Uncertainty and Time-to-Build in Bioenergy Crop Production

Jerome Dumortier[1], Nathan Kauffman[2], and Dermot J. Hayes[3]

[1]School of Public and Environmental Affairs, Indiana University – Purdue University Indianapolis, jdumorti@iupui.edu

[2]Omaha Branch - Federal Reserve Bank of Kansas City
nathan.kauffman@kc.frb.org

[3]Department of Economics, Iowa State University
dhayes@iastate.edu

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Abstract

Over the last years, the cellulosic biofuel mandate has not been enforced by the U.S. Environmental Protection Agency. The uncertainty surrounding the enforcement of the mandate in addition to high production and harvest cost contributes to farmers' hesitation to plant bioenergy crops such as switchgrass and miscanthus. Previous literature has shown that under uncertainty and sunk cost, the investment threshold is further increased because of the value associated from holding the investment option. This warrants the use of a real option model. In this paper, we extend previous literature by applying a real option model to bioenergy crop production in the United States. We show the spatial allocation of switchgrass under biomass price and agricultural return uncertainty. The empirical model identifies the counties in the contiguous United States that are most likely to change to switchgrass production. Our preliminary results indicate a very small share of land in switchgrass production even at high biomass prices.

1 Introduction

The Renewable Fuel Standard (RFS) calls for 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 of 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 the production of bioenergy crops that add to the low adoption rate. First, prices and returns for traditional commodities such as corn, soybeans, and wheat as well as bioenergy crops are stochastic and unknown at the time of planting. This uncertainty together with costly switching creates a barrier for farmers to adopt bioenergy crops, i.e., farmers hold a valuable option to wait (Song et al., 2011). This characteristic has been shown to warrant the use of real option models to assess the switching decision from one land-use to another. Second, switchgrass and miscanthus do not realize their full yield potential in the first year, i.e., there is a multi-year establishment phase where there is little to no revenue from bioenergy crops. During this period, the farmer would have earned revenue if he/she had stayed in traditional crop production. This aspect has not been modeled explicitly in the previous literature. Most analysis annualize the opportunity cost in the establishment period as well as the first year establishment costs over the life of the bioenergy crop which is between 10 to 15 years depending on the crop (Perrin et al., 2008; Khanna et al., 2008; Brechbill et al., 2011; Haque et al., 2014). 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 dedicated bioenergy crops.

In this paper, we use a real options framework to assess the implications of farmers bioenergy production decision when switching costs are paid in the first year. We extend the previous literature by applying our theoretical model to the contiguous U.S. and identify counties that are likely to grow bioenergy crops for cellulosic ethanol 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 and other stakeholders on what influences the adoption rate and where policies might need to be implemented to increase adoption of bioenergy crops. Our analysis is divided into a theoretical part and an empirical part. In a first step, we set up a real option framework to examine the decision of a landowner to switch from conventional crops to bioenergy crops under uncertainty and costly switching. The landowner can be in either of two regimes: agriculture or bioenergy crops. The empirical model is at the county level and focuses on three major field crops (corn, soybeans, and wheat) and switchgrass as the bioenergy crop. We concentrate on the three field crops as potential acreage for switchgrass because they represent almost 69% of total field crop area in the U.S. in 2013. We have switchgrass yield data for each county in addition to establishment period and production cost data. Those cost estimates are gathered from various literature sources. We can estimate the stochastic net returns from being in traditional crop production from historic data. For the biomass production, we simulate a biomass price processes that is consistent with previous literature.

2 Real Option Switching Model

At time t, the representative landowner of county i can be in either of two regimes k: agriculture (A) or bioenergy crops (G). Returns in both regimes are stochastic and the problem of the landowner is characterized by the possibility of switching from a regime which yields one stochastic return to a new regime which results in a flow of profits with different stochastic properties (Alvarez and Stenbacka, 2004; Décamps et al., 2006). The two stochastic processes in our model are associated with the net return from being in agriculture and the biomass price. Assume that the stochastic processes of agricultural returns can be written as

$$dB = \eta(\bar{B} - B)dt + \sigma_A B dz_A \tag{1}$$

and that the price of biomass evolves according to

$$dP = \mu_P P dt + \sigma_P P dz_P \tag{2}$$

Our approach follows closely Dumortier (2013) with the net return process for agricultural production following a mean reversion process. Let B be the per hectare return from agriculture. The parameter η is the mean reversion speed to the long-run equilibrium return in agriculture which is denoted $\bar{B}$. 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) and 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. The variance in agricultural production is denoted σ_A and dz_A is the increment of a Wiener process. In the empirical part of the model, we assume that long-run mean for county i, i.e., $\bar{B}_i$, is determined by the number of landowners in agricultural production q_t. In the absence of uncertainly, we determine the net return from agriculture for county i as $R_i(q_t)$. Let the disturbance term for agriculture of $\epsilon(t)$. We assume that $\bar{B}_i = R_i(q_t) \times \epsilon(t)$, i.e., the disturbance influences the net return from agriculture in a multiplicative way. The disturbance $\epsilon(t)$ summarizes the uncertainty associated with yield, price, and cost fluctuations. Using Itô's Lemma and the results from Leahy (1993), the multiplicative net return process can be written as in equation 1. 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 net revenue are endogenous to the model. If landowners decide to move from agriculture to bioenergy, less cropland is available for production, thus increasing the net returns and vice versa. Given the number of landowners that are in engaged in agriculture production and given parameters, we can fully characterize total agricultural production and net returns for landowner i.

For biomass production, 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. Our setup is similar to regime switching model such as used by Nøstbakken (2006), Song et al. (2011), or (Dumortier, 2013). The drift term and the variance of the biomass price are μ_P and σ_P, respectively. In this preliminary analysis, 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 for the moment because it reduces the computational time. The stochastic return from bioenergy $B_{i,G}(P(t))$ is determined by the biomass price in \$ per dry ton $P(t)$, the biomass yield per hectare and the cost per ton. That is, for biomass production, we assume $B_{i,G}(P(t)) = (P - c_i)y_i$ where c_i is the cost per ton and y_i is the yield per hectare. Implicit in this formulation are several assumptions. First, the cost per ton is held constant over the projection period. Second, once a landowner decides to abandon agricultural production, all the land will be put in bioenergy crop production.

Given the initial values of the state variables at $t = 0$ as $B(0)$ and $P(0)$, the maximization problem is written as (Tegene et al., 1999; Brekke and Øksendal, 1994; Behan et al., 2006; Vath and Pham, 2007):

$$J^A(B(t), P(t)) = \sup_{\tau} E\left[\int_0^{\tau} e^{-rt}B(t)dt + \int_{\tau}^{\infty} e^{-rt}B_G(P(t))dt - e^{-r\tau}C\right] \tag{3}$$

where r represents the discount rate and C is the cost of switching from agricultural production to biomass. The decision variable is τ which represents the switching time to bioenergy crops. The switching time τ cannot be found explicitly but is determined by the impulses $B(t)$ and $P(t)$ received by the land owner. The uncertainty in the net returns for agriculture is introduced by $\epsilon(t)$ which follows a stochastic process and 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. 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 for the new production level (Leahy, 1993; Zhao, 2003).

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:

$$V_A(B(t), P(t)) = \max \left\{ B(t) + e^{-rdt} E \left[V_A(B(t+dt), P(t+dt)), V_G(P) - C \right] \right\} \tag{4}$$

where the first part on the righthand side is the value from staying in agriculture and the second part represents the value from switching to biomass crops. Brekke and Øksendal (1994) show that the Hamilton-Jacobi-Bellman for equation (4) results in:

$$rV_A(B) \geq B + \eta(\bar{B} - B)\frac{\partial V_A}{\partial B} + \mu_P P \frac{\partial V_A}{\partial P} + \frac{1}{2}\sigma_A^2 \frac{\partial^2 V_A}{\partial B^2} + \frac{1}{2}\sigma_P^2 \frac{\partial^2 V_A}{\partial P^2} \tag{5}$$

where V_A represents the value function when in agriculture. The necessary value matching condition:

$$V_A(B) \geq V_G(P) - C \tag{6}$$

The landowner determines whether to switch or not by either equation (5) or (6) holding with equality. Both equations holding with equality defines the border of the switching region. If equation (5) 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 (5) holding with equality, equation (6) 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 and we rely on the collocation method discussed and implemented in Miranda and Fackler (2002) and Fackler (2004) to solve equations (5) and (6) 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

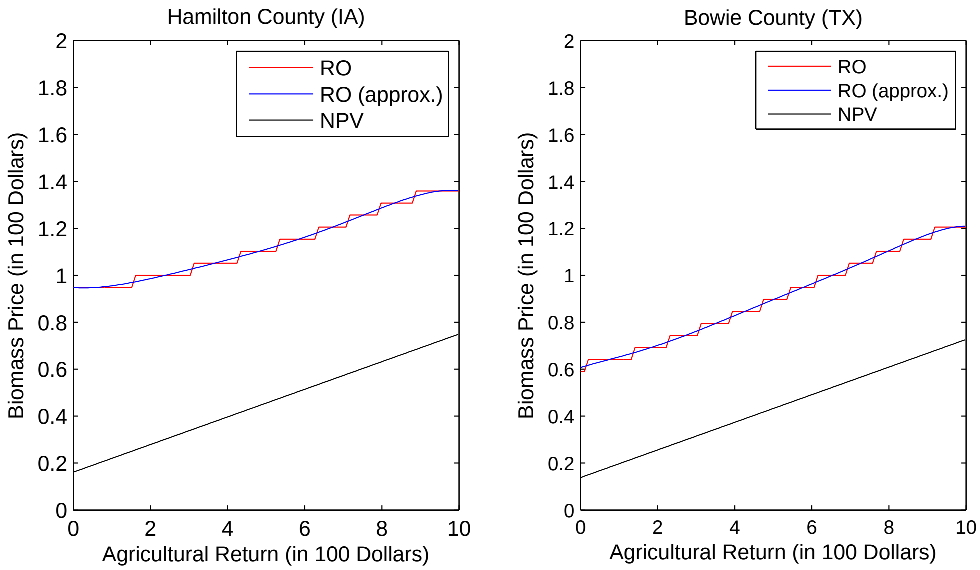

Figure 1: Comparison of Hamilton County (IA) and Bowie County (TX)

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 [0,2] for the price of biomass, i.e., the state space of the allowance price is assumed to be bounded at \$200. 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).

2.1 Example

The importance of the option value is illustrated in figure 1. Both counties have similar switchgrass yields, i.e., 13 t/ha and 15 t/ha in Hamilton and Bowie, respectively but the net

	γ_{jm}	Corn	Soybean	Wheat
Base price (\$ bu^{-1})		4.47	10.83	5.90
Base price (\$ t^{-1})		175.92	397.88	216.65
Food/Consumer Demand				
Corn	128.17	-0.230	-	-
Soybeans	710.78	-	-0.434	-
Wheat	53.80	-	-	-0.075
Feed Demand				
Corn	46.35	-0.201	-	-
Exports				
Corn	672.57	-0.570	-	0.120
Soybeans	1423.93	0.030	-0.63	0.020
Wheat	7095.97	0.170	0.040	-1.230

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

return in Bowie County (99 \$/ha) is significantly lower than Hamilton County (691 \$/ha). In order to invest in bioenergy crops, the difference between the net present value threshold and the real option threshold is significant.

3 Data and Model Parametrization

There are four components to our model that need to parameterized: (1) crop demand, (2) production of switchgrass, (3) production of corn, soybean, and wheat, and (4) stochastic process governing agriculture and bioenergy crop production. This section describes the data sources and model parametrization of those four components.

Crop Demand

The quantity Q for field crop j is determined by the demand function $Q_j = D(p, e)$ where p represents the vector of prices (i.e., corn, soybeans, and wheat) and e represents the quantity of used for ethanol. In our model, we include a constant demand for corn ethanol and thus, the value for e is zero for soybeans and wheat. For each crop, there are three demand sectors m: consumer/food, feed, and export. As in Dumortier (2016), we assume a constant

	Low Cost			High Cost		
	Year 1	Year 2	Rest	Year 1	Year 2	Rest
			Switchgrass			
Cost ($ ha^{-1})	334.60	117.12	87.06	820.25	313.31	182.29
Cost ($ t^{-1})		20.75	25.59		23.74	28.58
			Miscanthus			
Cost ($ ha^{-1})	2993.29	446.85	71.85	3147.98	1397.03	147.03
Cost ($ t^{-1})	0.00	10.33	14.65	0.00	12.00	16.32

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

elasticity demand function for crop j that is written as:

$$Q_j = D(p, e) = \sum_{m=1}^{M} \left[\gamma_{jm} \prod_{j=1}^{J} p_j^{\theta_{jm}} \right] + e$$

where γ_{jm} represents the constant and θ_{jm} is the cross/own-price elasticity (Table 1). Prices and demand are calibrated to the 2022 long-run equilibrium as reported in FAPRI (2013). 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.

Biomass Production

The cost of production for switchgrass and miscanthus can be subdivided into the establishment period and the production period (Table 2). The 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

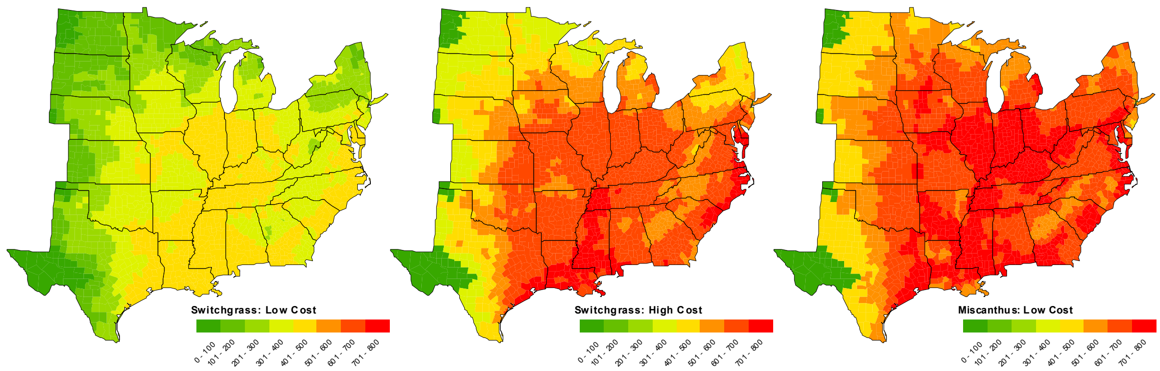

Figure 2: Cost in year 2 for establishing switchgrass and miscanthus ($ ha^{-1})

summarized in table 2.

Field Crop Production

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. If the landowner is currently in agriculture, then the decision variables are the area allocated to corn, soybeans, and wheat. The net revenue from field crops $B_i^f(\cdot)$ is expressed as:

$$B_i^f(a_{ij}^f) = \sum_{j=1}^{3} (p_j y_{ij} - \alpha_{ij}) \left(a_{ij}^f\right) - \sum_{j=1}^{3} \frac{\beta_{ij}}{2} \left(a_{ij}^f\right)^2 \tag{7}$$

The areas allocated to corn, soybeans, and wheat are denoted by a_{ij}^f and α_{ij} and β_{ij} are county and crop specific cost parameters. Note that $\partial C_{ij}(\cdot)/\partial a_{ij}^f > 0$ which represents 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. The equation (7) is subject to a binding land constraint and non-negativity constraints. Setting up the Lagrangian and deriving the first order conditions is straightforward. The maximum area available for crop production in county i is denoted with A_i. Note that the maximization problem in exhibits increasing marginal cost which guarantees a solution during the maximization procedure.

3.1 Stochastic Processes

In this preliminary analysis, we assume $\mu_G = 0.04$, $\sigma_G = 0.1$, $\sigma_A = 0.25$, and $\eta = 0.6$. A discount rate of 8% is used and the switching cost are \$335 per hectare.

4 Results

Figures 4 and 5 summarize preliminary results from our model simulated for 100 different agricultural returns and biomass price path. The figures indicate the probability of switching to bioenergy crops during those runs. Note that landowners in the Corn Belt are very unlikely to change production practices to switchgrass. Net returns from agricultural production, especially corn are too high and a switch to bioenergy crops is not profitable. Note that in this preliminary run, we do not include the forgone opportunity cost in the first year when biomass does not achieve full yield. In subsequent analysis, we believe that the probability of landowners will be further reduced and that switchgrass will not be profitable to grow but in few counties in the South and Southwest. Note that the switching cost of miscanthus is extremely high as noted in table 2. We believe that the probability of miscanthus being grown in the U.S. is almost zero.

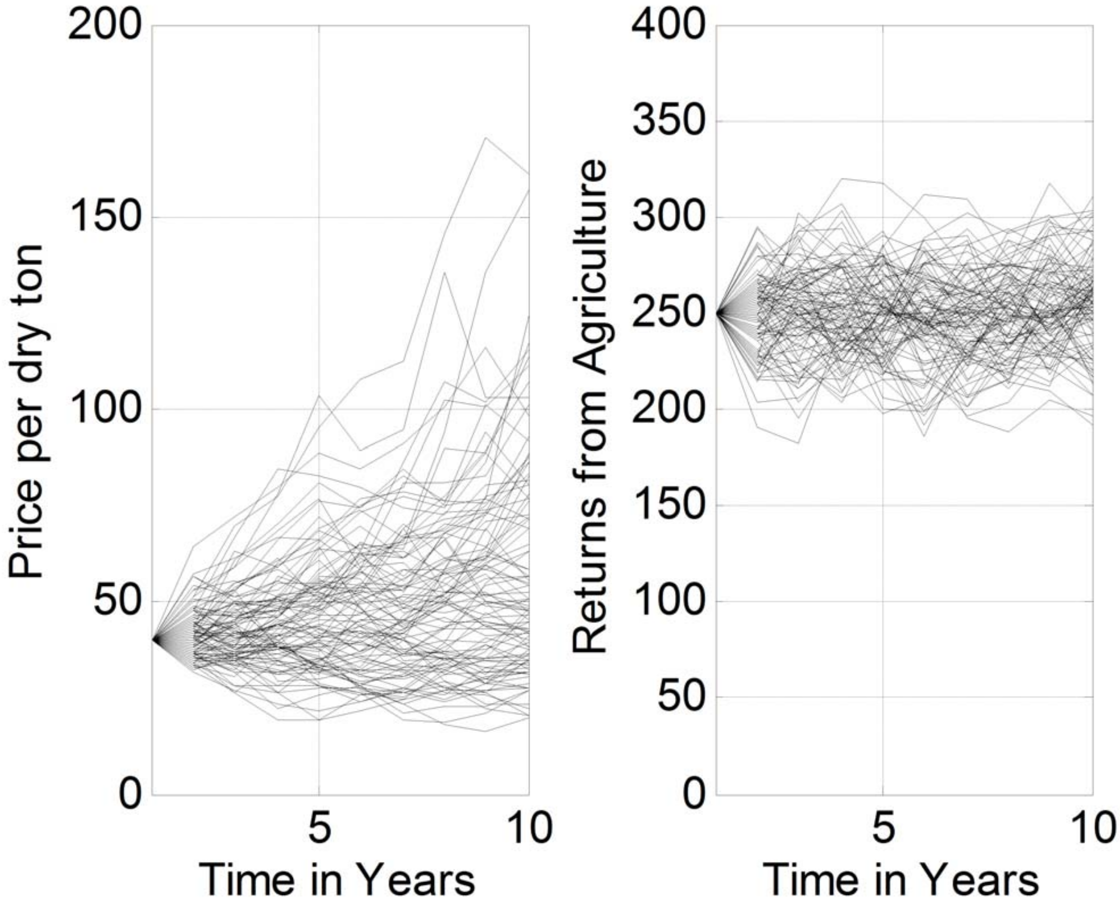

Figure 3: Simulation of 100 possible paths for the biomass price (left) and agricultural returns (right). We assume in this particular example that the long-run mean of agricultural returns is \$250.

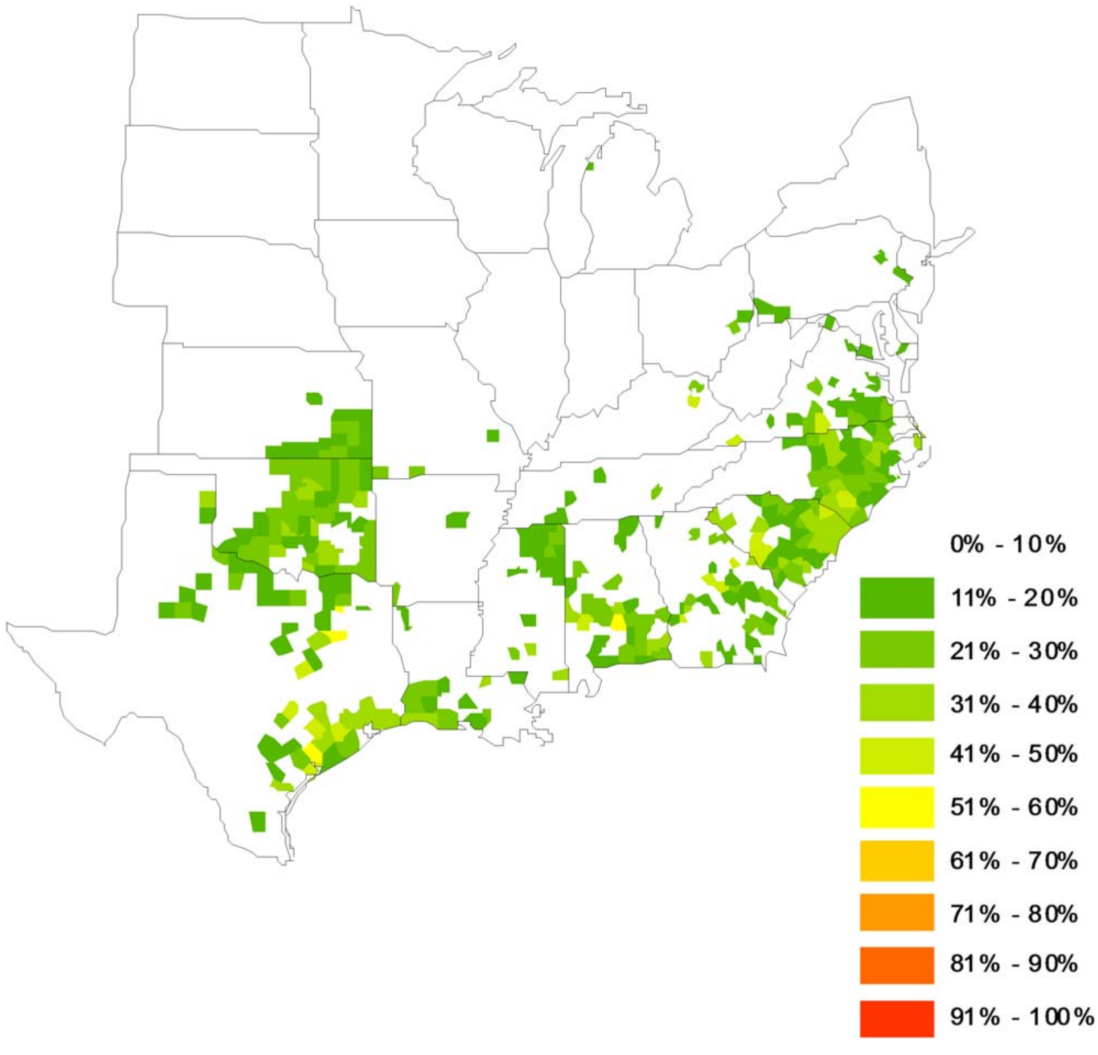

Figure 4: Average biomass price: approx. \$60 t^{-1}

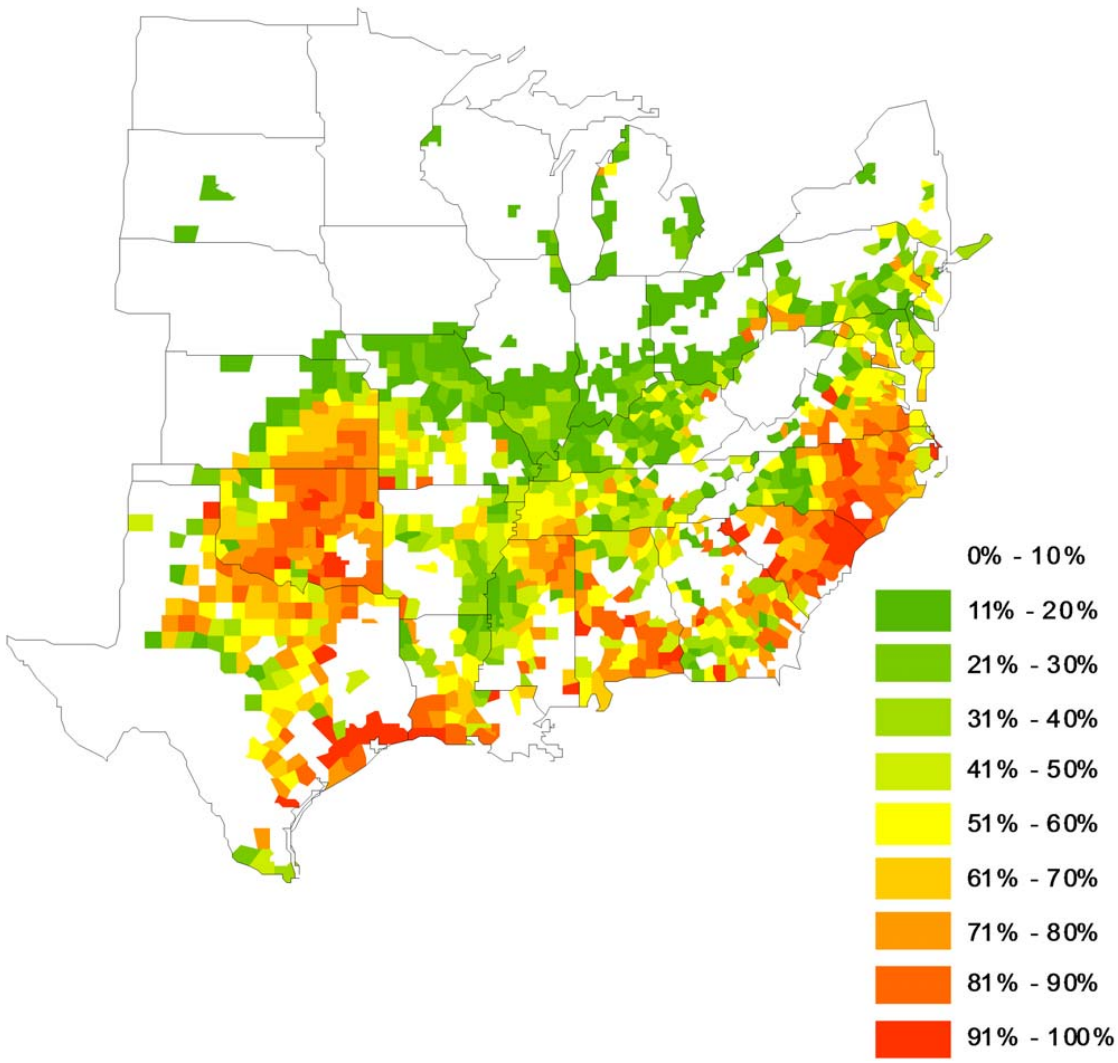

Figure 5: Average biomass price: approx. \$90 t^{-1}

5 Conclusion

High production and harvest cost hinder the supply of biomass for cellulosic ethanol production. In this paper, we extend previous literature by applying a real option framework to switchgrass production in the contiguous United States. Our preliminary 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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