Investment risk in bioenergy crops

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Abstract

Perennial, cellulosic bioenergy crops represent a risky investment. The potential for adoption of these crops depends not only on mean net returns, but also on the associated probability distributions and on the risk preferences of farmers. Using six-year observed crop yield data from highly productive and marginal sites in the southern Great Lakes region and assuming risk neutrality, we calculate expected breakeven biomass yields and prices compared to a base case of corn. Next we develop Monte Carlo budget simulations of stochastic output prices and yields. Crop yield simulations decompose risk into three components: crop establishment survival, time to maturity, and mature yield variability. Results reveal that corn with grain and stover removal is the least risky investment option, and it dominates all perennial systems considered across a wide range of constant absolute risk aversion levels. Perennial bioenergy crops have a higher potential to successfully compete with corn under marginal crop production conditions.

Keywords: Stochastic budgeting; Monte Carlo simulation; bioenergy; cellulosic biomass; energy crops; investment analysis; risk.

1. Introduction

Although annual corn is currently the most important bioenergy crop in the United States, perennial crops such as giant miscanthus[1] and switchgrass have shown the potential systematically to produce higher biomass yields (Heaton et al., 2008, Dohleman and Long, 2009). Perennial crops represent long-term investments, due to the initial cost of crop establishment and the delay before harvestable biomass is available. While production costs may be predicted with some confidence, farmers are exposed to potentially large variability in biomass yield and price (Bocquého and Jacquet, 2010). In order to understand the potential for adoption of bioenergy crops, there is a need to analyze profitability risk associated with investments in the production of perennial bioenergy crops, compared to existing crops.

A critical factor in adopting new crops, such as bioenergy crops, is their profitability relative to that of existing cropping systems. Landowners will allocate land to bioenergy crops only if the economic returns from these crops are at least equal to returns from the most profitable conventional alternatives (Jain et al., 2010). The adoption of new agricultural technologies is also affected by risk (Ghadim et al, 2005; Marra et al, 2003; Chavas, et al., 2009). Farmers' risk attitudes (Just and Zilberman, 1983) and perception about the distribution of future payoffs from the new technology (Marra et al, 2003), potential sunk costs (Chavas et al, 1994), and the opportunity cost of switching to a relatively unknown production system do affect the uptake of emerging agricultural technologies. The agronomic and economic characteristics of bioenergy perennials make them risky choices. Investment in perennial energy crops is characterized by high

[1] Specifically, hybrid *Giant miscanthus x giganteus* (Heaton et al., 2004a).

establishment cost (Lewandowski et al., 2003), establishment problems related to extreme climatic and pest events (Thinggaard, 1997; Clifton-Brown and Lewandowski, 2000), foregone income while awaiting mature yield (Song et al., 2012), and considerable removal costs to make land available for a new crop. Moreover, the risk of investing in perennial bioenergy crops is aggravated by the absence of commodity markets or crop insurance for these crops, as well as limited farming experience with them.

Breakeven budgeting addresses profitability risk by establishing a lower bound for price or quantity that is required to cover costs. Various studies have calculated the average profitability of different biomass feedstock crops (e.g., Lewandowski et al., 2003; Heaton et al., 2004b). Simple breakeven analysis studies have calculated the yields and prices at which a producer would cover costs of production (Mooney et al., 2009). One step more advanced are comparative breakeven analyses that calculate the yield or price required for a producer to earn profit at least equal to the return on a reference crop (Jain et al., 2010; Landers et al., 2012; Laporte et al., 2013; James et al., 2010). These studies relied mostly on secondary data, and they failed to account explicitly for risk. All of these studies ignored crop establishment risk and the temporal distribution of crop yield. Yet the highest biomass yielding bioenergy crop—giant miscanthus—has demonstrated susceptibility to winterkill during its first year (Kucharik et al, 2013), making establishment risk a serious concern. Moreover, risk associated with the time delay for perennial crops like giant miscanthus and switchgrass to reach harvestable yield may be substantial (Heaton et al. 2004b). Both of these risk factors supplement conventional year-to-year yield variability of mature crops in ways that could significantly affect their profitability appeal to potential adopters.

Past stochastic simulation studies that have calculated probability distributions of net returns from bioenergy crops have taken two approaches to the crucial step of simulating crop yields. In the absence of adequate data on bioenergy crop yields, one group has relied upon general crop growth simulation models, such as ALMANAC and DayCENT (Dolginow et al., 2014; Miao and Khanna, 2014). These models have the advantage of being able to simulate crop yield over large regions, however they have typically been validated at just a few individual sites, which may be problematic given that they lack well developed parameters for perennial bioenergy crops. One study (Clancy et al., 2012) statistically estimates yields of bioenergy crops across time, using a one-period-lagged, linear and plateau function and using residuals to simulation the probability distribution of random variability around expected yields. Importantly, Clancy et al (2012) recognize the relevance of winter survival risk in giant miscanthus, which they assume to be ten percent. Finally, Bocquého and Jacquet (2010) relied on interview responses and recorded secondary data for short-term empirical distributions of bioenergy crop yields.

This study draws on new bioenergy crop yield data to construct more nuanced, probabilistic, biomass yield functions for six bioenergy crop systems, linking those functions to stochastic price predictions through a stochastic investment budget model. Specifically, we make three contributions to the literature on economic risk of bioenergy crop production. First, this study uses new multi-year field data on cellulosic biomass production in the southern Great Lakes region to inform comparative breakeven analysis of perennial bioenergy crops relative to corn with grain and stover removal. Second, it explicitly considers three stochastic elements when evaluating bioenergy investment projects: a) crop failure risk, b) time to maturity risk, and c) variability in mature yields. Third, it evaluates the economic performance of a broad range of bioenergy crops that includes not only corn, giant giant miscanthus and switchgrass, but also restored prairie, native grasses and early successional (long-term fallow). While the geographic extent of the analysis refers to southern Michigan and Wisconsin, the modeling care offers broader insights about the comparative riskiness of these bioenergy crops and what drives that risk.

The remainder of the article is structured as follows. Section 2 introduces the methodology followed by a description of the used data. Results are analyzed in section 4, and discussion and conclusions presented in section 5.

2. Methodology

2.1 Conceptual framework

Rational decision makers are assumed to make crop production choices by choosing crop j to maximize a utility function (U) that includes the discounted value of net returns in light of the decision maker's risk preferences:

$$Max_j U\left(NPV_j, r\right) = \int_{t=1}^{T} \delta^t U\left(NPV_j, \lambda\right) f\left(NPV_j\right) dNPV_j \qquad (1)$$

where NPV is the net present value of crop j, δ is the discount factor, λ is a measure of risk aversion, and t is year.

When the model in (1) is applied to the case of growing bioenergy crops, an individual decision maker makes crop production choices using a multi-year model of cash flows. The *NPV* for cropping system *j* over a period of *T* years is defined as follows:

$$NPV_J = \sum_{t=1}^{T} \delta^t G_{jt} \qquad (2)$$

where G_{jt} denotes the gross margin of crop *j* cultivated in year *t*. Equation (2) provides the discounted value of annual gross margins. Financial and crop budget factors can vary from one year to another and thus constitute the dynamic elements of the model.

The appropriate ranking of biomass investment projects will depend on the investor's risk preference. For a risk-neutral decision maker, it is common to evaluate the expected net present value.[2] However, most investors are not indifferent to risk. We adopt an expected utility theory approach to decision making under risk (Mongin, 1997). Following a substantial body of empirical evidence that farmers are risk-averse (Pope and Just, 1991, Pannell et al., 2000, Hardaker, 2006), we assume that the decision maker exhibits constant absolute risk aversion and that risk preference λ takes the form of the coefficient of absolute risk aversion (CARA). Hence, the decision maker chooses crop system *j* to maximize utility of the probability distribution of *NPV*'s that are made up of discounted gross margins G_j):

$$\max_j [U(NPV)] = U(\sum_{t=1}^{T}(\delta^t G_{jt}, \lambda) f\left(G_{jt}\right) dG_{jt}) \qquad (3)$$

[2] Note, however, that real options theory shows why even for risk neutral decision makers, it may be preferable to delay action pending reception of new information before making a bioenergy production investment (Song et al., 2011).

Three yield quantity factors and on price element drive crop gross margin risk in the term, G_j, in Eq (3): a) survival risk, b) maturation risk, c) yield fluctuation risk in mature crops, and d) price risk. Survival risk in bioenergy perennials refers to mortality losses following the first season after planting. Extreme climatic conditions and pest infestations are common causes. In particular, giant miscanthus rhizomes have failed to survive the winter when soil temperatures at fall below -3.4 or 3.5 ^{o}C for a period of three days or more (Clifton-Brown and Lewandowski, 2000; Kucharik et al., 2013). Figure 1(Panel A) presents the effect of crop failure risk on the *NPV* of a biomass investment project. Crop failure, following the first season after planting, will increase the cost of investment and delay investment return. Mortality causing loss of the entire expected future income flow is especially problematic in a crop like giant giant miscanthus that is costly to plant. Maturation risk refers to variability in both the time required for a perennial crop to reach a plateau of mature yield and the level of the plateau that is reached. Figure 1 (Panel B) displays the effect of a delay in achieving a full yield potential on firm's returns. Delayed maturity permanently reduces investment return because early revenues have higher present value. Maturation risk can increase both the variance and skewness of the distribution of gross margins. Of course, as with annual crops, mature yields vary due to factors such as climate (Parry and Carter, 1985; Nuñez and Trujillo-Barrera, 2014), soil type (Dinkins and Jones, 2008), and pests (Skevas et al, 2013). Finally, revenue risk is driven also by price volatility. Agricultural prices vary due to changes in the economic environment in which farms operate (de Ridder et al, 2013).

2.2 Empirical model

2.2.1 Risk neutral case: Breakeven investment analysis

The economic performance of seven cellulosic biomass feedstock investment projects is computed using a discounted cash flow approach. The biomass investment projects include corn, giant giant miscanthus, switchgrass, native grasses, restored prairie, and early successional. Revenues and expenditures are used to calculate annual cash flows for each cropping system. For convenience in comparing results between annual and perennial crops, the sum of the present value of net returns (NPV) over time horizon, *T*, is annualized using the following annuity formula:

$$A = \left[\frac{rNPV}{1-1/(1+r)^T}\right] \qquad (4)$$

where *A* is the annual payment, and *r* is the discount rate. The time horizon is six years, and we assume a real discount rate of 5%, following Erickson et al (2004). Each cropping system has a different production cycle with corn resulting in harvestable yield each year of the six-year time horizon while the perennial cropping systems experience delays of 1-2 years before producing harvestable yield.

The comparative breakeven price and yield analyses to identify the cellulosic biomass prices and yields that would make perennials crops equally profitable with a reference enterprise, corn, in this case. The breakeven price analysis takes into account the direct costs of production, expected yields, and the opportunity cost of replacing the existing cropping system. Corn's returns come from harvesting both grain and 38% of available stover (Brechbill and Tyner, 2008). Following Kells and Swinton (2014) the breakeven price of a cellulosic perennial crop to replace corn is as follows:

$$BE_{pr} = \frac{NPV_D + \sum_t\left(\frac{c_t}{(1+r)^T}\right)}{\sum_t\left(\frac{y_{C_t} - y_{D_t}}{(1+r)^T}\right)} \quad (5)$$

Where BE_{pr} is the comparative breakeven price, NPV_D is the expected *NPV* of the "defender" crop (corn), c_t the expected cost of producing the new biomass crop, y_{Ct} is the expected biomass yield achieved by the "challenger" bioenergy crop, y_{Dt} is the expected biomass yield of the "defender crop", and *r* and *T* as previously defined. is the *NPV* of the defender crop. The denominator represents the biomass yield gain of the "challenger" crop over the "defender" cropping system and implies that a "challenger" crop breaks even only if its yield exceeds the yield of the "defender" crop.

Breakeven yield shows the minimum cellulosic yield required for a producer to earn equal profit to corn, given an expected biomass price. Using the same notation as above, the breakeven yield Y_{BE} is computed as follows:

$$Y_{BE} = \frac{NPV_D + \sum_t\left(\frac{adc_t}{(1+r)^T}\right)}{\sum_t\left(\frac{P_t - ydc_t}{(1+r)^T}\right)} \quad (3)$$

where adc_t is acreage dependent costs (i.e. cost of planting material, agrochemicals, and machinery-labor), P_t is the expected biomass price, and *ydc* is yield dependent costs (i.e. baling, and bale transportation cost).

Finally, financial assistance to growers of perennial energy crops may be provided by the U.S. Department of Agriculture's Biomass Crop Assistance Program (BCAP) (USDA, 2014). This study examines the impact of three BCAP payments on the profitability of the six biomass investment projects. The BCAP payments include: a) establishment payments, b) annual rental payments, and c) matching payments. Establishment payments cover 50 percent of the costs of establishing dedicated energy crops and the total payments per acre are capped at $500. Annual rental payments include a payment (for a maximum of five years) based on typical rental rates for cropland, marginal land or forest land and are used to cover the foregone income from the land during the establishment phase (before the crop reaches economically harvestable levels). Matching payments of $20 per ton (for a maximum of two years) are used to mitigate the cost of harvesting and transporting biomass to a biorefinery. The annual payment is reduced when a matching payment has been earned.

2.2.2 Risk averse case: Stochastic capital budgeting

The stochastic capital budgeting model introduces the three forms of yield risk plus price risk into simulation of probability distributions of NPV's for each bioenergy crop, along with the monetary value of the certainty equivalent for a range of decision makers with CARA risk preferences. Figure 2 is a flow chart of the steps performed in implementing the stochastic capital budgeting analysis.

Estimation of stochastic biomass yields was done in three parts: first, estimation of the chance of giant miscanthus failure at each site, second, estimation of time to maturity trajectories for each crop at Arlington (ARL) in south-central Wisconsin and the Kellogg Biological Station (KBS) in southwest Michigan, and third, fitting of probability distributions for additive random errors. Estimations of time-to-maturity risk and risk in mature yields were based on six years of field experiments from 2008-2013. At each site, there were five plots each of switchgrass, giant miscanthus, restored prairie, mixed native grasses, and early successional treatments. At ARL, there was winter kill of giant miscanthus in 2008/2009, and it was not re-planted until 2010. In addition, at KBS, switchgrass, native grasses, and restored prairie all experienced crop failure in 2008 due to heavy rains, they and were replanted in 2009. As a result, these crops have fewer years of data.

Simulation of the probability of winterkill was conducted for giant miscanthus, based on evidence of plant mortality when soil temperatures at a depth of 10 cm fall below -3.5 degrees C. for a duration of three or more days (Kucharik et al., 2013). Soil temperature data from the UW Extension Ag Weather network spanning twenty years (August 1994-June 2014) revealed that 9 of 20 years exceeded that threshold at ARL, for a 45% chance of rhizome winterkill. Soil temperature data from KBS was not available; instead, data from MSU's Enviroweather series collected in East Lansing between January 1996 and December 2014 was used. Because average soil temperature at 10 cm was not available, the 10 cm minimum and maximum temperatures were averaged and three-day running means were calculated. Two out of nineteen years of data (including 1996) saw soil temperatures fell below the -3.5 degree threshold, for a 10.5% probability of winterkill at KBS.

Data from the ARL and KBS were used to estimate the trajectory of yield over the first few years of growth at the south-central Wisconsin and southwest Michigan research site locations. Table 1 shows the functional forms and parameter estimates for yield trajectories of perennial crops at ARL and KBS. Spillman and Mitscherlich functions were among those evaluated, as both increase to a plateau or upper asymptote. Coefficients for each crop at each location were estimated using nonlinear least squares. The Mitscherlich function and simpler linear functions performed well for crops that take time to reach mature yields such as switchgrass, giant miscanthus, and native grasses. For these crops that exhibited time-to-maturity risk, that risk was simulated using random slope coefficients, where the coefficients were drawn from normal distributions with mean at the estimated parameter and standard deviation equal to the estimated coefficient standard error. For early successional and restored prairie, yield does not change over time, so mean values were used to represent risk-free yields. All choices of functional form were based on theoretical consistency supported by Davidson-MacKinnon tests. In addition to time to maturity risk, yields were assumed to have an additive random error to account for yearly fluctuations on yield. Table 2 presents the probability distributions of random additive annual yield disturbance terms that were drawn from continuous distributions fitted from regression residuals using @Risk.

In order to abstract from current market conditions, biomass prices were drawn at random from stochastic simulations of corn and warm season grass prices in 2018 that were prepared for the March 2014 outlook report by Food and Agricultural Policy Research Institute at University of Missouri (FAPRI-MO)[3].

[3] Personal communication by Wyatt Thompson to Scott Swinton by email, Dec. 13, 2014.

The stochastic budgeting model was programmed in excel and simulated using @Risk. A Latin Hypercube sampling with a sample of k=1000 was used to estimate the distribution of the stochastic variables for each risky investment.

The risky alternatives are then compared using stochastic dominance criteria. These criteria allow ranking of investment prospects by comparing their empirical distributions of investment returns without requiring explicit knowledge of individual preferences. Common stochastic dominance criteria are first (FSD) and second degree stochastic dominance (SSD). FSD requires only the assumption decision makers prefer higher returns to lower returns. SSD requires the added assumption that the decision makers are risk averse. Both approaches involve comparisons of the cumulative distribution functions (CDF) of alternative investment option returns. An alternative approach that has more restrictive assumptions but stronger discriminating power than FSD or SSD is stochastic efficiency with respect to a function (SERF) (Hardaker et al., 2004). Under the assumption that a decision maker's risk preference parameters are known, certainty equivalent (CE) values can be calculated in monetary terms. SERF ranks a set of risky alternatives in terms CE's. Following Pratt (1964), we use the negative exponential constant absolute risk aversion (CARA) utility function: $U_{CARA}(G) = -e^{-\lambda G}$. Using this function, the CE is computed as follows:

$$CE_{CARA}(G, \lambda) = {-ln\left(-\frac{1}{n}\sum_i^n e^{-\lambda G}\right)} \Big/ {\lambda}$$

The CE represents the amount of money a decision maker would require to be indifferent between receiving that amount for certain and receiving a potential result from the risky investment. When using agronomic experimental data, CARA is an appropriate utility function because there is no need to account for heterogeneity in decision maker wealth levels. Following King and Robison (1981) and Cochran et al. (1985), the risk aversion coefficients used in this analysis range from 0 (risk neutral) to 0.001 (highly risk averse).

3. Data

The analyses reported here draw bioenergy crop management practices and yields from the six year period 2008-13 from the Great Lakes Bioenergy Research Center (GLBRC) Biofuel Cropping System Experiment installed at the Kellogg Biological Station (KBS) at Hickory corners, MI, and at the Arlington (ARL) Agricultural Research Station in Arlington, WI (see details at http://data.sustainability.glbrc.org/pages/1.html). The cropping system treatments discussed here include corn (with stover removal), giant miscanthus, switchgrass (Cave-in-Rock variety), native grasses, restored prairie, and early successional. Yield data and output prices are presented in Table 3. For the breakeven investment analysis, 2008-2013 output prices for corn from the National Agricultural Statistics Service (NASS) are used (NASS, 2014), while cellulosic feedstock price is assumed to be $50/mg. This price was selected because it is close to the rounded average of the 2018 Food and Agricultural Policy Research Institute (FAPRI) price forecasts for warm season grass (i.e. $50.79/mg) and the Michigan State University T.B. Simon power plant energy biomass purchases (of switchgrass and restored prairie) from GLBRC in 2013 (i.e. $51.14/Mg). The Simon power plant payments are meaningful, because they are based on the energy equivalent of coal, and thus indicative of what commercial power plants would pay for delivered biomass for co-firing with coal. For the stochastic capital budgeting, 2018 FAPRI price forecasts for corn and warm season grass were used. These prices are calculated from 500 simulated iterations. The average FAPRI price for corn and warm season grass was $159/Mg and $51/Mg, respectively. Tables 1 and 2 in the appendix present the costs of the main inputs used in crop production for each cropping system and location. These costs include planting materials, agrochemicals, machinery-labor and, post-harvest. Input cost data come from secondary sources and when there was a lack of cost data for Wisconsin or Michigan cost data from neighboring states were used. The input cost data used in the current study represent 2008-2013 production conditions in the southern Great Lakes region.

4. Results

4.1 Profitability by cropping system at current prices and yields

The mean profitability of the bioenergy cropping systems at KBS in southwest Michigan and ARL in south-central Wisconsin is presented as annualized NPV in Figures 3 and 4. In both locations the profitability of corn far exceeded that of any of the perennial crop systems. The reason, of course, is that corn revenues benefit from two components: the valuable grain product plus the less valuable cellulosic biomass product. Although agrochemicals are more costly in corn than any of the other cropping systems, revenues offset those costs. By contrast, the high cost of giant miscanthus planting material (rhizomes) is not fully compensated at current prices, despite the high biomass yield of giant miscanthus. Due to better soils at ARL than KBS, all crops except giant miscanthus yielded better at ARL. However, the relative benefit of good soils was greater for corn yield than for the biomass yield of giant miscanthus, switchgrass and early successional—

indicating that KBS shows a higher potential for perennial crops to successfully compete with corn. The following breakeven analysis examines just how close each site and cropping system is to equaling the profitability of corn.

4.2 Comparative breakeven prices

Breakeven prices for cellulosic biomass refer to prices that producers of continuous corn must receive in order to earn equal profit from a cellulosic perennial crop. Table 4 presents breakeven prices for each cropping system assuming a corn grain price of \$196 Mg^{-1} (\$5 bu^{-1}). The giant miscanthus figures are underestimates, because they ignore the risk of winterkill. Even so, no system can breakeven at ARL because the mean corn stover yield there exceeded the mean biomass yield of any of the perennial bioenergy crops. At KBS, however, corn stover yields were lower, and three perennial bioenergy crops have the potential to break even at a sufficiently high biomass price. Giant miscanthus, the crop with highest biomass yield could match the profitability of corn at a biomass price of \$243 Mg^{-1}. Switchgrass would require \$885 Mg^{-1}, while the native grasses would require the price of a small car for each ton of biomass, because its mean yield barely exceeded that of corn stover. Restored prairie and early successional in KBS produce less biomass than corn stover and so cannot break even at any biomass price.

4.3 Comparative breakeven yields

Table 5 presents comparative breakeven yields for each cropping system at the ARL and KBS sites, assuming a biomass price of \$50 Mg^{-1}. Breakeven yield shows the minimum yield required for a producer to earn equal profit to corn. Breakeven yields for all crops are higher at ARL compared to KBS, due to higher yields of the corn system in the former. The crop with the lowest breakeven yield in both states is early successional, which has the lowest costs—just the cost of biomass harvest. Next lowest are the native grasses, switchgrass and restored prairie. Comparing current yields and breakeven yields, it can be stated that proportionately large yield increases are required (i.e., >100%) for the perennial bioenergy crop to break even in almost all cropping systems. However, the magnitude of yield gains needed is smaller at KBS than at ARL, due to the lower productivity of the corn reference system at the KBS site.

4.4. BCAP results

While breakeven prices and yields are fictive benchmarks, the USDA Biomass Crop Assistance Program (BCAP) is a current policy designed to enhance the profitability of dedicated bioenergy crops. Figures 5 and 6 compare the profitability of the bioenergy cropping systems at ARL and KBS under no BCAP financial assistance and four different BCAP scenarios: matching payments for biomass at time of sale, annual rental payments, establishment cost share payments, and all three combined. An important observation is that BCAP payments cannot bridge the profitability gap between corn and bioenergy perennials. However, in the all BCAP payments combined scenario, the profitability of most bioenergy perennials turned from negative to positive. This is the case for all bioenergy perennials except giant miscanthus in both locations. In a few cases (i.e. switchgrass at KBS and switchgrass and early successional at ARL), individual BCAP payments such as annual rental and matching payments can also reverse negative profitability trends.

4.5 Stochastic simulation results

Up to this point, all results have been based on mean values, so they ignored production and price risk. Summary statistics from 1000 stochastic simulations of the six bioenergy cropping systems at KBS and ARL are presented in Table 6. The corn systems stand out as having the highest mean profit and much the highest maximum at both sites. However, corn presents a high standard deviation, and its minimum values are lower than several perennial bioenergy cropping systems. Giant miscanthus did poorly at both sites because of winter kill. Over the 20-year simulation period, giant miscanthus had a 45% chance of winter kill at ARL and a 10.5% chance at KBS.

First and second-degree stochastic dominance identified certain systems as relatively efficient in the sense that they were not dominated by any other cropping system at their site. Corn appeared in the efficient set at both sites, joined by native grasses and early successional at ARL and by switchgrass at KBS. Giant miscanthus was dominated by all other crops under one criterion or the other. At ARL it did so poorly that it lost money even in its best iteration. Consequently, it was strictly dominated under FSD by all of the other crop systems at ARL. At KBS, giant miscanthus was dominated under FSD by switchgrass, native grasses and corn and under SSD by restored prairie and early successional. The restored prairie treatment also fared poorly, being dominated at KBS under FSD by switchgrass, native grasses, early successional and corn, as well as dominated at ARL under SSD by corn. The remaining perennial bioenergy crops differed in their stochastic dominance results between the two sites. Although switchgrass was in the efficient set at KBS, at ARL it was dominated under FSD by native grasses and early successional. The early successional and native grass treatments that were in the efficient set at ARL were dominated at KBS under FSD by switchgrass.[4]

Although corn was accompanied in the FSD and SSD risk efficient sets by switchgrass at KBS and by native grasses and early successional at ARL, corn was the more profitable system under all but the very worst outcomes simulated. At ARL, corn was more profitable than native grasses and early successional in over 99.5% of the outcomes. Likewise at KBS, corn was more profitable than switchgrass 95% of the time. Only when the higher cost corn crop failed repeatedly did it fail to come out ahead of its closest competitors.

Because more than one cropping system remained in the risk efficient sets at each site under FSD and SSD, SERF was used to rank the full set of bioenergy investment projects at each site. Certainty equivalent (CE) values for corn and perennial crops are presented for the range of CARA levels from 0 (risk neutral) to 0.001 (highly risk averse) in Figures 7 and 8. At CARA=0, the CEs equal the mean expected annualized NPV. The CEs decline as risk aversion increases (i.e. as CARA values become larger). In both locations the locus of CE values for corn is everywhere higher than that for all bioenergy perennials, indicating that producers who are both risk-neutral and risk-averse over a very wide range of risk aversion would prefer corn to bioenergy perennials. The next best alternative investment is restored prairie in ARL or switchgrass in KBS, but the differences compared to all other perennial crops but giant miscanthus are very small.

[4] The FSD and SSD results are not reported in full detail in this paper, but can be provided by the authors upon request.

On comparing the capital budgeting (i.e. risk-neutral case) and the stochastic budgeting (i.e. risky case) results, we see both similarities and differences in the ranking of risky bioenergy investment projects. Corn is the preferred cropping system in both the risk-neutral and the risky cases and at both locations. The difference between corn and bioenergy perennials is consistently higher at ARL than at KBS, which is attributable to more fertile soils in the former that result in higher corn yields at ARL. The most prominent difference when comparing the results of the risk-neutral and the risky case is the change in the ranking of bioenergy perennials (e.g., early successional ranks second in the risk-neutral case in both locations, but when comes to the risky-case it takes the third and fourth place in ARL and KBS, respectively). Small differences in the profitability of most bioenergy perennials (except giant miscanthus) and the fact that stochastic simulation covers a wide range of states of nature may explain ordering changes when moving from the risk-neutral to the risky-case.

5. Discussion and conclusions

This paper supplements standard capital budgeting and comparative breakeven analysis with stochastic simulation to assess the competiveness of bioenergy perennials relative to corn with grain and stover removal. Using data from 2008-13 from sites at Arlington, WI, and KBS at Hickory Corners, MI, we simulate four stochastic variables that affect returns to investments in six bioenergy cropping systems: crop failure risk, time to maturity risk, variability in mature yields, and price risk.

The standard capital budgeting analyses shows that corn dominates in terms of profitability all other cropping systems in both sites. The lack of yield lag in corn production compared to that of most bioenergy perennials and the fact that corn provides income from both grain and cellulosic biomass, make it the most profitable bioenergy crop system. BCAP payments can reduce profitability losses from adopting perennial bioenergy crops, but they are not sufficient to bridge the profitability gap between them and corn. Future research could seek to assess how much this could feasibly be further narrowed using policies that provide farmers with payments for ecosystem services related to perennials cultivation.

The comparative breakeven price analysis shows that all perennials fail to break even at ARL while switchgrass, giant miscanthus, and native grasses require very high prices to break even at KBS. Concerning breakeven yields, high yield gains are required for perennials to generate net revenue equal to corn at both sites. At KBS however, the required yield increases are relatively smaller. Both the breakeven price and yield analyses show a greater potential for bioenergy crops to successfully compete with corn at KBS, because corn productivity is lower in the less fertile soil at KBS.

Overall, stochastic efficiency analysis of the investment return results show annual corn to be an even more resilient benchmark than prior profitability studies that ignored risk of establishment failure and time to maturity of perennial bioenergy crops. Corn was the only crop in the risk efficient set under FSD and SSD at both sites. Under the SERF analysis, it dominated all other systems at all of the risk aversion levels simulated at both locations. No other system came close at ARL in Wisconsin. At KBS in Michigan, switchgrass came second—within competitive range at the \$50 Mg^{-1} biomass price if corn grain prices were to fall to levels of the 1990's and early 2000's. In general, more bioenergy crops generated positive profits at KBS significant portions of the time, including switchgrass (98%), native grasses (75%), and early successional (70%). In ARL, apart from corn, only prairie generated positive net returns most of the time (73% of cases).

Although earlier studies found that giant miscanthus performs better than other bioenergy perennials (Clancy et al., 2012; Dolginow et al., 2014), we find that it has an extremely high probability of generating negative return. Our more negative results were driven by high current rhizome costs and the high probability of winter kill in the establishment year in ARL and lower but still notable probability of winter kill in KBS.

In the absence of changes in agronomic technology or market prices, the pattern of low investment returns from perennial bioenergy crops implies a need for large subsidies to make perennial bioenergy crops equally attractive with corn, with mean differences ranging from \$75-385/acre in KBS to \$343-717/acre in ARL. The bioenergy crops with the lowest subsidy requirements were switchgrass at KBS and restored prairie at ARL. One factor mitigating potential subsidies required is that the variance of investment returns for bioenergy perennials is lower than for corn (except for giant miscanthus in ARL). Another measure that can increase the attractiveness of bioenergy perennials is BCAP payments. Although these payments cannot make bioenergy perennials equally attractive to corn, they can reduce expected losses and (except for giant miscanthus) the probability of a negative investment return.

The results also show evidence of potential regional comparative advantage. The lower corn yields on poorer soils at KBS reduce the revenue gap between corn and most bioenergy perennials, compared to the gap at ARL. While bioenergy crops remain significantly poorer investments than corn, their lower opportunity cost under the more marginal crop production conditions at KBS indicates the potential for regional comparative advantages at more marginally productive sites if relative prices, technological change, or policy advantages were to favor perennial bioenergy crops.

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Tables

Table 1. Yield trajectories of perennial crops at ARL and KBS: functional forms and parameter estimates (explanatory variable *t* = 0 to 5 is years since planting).

Crop (location)	Functional form	Maximum (α)	Slope (β, m)	Intercept (b)	Mean (a)
Switchgrass (ARL)	Mitscherlich $y=\alpha(1-exp(-\beta t)$	9.0392*** (.7983)	0.4521*** (0.0923)	n/a	n/a
Switchgrass (KBS)	Linear $y=0$ if $t=0$ $y=mt+b$ if $t>0$	n/a	1.6358*** (0.3018)	3.5848*** (0.5647)	n/a
Giant miscanthus (ARL)	Mitscherlich $y=\alpha(1-exp(-\beta t))$	15.0085*** (2.7872)	0.8912* (0.4503)	n/a	n/a
Giant miscanthus (KBS)	Mitscherlich[a] $y=\alpha(1-exp(-\beta t))$	28.8517* (14.2383)	0.2182** (0.1661)	n/a	n/a
Native grasses (ARL)	Linear $y=0$ if $t=0$ $y=mt+b$ if $t>0$	n/a	0.3300* (0.1710)	4.4244*** (0.4189)	n/a
Native grasses (KBS)	Linear $y=0$ if $t=0$ $y=mt+b$ if $t>0$	n/a	0.7876* (0.4311)	3.2506*** (0.8065)	n/a
Early successional (ARL)	Mean value $y=a$	n/a	n/a	n/a	2.9843
Early successional (KBS)	Mean value $y=a$	n/a	n/a	n/a	2.365
Restored prairie (KBS)	Step to mean value $y=0$ if $t=0$ $y=a$ if $t>0$	n/a	n/a	n/a	2.8925
Restored prairie (ARL)	Step to mean value $y=0$ if $t=0$ $y=a$ if $t>0$	n/a	n/a	n/a	4.1296

[a] Davidson-MacKinnon test was inconclusive.

Note: Numbers in parenthesis are standard errors of parameter estimates. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 2. Probability distributions of additive random annual crop biomass yield disturbance terms that were drawn using @Risk.

Crop	Site	Distribution
Giant miscanthus	ARL	Logistic(-0.1015, 1.8406)
	KBS	Normal(0.0702, 4.8657)
Switchgrass	ARL	Logistic(0.0212, 0.4584)
	KBS	ExtValueMin(0.7540, 1.2934)
Restored prairie	ARL	Weibull(2.8858,4.4978) -4.0046*
	KBS	ExtValue(-0.5164, 0.9432)
Native Grasses	ARL	ExtValue(-0.5765, 0.9889)
	KBS	ExtValueMin(1.0837,1.8946)
Early successional	ARL	Weibull(1.8545,2.4424) -2.1731*
	KBS	ExtValueMin(0.5234, 0.9372)

*Weibull distribution shifted down by value of this constant (RiskShift parameter in @Risk).

Table 3. Crop yields and prices in the southern Great Lakes area in 2008-2013.

Crop	Location	Yield[a] (Mg/ha) Mean	St.dev	Output price[b] ($/mg)
Corn Grain	ARL	12.65	1.61	196
	KBS	9.82	3.19	
Corn Stover	ARL	5.88	1.40	50
	KBS	2.62	1.58	
Switchgrass	ARL	4.88	3.21	50
	KBS	4.08	3.46	
Giant miscanthus	ARL	5.93	6.75	50
	KBS	11.02	8.16	
Native grasses	ARL	4.24	2.30	50
	KBS	2.95	2.93	
Early successional	ARL	2.99	1.23	50
	KBS	2.37	1.10	
Restored Prairie	ARL	3.44	2.11	50
	KBS	1.89	1.61	

[a] Yield data are from field trials at the Great Lakes Bioenergy research Center (GLBRC) intensive research sites at the University of Wisconsin agronomic research station at Arlington (ARL) in south-central Wisconsin and at the Kellogg Biological Station (KBS) in Hickory Corners, Southwest Michigan.

[b] Corn grain price is an average for the 2008-2013 period (NASS, 2014). The respective corn grain price in $/bu is 5. Biomass price is derived using the average (FAPRI) price forecasts for warm season grass and the Michigan State University T.B. Simon power plant energy biomass purchases (of switchgrass and restored prairie) from GLBRC in 2013.

Table 4. Breakeven prices ($/Mg) of biomass feedstocks with respect to a corn grain price of $5.00/bu ($196/Mg) at ARL and KBS sites.

Crop	ARL	KBS
Switchgrass	N/A[a]	885
Giant miscanthus	N/A	243
Native grasses	N/A	20,698
Restored prairie	N/A	N/A
Early successional	N/A	N/A

[a] N/A denotes that the cropping system cannot break even since it does not produce as much biomass as corn stover.

Table 5. Breakeven yields ($/Mg) of biomass feedstocks with respect to a biomass price of $50/Mg at ARL and KBS sites.

Crop	ARL	KBS
Switchgrass	74	44
Giant miscanthus	113	83
Native grasses	70	44
Restored prairie	74	45
Early successional	70	40

Table 6. Stochastic annualized NPVs of bioenergy crops at ARL and KBS sites, 1000 simulation iterations (in U.S. dollars).

	ARL					KBS				
Crop	Mean	Stdev	Median	Min	Max	Mean	Stdev	Median	Min	Max
Corn	943	439	932	-265	2527	328	168	319	-136	830
Switchgrass	-83	40	-81	-199	34	141	66	140	-71	346
Giant miscanthus	-830	145	-821	-1175	-361	-623	272	-670	-1148	311
Native grasses	-43	39	-40	-153	112	63	85	56	-129	353
Prairie	94	135	86	-278	503	-63	49	-65	-176	120
Early successional	-39	61	-43	-183	215	34	55	28	-80	222

Figure 1. Establishment failure (left) and delayed maturity (right) implications on the NPV of a biomass investment project

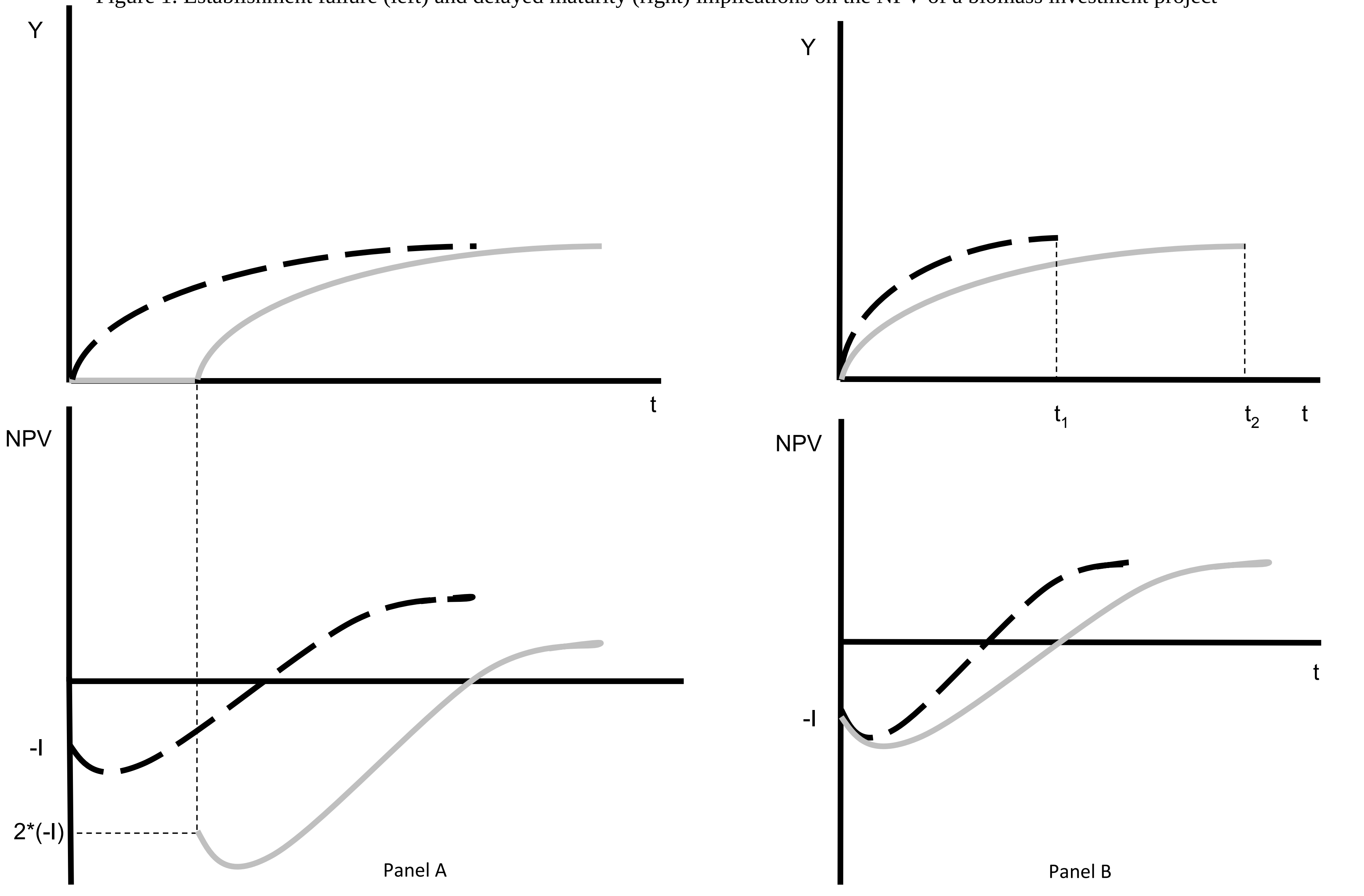


Figure 2. Flow chart of stochastic simulation of six-year net present values of investment returns.

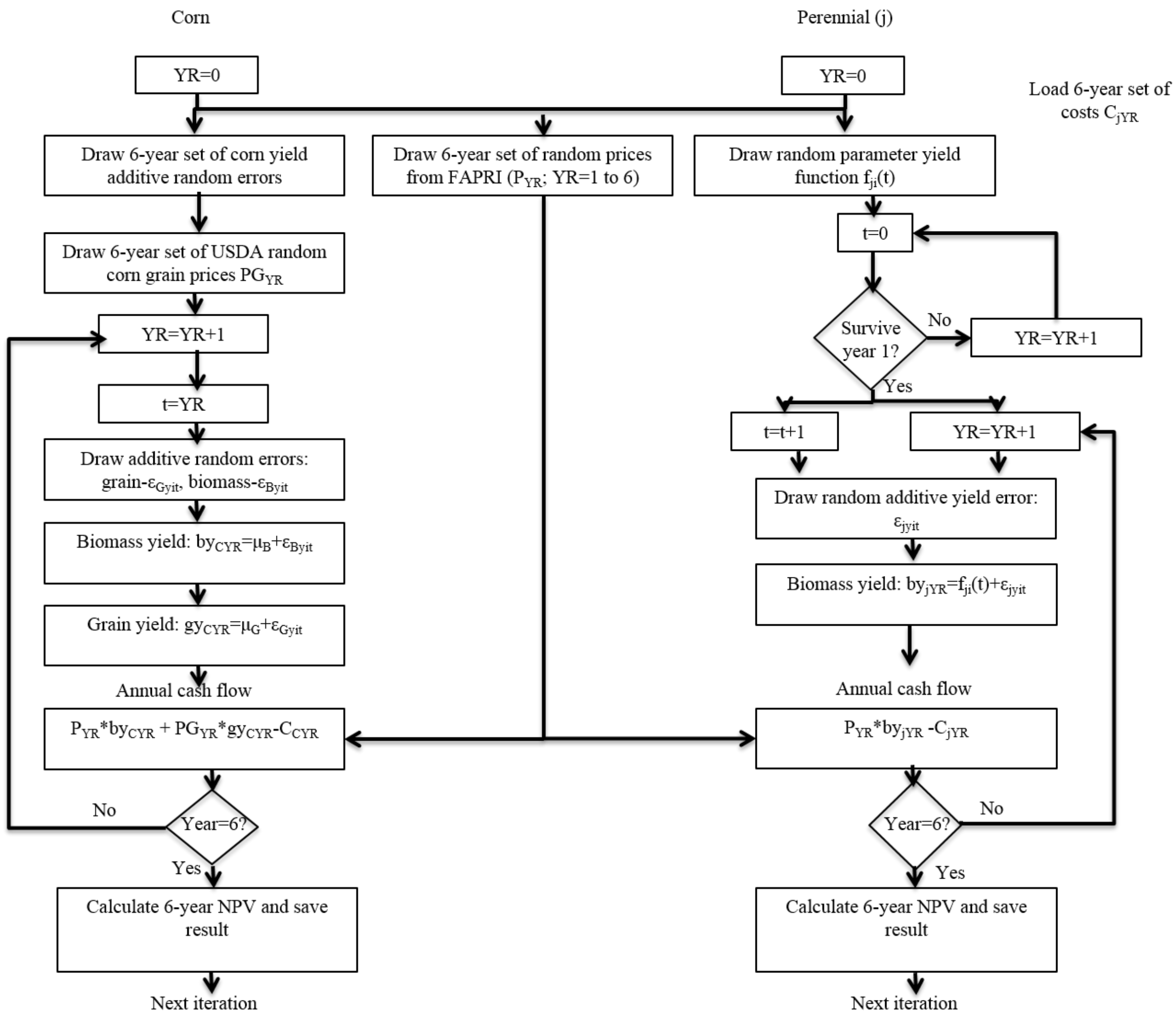


Figure 3. Revenues and production costs (annualized NPV in $/ha) of biomass crops, ARL, WI.

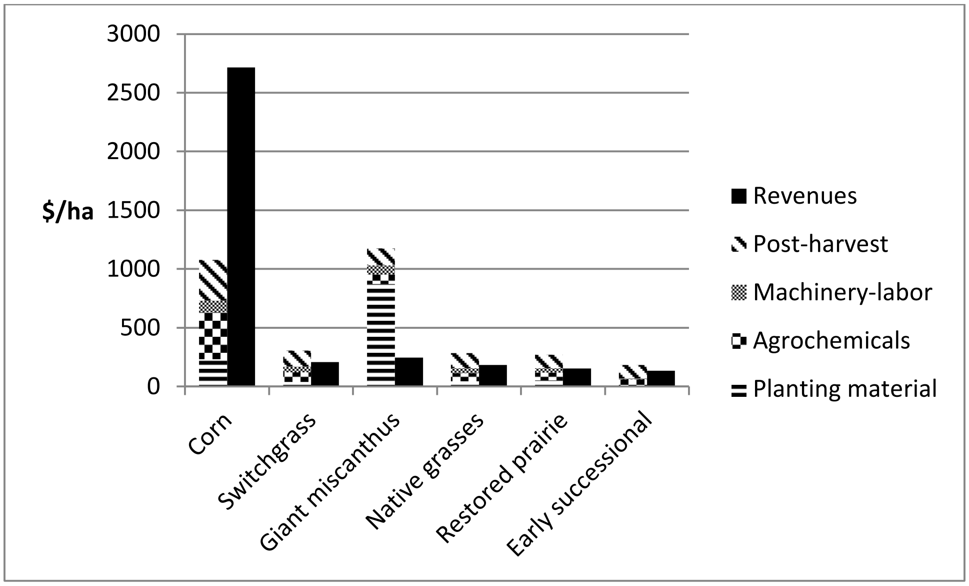


Figure 4. Revenues and production costs (annualized NPV in $/ha) of biomass crops, KBS, MI.

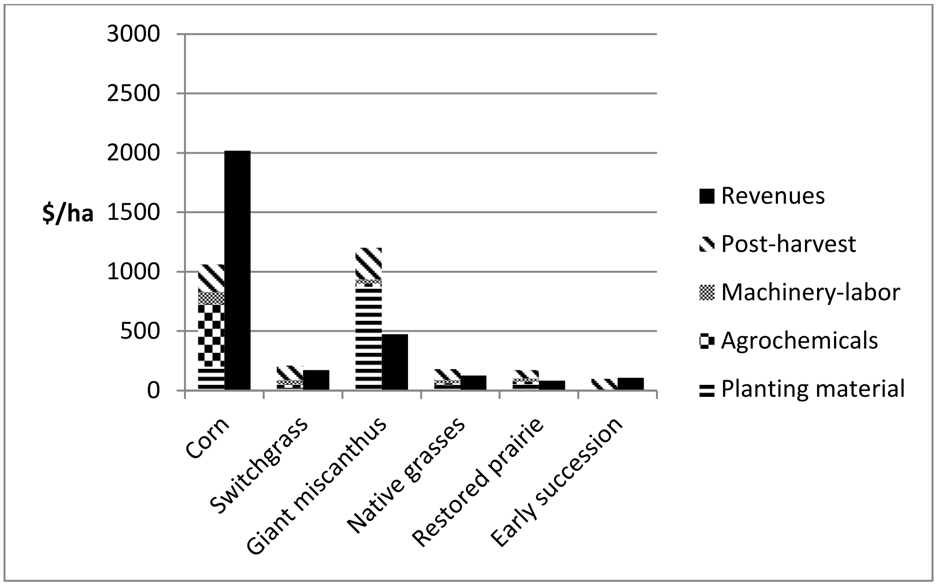


Figure 5. BCAP scenarios, ARL, WI.

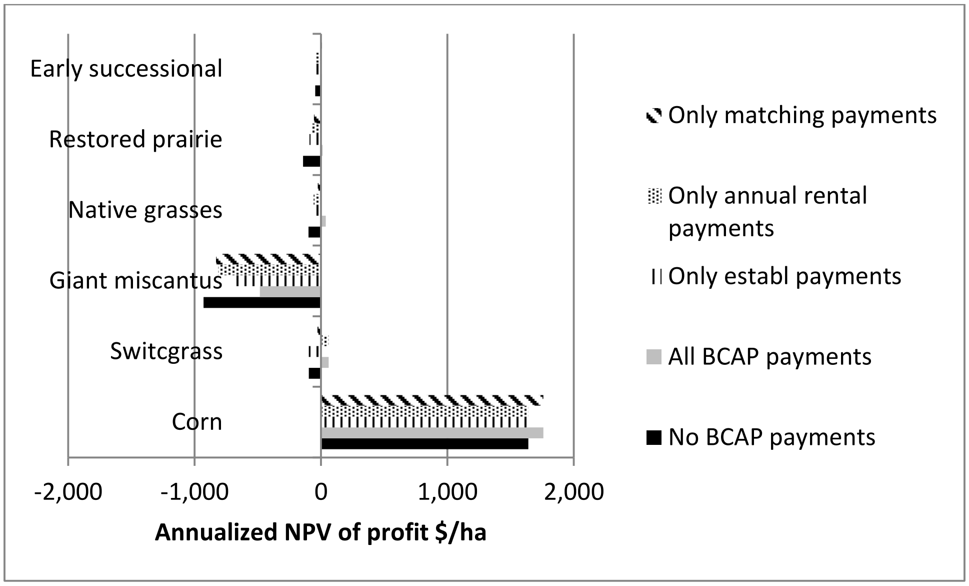


Figure 6. BCAP scenarios, KBS, MI.

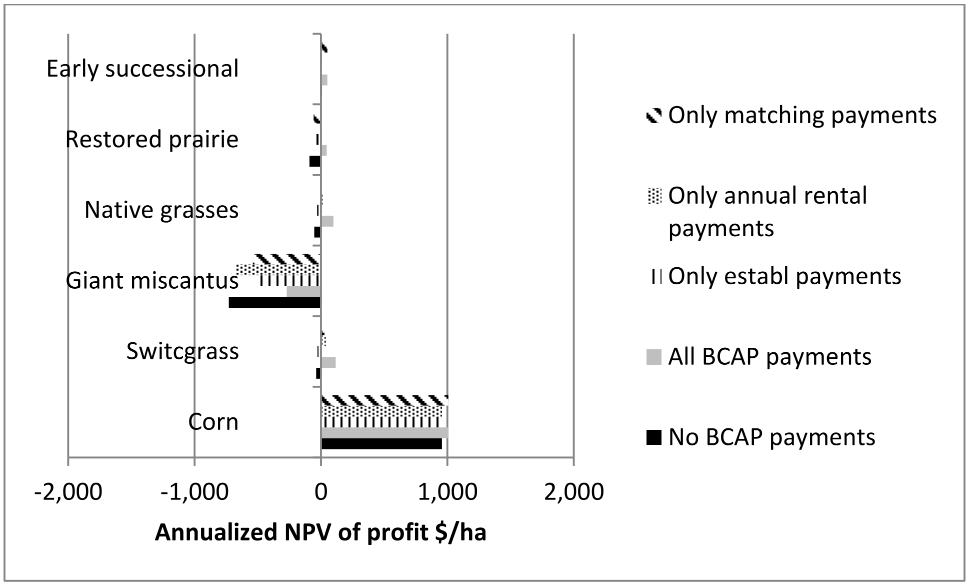


Figure 7. Certainty equivalents for risk-neutral and ten levels of constant absolute risk aversion: Stochastic efficiency with respect to a function (SERF) comparison of results from 1000 stochastic simulations of annualized net returns from bioenergy investment projects in Arlington, WI.

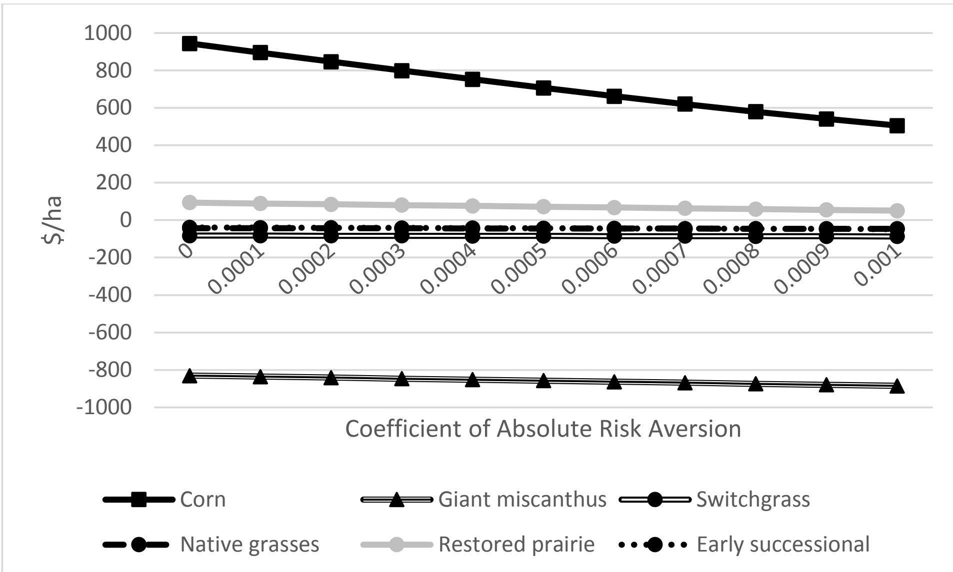
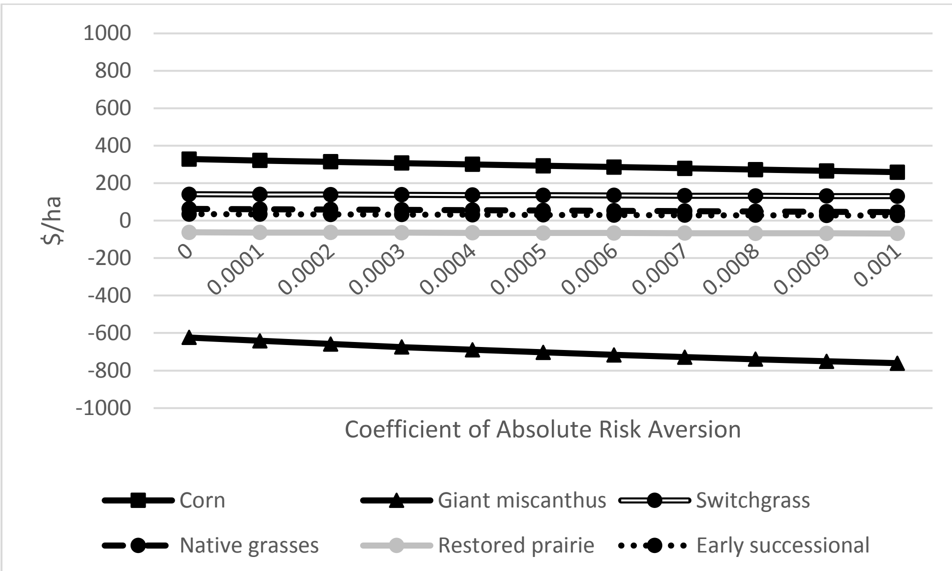


Figure 8. Certainty equivalents for risk-neutral and ten levels of constant absolute risk aversion: Stochastic efficiency with respect to a function (SERF) comparison of results from 1000 stochastic simulations of annualized net returns from bioenergy investment projects at Kellogg Biological Station (KBS), MI.



Appendix

Table 1. Costs of production ($/ha) for each bioenergy feedstock, Arlington, WI.

Crop	Type of cost in $/ha	Year								
		1	2	3	4	5	6	Annual Mean	NPV 6-year period	Annualized NPV 6-year period
Corn	Planting material	189	189	259	270	205	294	234	1177	232
	Agrochemicals	378	351	274	317	649	477	407	2039	402
	Machinery-labor	163	84	84	84	84	84	97	502	99
	Post-harvest	356	372	369	346	251	361	343	1746	344
	Total cost	1085	997	987	1016	1189	1216	1082	5465	1077
Switchgrass	Planting material	121	92	0	0	0	0	36	199	39
	Agrochemicals	90	32	36	96	139	100	82	409	81
	Machinery-labor	128	35	35	35	35	14	47	250	49
	Post-harvest	0	49	167	205	201	236	143	690	136
	Total cost	339	208	238	337	375	350	308	1548	305
Giant miscanthus	Planting material	4650	0	0	0	0	0	775	4429	873
	Agrochemicals	108	11	74	115	112	57	79	401	79
	Machinery-labor	166	42	88	56	56	56	77	404	80
	Post-harvest	0	0	0	283	255	397	156	729	144
	Total cost	4924	53	162	453	423	511	1088	5963	1175
Native grasses	Planting material	238	0	0	0	0	0	40	226	45

	Agrochemicals	90	21	30	96	88	100	71	353	70
	Machinery-labor	115	21	35	35	14	14	39	208	41
	Post-harvest	0	146	165	152	150	190	134	659	130
	Total cost	442	188	230	283	252	304	283	1446	285
Restored prairie	Planting material	278	0	0	0	0	0	46	265	52
	Agrochemicals	90	21	25	86	88	100	68	340	67
	Machinery-labor	136	14	14	14	14	14	34	186	37
	Post-harvest	0	180	155	117	110	135	116	580	114
	Total cost	503	215	193	217	211	249	265	1371	270
Early successional	Planting material	0	0	0	0	0	0	0	0	0
	Agrochemicals	71	0	25	86	88	100	62	304	60
	Machinery-labor	0	0	14	14	14	14	9	44	9
	Post-harvest	140	104	122	90	84	142	114	580	114
	Total cost	211	104	160	190	186	256	185	927	183

Table 2. Cost of production ($/ha) for each bioenergy feedstock, KBS, MI.

Crop	Type of cost in $/ha	Year 1	2	3	4	5	6	Annual Mean	NPV 6-year period	Annualized NPV 6-year period
Corn	Planting material	155	155	214	233	182	290	205	1024	202
	Agrochemicals	434	480	498	757	512	509	532	2683	529
	Machinery-labor	162	84	84	84	84	84	97	502	99
	Post-harvest	152	223	265	249	185	332	234	1174	231
	Total cost	905	943	1061	1323	962	1215	1068	5382	1060
Switchgrass	Planting material	121	0	0	0	0	0	20	115	23
	Agrochemicals	0	69	41	30	11	31	30	154	30
	Machinery-labor	94	21	35	14	14	14	32	171	34
	Post-harvest	0	54	125	190	152	260	130	627	124
	Total cost	214	133	171	205	155	263	192	971	191
Giant miscanthus	Planting material	4650	0	0	0	0	0	775	4429	873
	Agrochemicals	0	56	30	30	11	31	26	132	26
	Machinery-labor	124	14	14	14	14	14	32	175	35
	Post-harvest	0	112	358	412	253	556	282	1363	269
	Total cost	4775	181	402	456	277	600	1115	6099	1202
Native grasses	Planting material	238	0	0	0	0	0	40	226	45

	Agrochemicals	0	0	30	30	11	31	17	82	16
	Machinery-labor	94	0	14	14	14	14	25	133	26
	Post-harvest	0	0	143	140	81	221	97	466	92
	Total cost	331	0	187	184	105	265	179	908	179
Restored prairie	Planting material	278	0	0	0	0	0	46	265	52
	Agrochemicals	0	30	30	30	11	31	22	109	22
	Machinery-labor	94	14	14	14	14	14	27	146	29
	Post-harvest	0	0	123	127	79	113	74	356	70
	Total cost	372	44	167	171	103	157	169	876	173
Early successional	Planting material	0	0	0	0	0	0	0	0	0
	Agrochemicals	0	0	0	0	0	0	0	0	0
	Machinery-labor	0	0	0	0	0	0	0	0	0
	Post-harvest	112	68	118	107	74	121	100	506	100
	Total cost	112	68	118	107	74	121	100	506	100