the probability of switching to dedicated bioenergy crops remains largely the same. The intuition behind this result is that the driving factor for switching to bioenergy crops is the

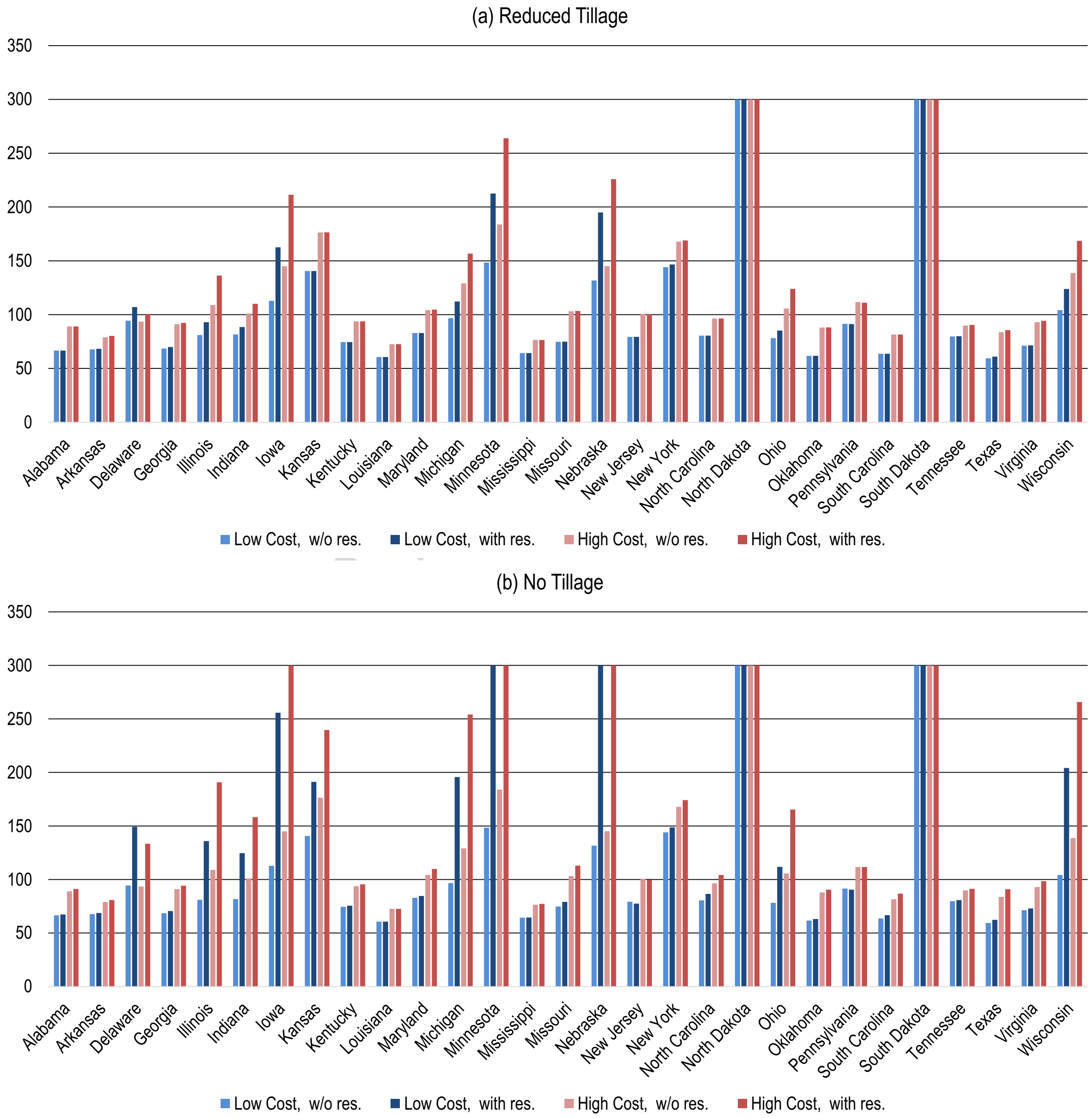


Figure 6: Median break-even prices in \$ ha^{-1} for miscanthus. The biomass price threshold for a two-way switching under low production cost without residues (ML7) and with residues (ML8) as well us under high production cost without (MH7) and with (ML8) agricultural residues.

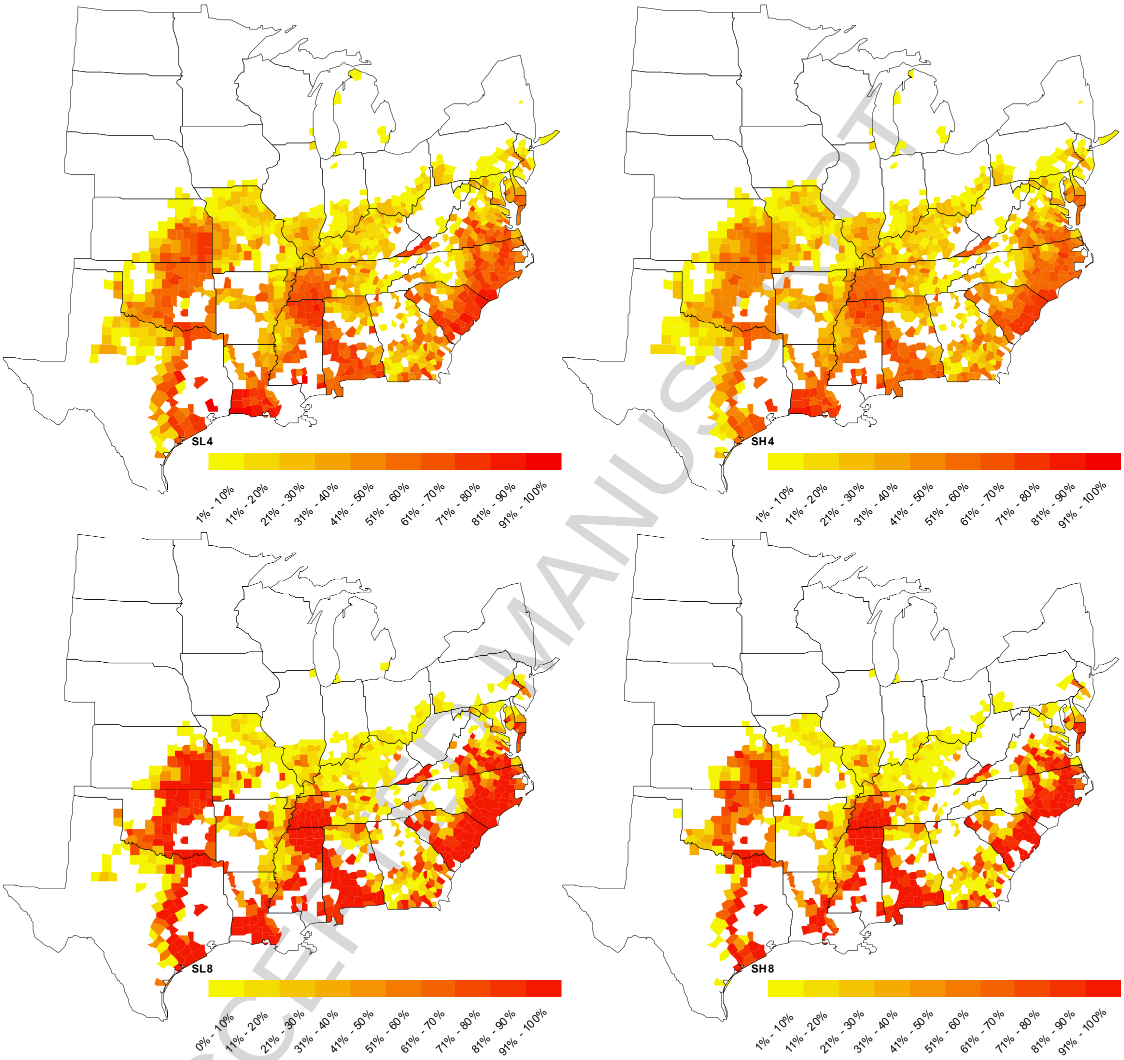


Figure 7: Probability (>1%) of allocating land to switchgrass to reach a mandate of 60 billion gallons under reduced tillage. Under low cost and a GBM biomass price evolution (SL4), high cost and GBM biomass price evolution (SH4), low cost and a MRP biomass price evolution (SL8), high cost and MRP biomass price evolution (SH8).

relationship between production cost and yield. The same counties that switch under high commodity prices will switch under low commodity prices, i.e., the “sequencing” does not change.

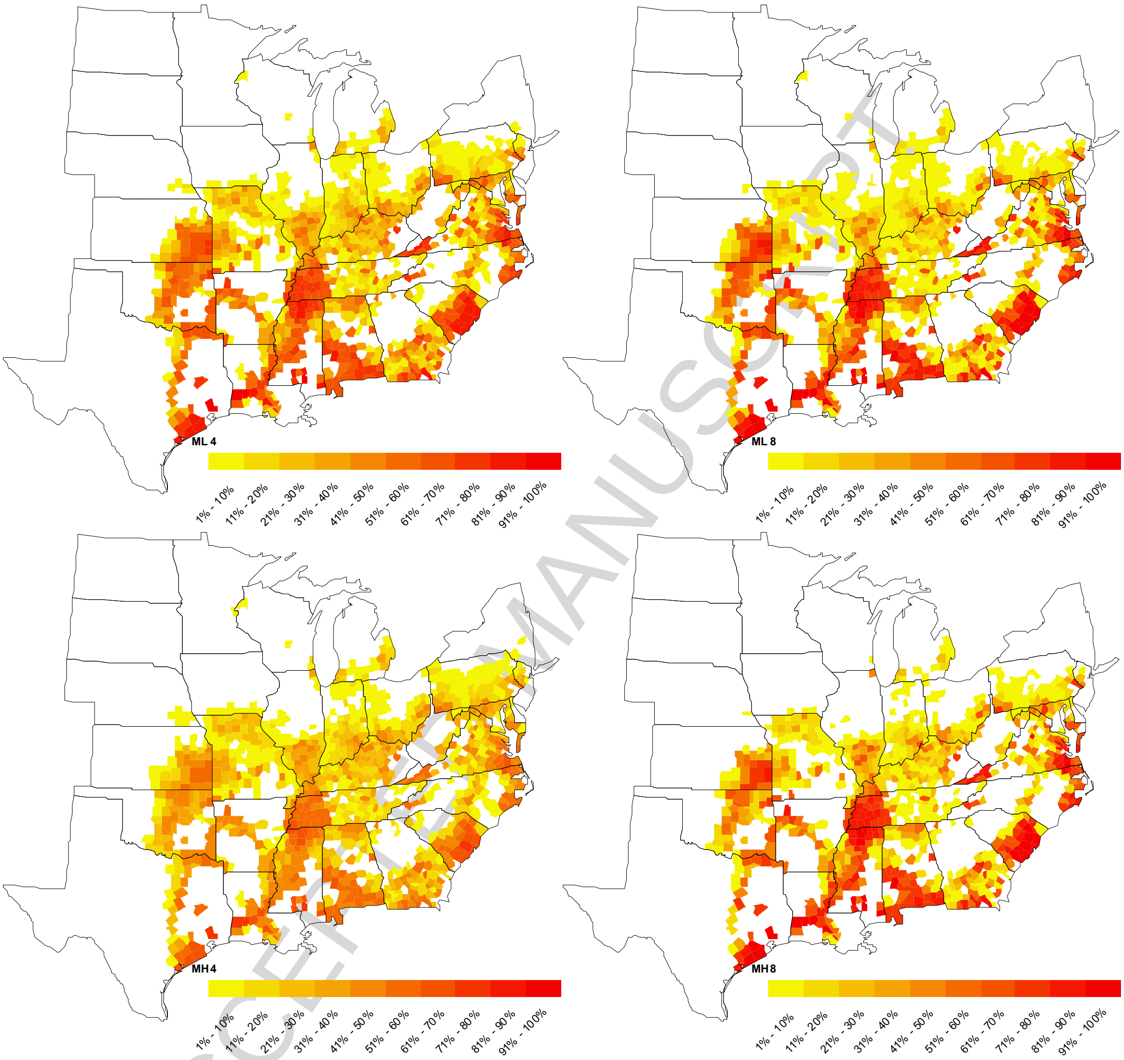
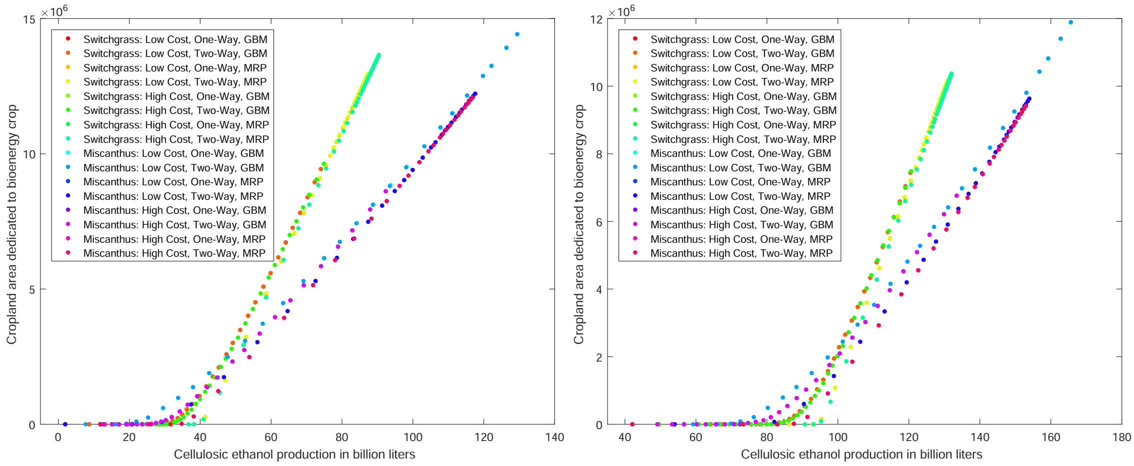


Figure 8: Probability (>1%) of allocating land to miscanthus to reach a mandate of 60 billion gallons under reduced tillage. Under low cost and a GBM biomass price evolution (ML4), high cost and GBM biomass price evolution (MH4), low cost and a MRP biomass price evolution (ML8), high cost and MRP biomass price evolution (MH8).

5 Discussion

There are assumptions in our model that require further discussion. In particular, the effect of time-to-build and correlated stochastic processes between the biomass price and agricultural returns. As was mentioned in the introduction, bioenergy crops do not reach full yield potential in the first year.

Previous literature assessing the effects of time-to-build generally found that longer time-to-build pe-



(a) Low removal   (b) High removal

Figure 9: Expected area in hectares allocated to switchgrass and miscanthus

riods result in lower investment thresholds (Majd and Pindyck, 1987; Bar-Ilan and Strange, 1996, 1998; de Almeida and Zemsky, 2003; Martins and da Silva, 2005). Bar-Ilan and Strange (1996) conclude that "investment lags offset uncertainty and tend to reduce inertia, contrary to conventional wisdom." Some of the assumptions made in the previous literature are not applicable to our model. This includes the investment project not yielding any return until completion (Majd and Pindyck, 1987) or the possibility of suspending the investment project (Bar-Ilan and Strange, 1998). Bioenergy crop productions yields a return that is below the full potential even in the first year. Also the possibility of a regime that yields a stochastic return outside of the investment opportunity, i.e., agricultural returns in our case, is not included in the previous literature. Majd and Pindyck (1987) show that although the investment threshold is decreases with an increase in the investment lag, high opportunity costs increase the investment threshold. Thus, we conclude that our results either overestimate the investment threshold due to time-to-build or may be close to our estimates because of the opportunity cost associated with agricultural returns. The analysis of time-to-build is further complicated by the presence of perfect competition. Grenadier (2000) argues that the presence of time-to-build in a perfectly competitive environment is close to the net present value threshold. This result holds if the investment project is governed by perfect competition, a case we abstract from in this paper. We leave the numerical assessment of the time-to-build feature to future research because the current model is computationally very intensive. The inclusion of time-to-build into the model would require solving the model backwards, i.e., via backward induction, in time.

The second assumption that requires discussion is the nature of correlation between the stochastic processes. Song et al. (2011) argue that the returns from agriculture and bioenergy crops could either be positively or negatively correlated depending on the relationship with the crude oil price. If the price of biomass is positively related to the oil price (because it is acting as a substitute for gasoline) and corn-soybean returns increase as well because corn ethanol is a substitute as well, then we would see a positive correlation. On the other hand, energy is an important input in the production process of crops (nitrogen) and thus, the two processes could be negatively correlated as well.

Our model does also not incorporate crop insurance explicitly. Crop insurance arguably reduces uncertainty/risk of growing crops. If the decision to switch is significantly predicated on farmers' perception of

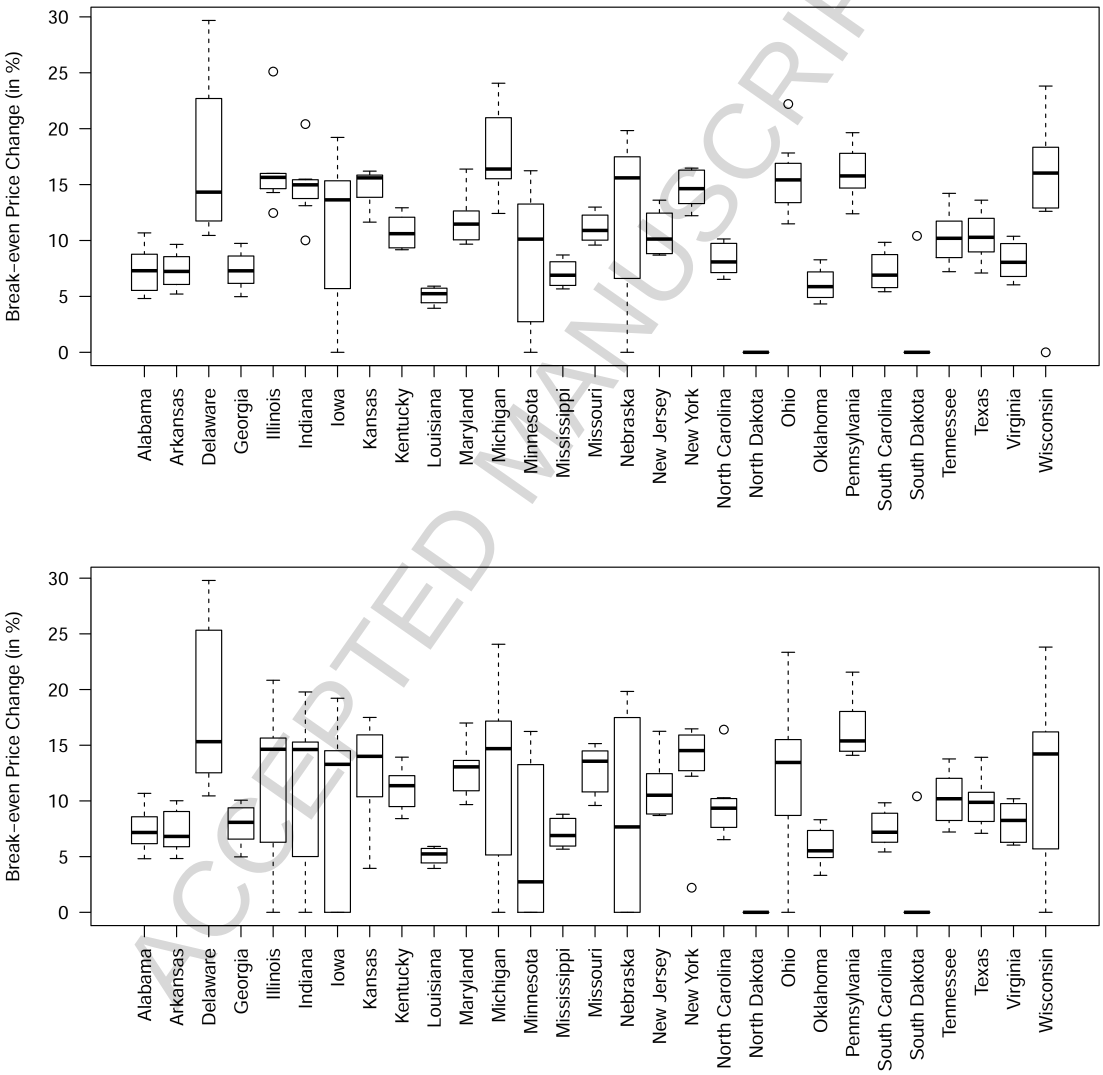


Figure 10: Sensitivity Analysis: The prices for corn, soybeans, and wheat reported in FAPRI (2013) were 24%, 21%, and 20% higher than the prices used in this analysis.

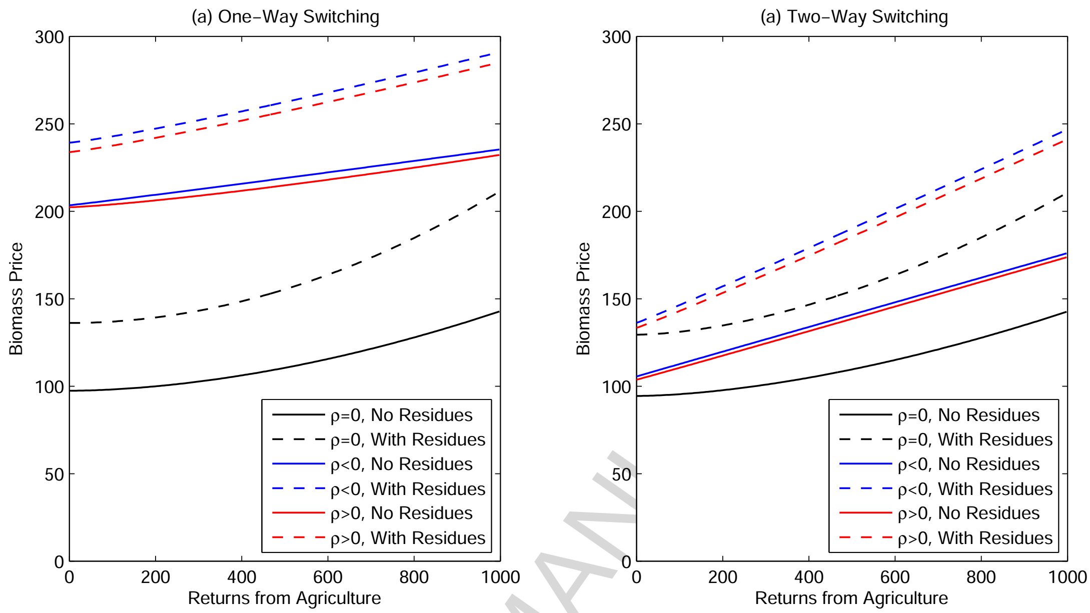


Figure 11: Sensitivity Analysis

risk in either of the two regimes, crop insurance would be an important part of this decision. Incorporating the nuances of crop insurance is beyond the scope of the paper. Although, crop insurance would reduce the variability associated with the regime "agriculture." In addition, the risk of being in agriculture could also be reduced if farmers have the ability to further diversify the crops grown and including livestock activities that would reduce volatility.

Another possibility for extending our analysis in the future is to incorporate a spatial component. Intuition might suggest many reasons why farmers in the Corn Belt choose to not convert to switchgrass, e.g., likelihood of strong basis, access to services or other information, synergies with other markets, etc. Accounting for those various reasons as "spatial autocorrelation," we hypothesize an even stronger support for showing alternative crops only being grown at the periphery of the Corn Belt.

6 Conclusion

High production and harvest cost hinder the supply of biomass for cellulosic ethanol production. In this paper, we extend the previous literature by applying a real option framework to switchgrass and miscanthus production in the contiguous United States. Our results indicate that switchgrass production is very unlikely in the United States based not only on the high harvest cost but also on the option value associated with waiting to switch land-uses. Landowners planting switchgrass are faced with uncertainty in the evolution of the biomass price, one-time switching cost associated with the establishment of switchgrass, replanting of switchgrass every 10 to 15 years, and the cost of forgone revenue in the first year after planting. Previous research has shown that a majority of the cellulosic mandate can be covered by agricultural residues. In general, the likelihood of switchgrass covering the majority of the cellulosic biofuel mandate is very low.

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