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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 6-year observed crop yield data from highly productive and marginally productive sites in the southern Great Lakes region and assuming risk neutrality, we calculate expected breakeven biomass yields and prices compared to corn (*Zea mays* L.) as a benchmark. Next we develop Monte Carlo budget simulations based on stochastic crop prices and yields. The crop yield simulations decompose yield risk into three components: crop establishment survival, time to maturity, and mature yield variability. Results reveal that corn with harvest of grain and 38% of stover (as cellulosic bioenergy feedstock) is both the most profitable and the least risky investment option. It dominates all perennial systems considered across a wide range of farmer risk preferences. Although not currently attractive for profit-oriented farmers who are risk neutral or risk averse, perennial bioenergy crops have a higher potential to successfully compete with corn under marginal crop production conditions.

Keywords: bioenergy, cellulosic biomass, energy crops, investment analysis, Monte Carlo simulation, risk, stochastic budgeting

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Introduction

Although annual corn is currently the most important bioenergy crop in the United States, perennial crops such as giant miscanthus (*Miscanthus* × *giganteus* Greef & Deuter ex Hodkinson & Renvoize) and switchgrass (*Panicum virgatum* L.) have shown the potential systematically to produce higher biomass yields (Heaton *et al*., 2008; Dohleman & 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 & Jacquet, 2010). 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 relative to crops that farmers already choose to grow.

A critical factor in adopting new crops, such as bioenergy crops, is their profitability relative to that of existing cropping systems. Most farmers 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; James *et al*., 2010; Kells & Swinton, 2014). 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 & 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. An extensive literature models the investment uncertainty associated with adopting new agricultural technologies (Price & Wetzstein, 1999; Khanna *et al*., 2000; Pietola & Myers, 2000; Carey & Zilberman, 2002; Isik & Yang, 2004; Odening *et al*., 2005; Koundouri *et al*., 2006; Tozer, 2009; Schoengold & Sunding, 2014; Anderson & Weersink, 2014). Yet scant empirical evidence is available on how investment uncertainty affects the adoption of bioenergy perennials. A notable exception is the study by Song *et al*. (2011) who model land conversion decisions between tradi-

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tional crops and switchgrass under costly reversibility, and revenue uncertainty. However, these authors rely on secondary data and fail to account explicitly for the effects of crop failure and variable yield trajectories on investment returns from perennial bioenergy crops.

The agronomic and economic characteristics of bioenergy perennials make them risky choices. Investment in perennial energy crops is characterized by high establishment cost (Lewandowski *et al.*, 2003), establishment problems related to extreme climatic and pest events (Thinggaard, 1997; Clifton-Brown & Lewandowski, 2000), foregone income while awaiting mature yield (Song *et al.*, 2011), 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.*, 2004). 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; DeLaporte *et al.*, 2014; James *et al.*, 2010). These studies rely mostly on secondary data, and they fail to account explicitly for risk. All of these studies ignore 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.*, 2004). 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 & 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 simulate the probability distribution of random variability around expected yields. The Clancy *et al.* (2012) study is unique in recognizing the relevance of winter survival risk in giant miscanthus, which they assume to be ten percent. Finally, Bocquého & Jacquet (2010) relied on interview responses and recorded secondary data for short-term empirical distributions of bioenergy crop yields.

Our research 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, this study makes three contributions to the literature on economic risk of bioenergy crop production. First, it uses new multiyear field data on cellulosic biomass production 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: (i) crop failure risk, (ii) time to maturity risk, and (iii) variability in mature yields. Third, it evaluates the economic performance of a broad range of bioenergy crops that includes not only corn, giant miscanthus, and switchgrass, but also restored prairie, native grasses, and early successional vegetation (long-term fallow). Using data from southern Michigan and Wisconsin, the modeling approach offers broader insights about the comparative riskiness of these bioenergy crops and what drives that risk.

Materials and methods

Conceptual framework

Rational economic decision-makers are assumed to make crop production choices by choosing crop j to maximize a utility function (U) that includes the value of net returns across a range of possible states of nature (i) in light of the decision-maker's risk preferences:

$$\mathrm{Max}_j U(\mathrm{NPV}_{ij}, \lambda) = \int_{i=1}^{N} U(\mathrm{NPV}_{ij}, \lambda) f(\mathrm{NPV}_{ij}) \mathrm{dNPV}_{ij} \quad (1)$$

where NPV is the net present value of crop j, $j = 1,2, \ldots, M$, λ is a measure of risk aversion, t is year, and T is the final year of the planning horizon. Location matters as well, but we suppress that factor to simplify notation.

When the model in Eqn (1) is applied to the case of growing bioenergy crops, an individual decision-maker makes crop production choices based on cash flows over the time horizon (T)

for the crop investment. The NPV for cropping system j over a period of T years is defined as follows:

$$\mathrm{NPV}_{ij} = \sum\nolimits_{t=1}^{T} \delta^t G_{ijt} \qquad (2)$$

where δ is the discount factor, and G_{ijt} denotes the gross margin (cash flow) of crop j cultivated in year t under state of nature i. Eqn (2) provides the discounted value of annual gross margins. Because crop prices and yields are stochastic, each time NPV_{ij} is a random draw representing state i from the probability distribution of possible discounted investment net returns.

The appropriate ranking of biomass investment projects will depend on the investor's risk preference. For a risk neutral decision-maker ($\lambda = 0$), maximizing Eqn (1) is equivalent to maximizing the expected net present value. However, most investors are not indifferent to risk. We adopt an expected utility theory approach to decision-making under risk (Hernstein & Milnor, 1953; Mongin, 1997). Following a substantial body of empirical evidence that farmers are risk averse (Pope & Just, 1991, Pannell et al., 2000; Hardaker, 2006), we assume that the decision-maker exhibits constant absolute risk aversion (CARA; Pratt, 1964) and that risk preference is embodied in the CARA function coefficient aversion, λ, that can vary over a range from risk neutral to highly risk averse.

Crop gross margin risk in the term, G_{ijt}, in Eqn (2) can be decomposed into three yield quantity factors and one price element drive: (i) survival risk, (ii) maturation risk, (iii) yield fluctuation risk in mature crops, and (iv) 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 fall below −3.5 °C for a period of 3 days or more (Clifton-Brown & Lewandowski, 2000; Kucharik et al., 2013). Figure 1 depicts the effect of establishment failure, and delayed maturity on the NPV of an investment project of perennial biomass crops. Figure 1 (Panel a) illustrates the effect of crop failure risk on the NPV of a biomass investment project. The top graph shows how establishment failure delays the flow of biomass yield (Y), while the bottom graph shows the consequences for NPV. At t_0, crop establishment costs ($-I$) have been incurred and therefore the NPV (bottom of both panels) of a biomass cropping system is negative. In the subsequent period, the NPV continues to decrease due to a lack of harvestable biomass (and, thus absence of revenues), alongside rising crop variable costs, such as fertilization and crop protection. Following this period, as harvestable biomass becomes available, the NPV increases, potentially breaking even. Establishment failure is especially problematic in a crop like 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. The top graph illustrates how random factors may delay the maturation of a perennial crop causing the biomass

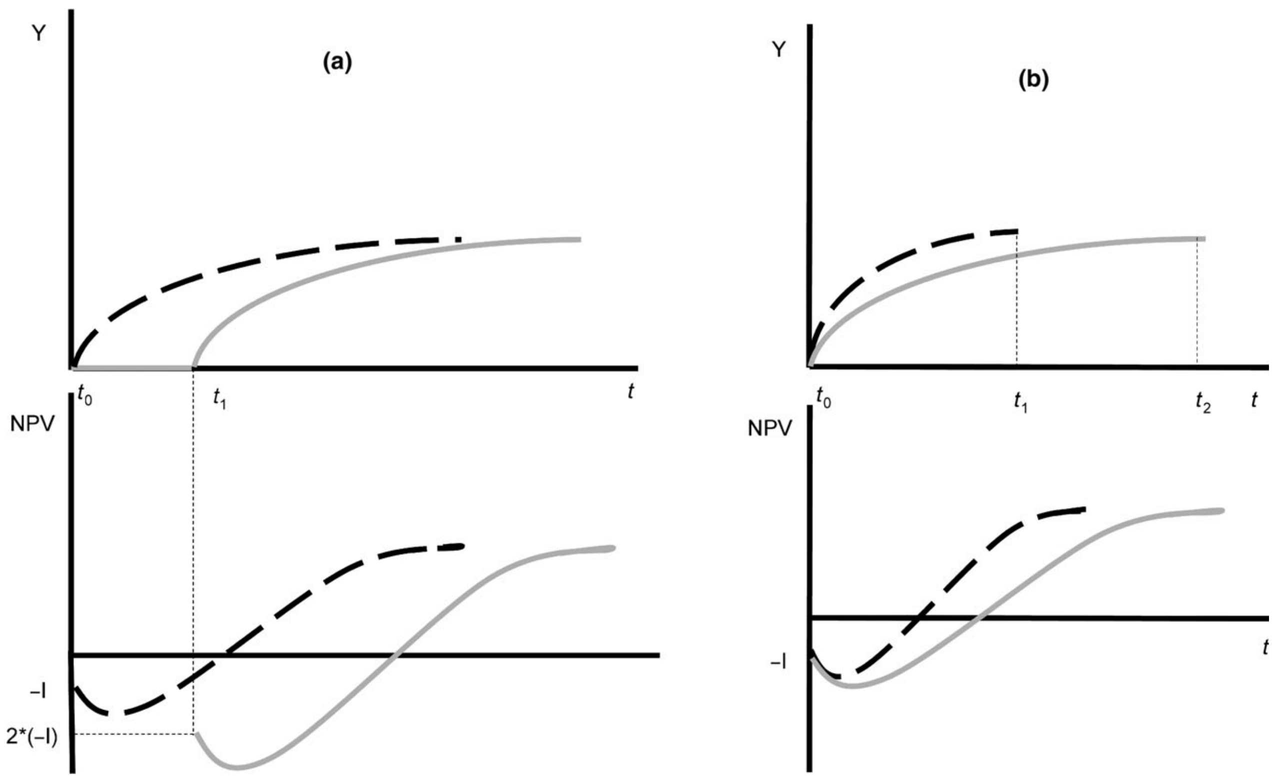

Fig. 1 Establishment failure (left) and delayed maturity (right) implications on the NPV of an investment project of bioenergy perennials.

yield trajectory to shift from the dashed black linen to the solid gray line. This delay shifts the NPV accumulation trajectory in the bottom graph to one that takes longer to break even. 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.

Finally, as with annual crops, revenue risk is also driven by regular fluctuations in mature yield and in crop prices. Mature yields vary due to factors such as climate (Parry and Carter, 1985; Nuñez & Trujillo-Barrera, 2014), soil type (Dinkins & Jones, 2008), and pests (Skevas *et al.*, 2013). Agricultural prices vary due to changes in markets, which vary spatially from local to global (Harwood *et al.*, 1999). We next present the empirical methods used to analyze how these four sources of risk are likely to affect farmer decisions about adopting bioenergy crops.

Empirical model

To examine the effect of risk on likely farmer adoption choices, we compare results from comparative breakeven budgeting to those from stochastic simulation of investment analysis. Comparative breakeven budgeting is a simple, widely used method that identifies the minimum price or yield needed for revenues to cover costs (Dillon, 1993). The version used here is adapted for investment analysis using the NPV method, so it incorporates discounting of future cash flows to adjust all values to initial year 'present' values (Kells & Swinton, 2014). To calculate a comparative breakeven price, crop yield and opportunity of not adopting the best alternative crop must be known; to calculate a breakeven yield, crop price and opportunity cost must be known. To accommodate policy incentives to encourage adoption of bioenergy crops, we do sensitivity analysis with both direct subsidies and crop insurance.

Stochastic simulation for investment analysis allows developing probability distributions of NPVs that allow comparison of bioenergy investment alternatives over a broad range of yield and price conditions and for decision-makers with different levels of risk aversion. We first describe methods for comparative breakeven analysis, including incentive policy scenarios; then, we move to methods for stochastic simulation and comparison of probability distributions of NPVs.

Risk neutral case: Comparative breakeven investment analysis

Comparative breakeven investment analysis is used to compute the economic performance of cellulosic biomass feedstock investment projects. The six biomass investment alternatives are corn, giant miscanthus, switchgrass, native grasses, restored prairie, and early successional vegetation (fallow). Revenues and expenditures are used to calculate annual cash flows for each cropping system. For convenience in comparing results between annual and perennial crops, we present all results as annualized values using the following annuity formula to convert NPVs to annual equivalents (Weston & Copeland, 1986):

$$A = \left[\frac{r\text{NPV}}{1 - 1/(1+r)^T}\right] \tag{3}$$

where A is the annual payment, and r is the discount rate. The time horizon is 6 years, a time horizon sufficient for most perennial crops to have attained mature yield for 3–4 years and hence for farmers to judge the appeal of adopting them. However, there is evidence that the optimal replacement interval of bioenergy perennials such as miscanthus and switchgrass can exceed 10 years (Pyter *et al.*, 2007). 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 6-year time horizon, while the perennial cropping systems experience delays of 1–2 years before producing harvestable yield.

The appeal of comparative breakeven budgeting for predicting adoption of new crops is that it builds in the opportunity cost of foregoing new income from the best benchmark crop. Given that corn is the most widely grown field crop in the United States, we treat it as the benchmark crop—the basis for comparison. We conduct the comparative breakeven price and yield analyses to identify the cellulosic biomass prices and yields that would make perennial crops equally profitable with corn. The breakeven price analysis takes into account the direct costs of production, expected yields, and the opportunity cost of replacing the existing cropping system. Net returns from corn are assumed to come from harvesting all grain plus 38% of stover (Brechbill & Tyner, 2008), a level of stover harvest consistent with maintaining soil organic matter. Following Kells & Swinton (2014), the comparative breakeven price of a cellulosic perennial crop to replace corn is as follows:

$$\text{BE}_{\text{pr}} = \frac{\text{NPV}_D + \sum_t \left(\frac{c_t}{(1+r)^T}\right)}{\sum_t \left(\frac{y_{C_t} - y_{D_t}}{(1+r)^T}\right)} \tag{4}$$

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_{C_t} is the expected biomass yield achieved by the 'challenger' bioenergy crop, y_{D_t} is the expected biomass yield of the defender crop, and r and T as previously defined. The denominator represents the biomass yield gain of the challenger crop over the defender cropping system and implies that a new bioenergy crop breaks even in the comparative sense only if its biomass yield exceeds that of corn stover.

Comparative breakeven yield identifies the minimum yield of cellulosic biomass required for a producer to attain annualized investment returns earn equal to corn, given an expected biomass price. Using the same notation as above, the breakeven yield Y_{BE} is computed as follows:

$$Y_{\text{BE}} = \frac{\text{NPV}_D + \sum_t \left(\frac{\text{adc}_t}{(1+r)^T}\right)}{\sum_t \left(\frac{P_t - \text{ydc}_t}{(1+r)^T}\right)} \tag{5}$$

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 (e.g., baling, storage, and bale transportation).

Policy incentives for bioenergy crops: Subsidies and insurance

As variants of the comparative breakeven investment analysis, we consider two sets of policy incentives to encourage adoption of perennial bioenergy crops. The first set already exists in the form of the U.S. Department of Agriculture's Biomass Crop Assistance Program (BCAP) (USDA, 2014). The second policy is based on existing crop revenue insurance that has not so far been extended to perennial bioenergy crops.

Under BCAP, we examine the impact of three BCAP payment forms on the investment returns from the bioenergy crop alternatives. The BCAP payments include the following: (i) establishment payments, (ii) annual rental payments, and (iii) 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 5 years) based on typical rental rates for cropland, marginal land or forest land. They 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 2 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.

A second potential type of policy would allow growers of bioenergy crops to purchase revenue insurance to offset some of the risk associated with production variability. This study calculates insurance premiums that would support a policy that would pay off whenever the NPV did not reach the zero threshold. Based on the insurance premium approach presented in Goodwin (1994), a premium that is free of distributional assumptions and accounts for the time that net revenues cross the zero threshold can be calculated as follows:

$$\text{Premium}_j = \sum\nolimits_{i=1}^{n} \theta_{ij}/n \qquad (6)$$

where $\theta_{ij} = 0 - \text{NPV}_{ij}$ if $\text{NPV}_{ij} < 0$, and 0 otherwise. The calculation of insurance premiums can indicate the cost of reducing net revenue risk exposure to potential adopters of bioenergy crops.

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 NPVs for each bioenergy crop. It also enables calculation of the monetary value of the certainty equivalent of each NPV distribution for a range of decision-makers with CARA risk preferences. The steps involved in building the stochastic (Monte Carlo) investment analysis model are detailed below. They include (i) statistical estimation of the equations for the three forms of biomass yield risk using appropriate functional forms, (ii) retention of coefficient standard errors to simulate random coefficient models, (iii) fitting of parameters to appropriate probability distributions for additive random errors, (iv) collection of suitable random price data, (v) synthesis of these components into a stochastic simulation of NPV distributions by crop, and (vi) analysis of results as certainty equivalents for risk neutral and risk averse decision-makers.

Estimation of stochastic biomass yields was performed in three parts: first, estimation of the chance of crop establishment failure at each site (giant miscanthus only); second, estimation of time-to-maturity trajectories for each crop; and third, fitting of probability distributions for additive random errors. Estimations of time-to-maturity risk and risk in mature yields were based on 6 years of field experiments from 2008 to 2013 at Arlington (ARL) in south-central Wisconsin and the Kellogg Biological Station (KBS) in southwest Michigan. At each site, there were five plots each of corn, switchgrass, giant miscanthus, restored prairie, mixed native grasses, and early successional vegetation treatments. At ARL, there was winter kill of giant miscanthus in 2008/2009, and it was not replanted until 2010. In addition, at KBS, switchgrass, native grasses, and restored prairie all experienced crop failure in 2008 due to heavy rains 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 University of Wisconsin Extension Ag Weather network spanning 20 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 were not available; instead, data from Michigan State University's Enviroweather series collected in East Lansing between January 1996 and December 2014 were used. Because average soil temperature at 10 cm was not available, the 10 cm minimum and maximum temperatures were averaged and 3-day running means were calculated. Two 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 two sites were used to estimate the trajectory of biomass yield over the first 6 years, using a set of theoretically consistent functional forms. The functions evaluated included Spillman and Mitscherlich, as both increase to a plateau or upper asymptote, as well as linear and step-to-plateau functions. 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 the crop yield trajectories that were modeled using the Mitscherlich function, coefficients were estimated using nonlinear least squares. Table 1 shows the functional forms and parameter estimates for yield trajectories of perennial crops at ARL and KBS. The Mitscherlich function has a marginal product that is unrestricted but nonswitching in sign, the linear function has a marginal product that is unrestricted in sign but constant in value. For further background, Griffin *et al.* (1987) review the properties of these functional forms and their optimality conditions. For these crops that

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

Crop (location)	Functional form	Maximum (α)	Slope (β, m)	Intercept (b)	Mean (a)
Switchgrass (ARL)	Mitscherlich $y = \alpha(1\text{-}\exp(-\beta t))$	9.0392*** (.7983)	0.4521*** (0.0923)	n/a	n/a
Switchgrass (KBS)	Linear $y = 0$ if $t = 0$ $y = \mathrm{m}t + b$ if $t > 0$	n/a	1.6358*** (0.3018)	3.5848*** (0.5647)	n/a
Giant miscanthus (ARL)	Mitscherlich $y = \alpha(1\text{-}\exp(-\beta t))$	15.0085*** (2.7872)	0.8912* (0.4503)	n/a	n/a
Giant miscanthus (KBS)	Mitscherlich† $y = \alpha(1\text{-}\exp(-\beta t))$	28.8517* (14.2383)	0.2182** (0.1661)	n/a	n/a
Native grasses (ARL)	Linear $y = 0$ if $t = 0$ $y = \mathrm{m}t + b$ if $t > 0$	n/a	0.3300* (0.1710)	4.4244*** (0.4189)	n/a
Native grasses (KBS)	Linear $y = 0$ if $t = 0$ $y = \mathrm{m}t + b$ 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

Note: Numbers in parenthesis are standard errors of parameter estimates. ***Significant at 1% level, **significant at 5% level, *significant at 10% level.
†Davidson–MacKinnon test was inconclusive.

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 vegetation and restored prairie, yields showed no trend over time, so mean values suffice. Choices of functional form were based chiefly on theoretical consistency and supported by Davidson–MacKinnon tests (this test is not valid when comparing linear functions vs. mean values because of collinearity). Although linear yield functions fail to exhibit the expected diminishing marginal product over time, these functions were selected as the best fit for the native grasses, and they are acceptable for simulations that are limit to a 6-year time horizon.

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 the @Risk add-in to Microsoft Excel.

To abstract from current market conditions, biomass prices were drawn at random from stochastic simulations of corn and warm season grass prices projected to 2018 that were prepared for the March 2014 outlook report by Food and Agricultural Policy Research Institute at University of Missouri (FAPRI-MO) (Personal communication by Wyatt Thompson to Scott Swinton by email, Dec. 13, 2014).

The stochastic budgeting model was programmed in Microsoft Excel and simulated using @Risk. Latin hypercube sampling with a sample size of 1000 was used to estimate the distribution of the stochastic variables for each risky investment.

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).

The flowchart of the steps performed in implementing the stochastic capital budgeting analysis appears in Fig. 2. The stochastic simulation cycles differed between corn, an annual, and the five perennial bioenergy crops. As shown on the left side of Fig. 2, each 6-year corn simulation cycle begins with drawing six corn grain prices and six biomass prices. For each

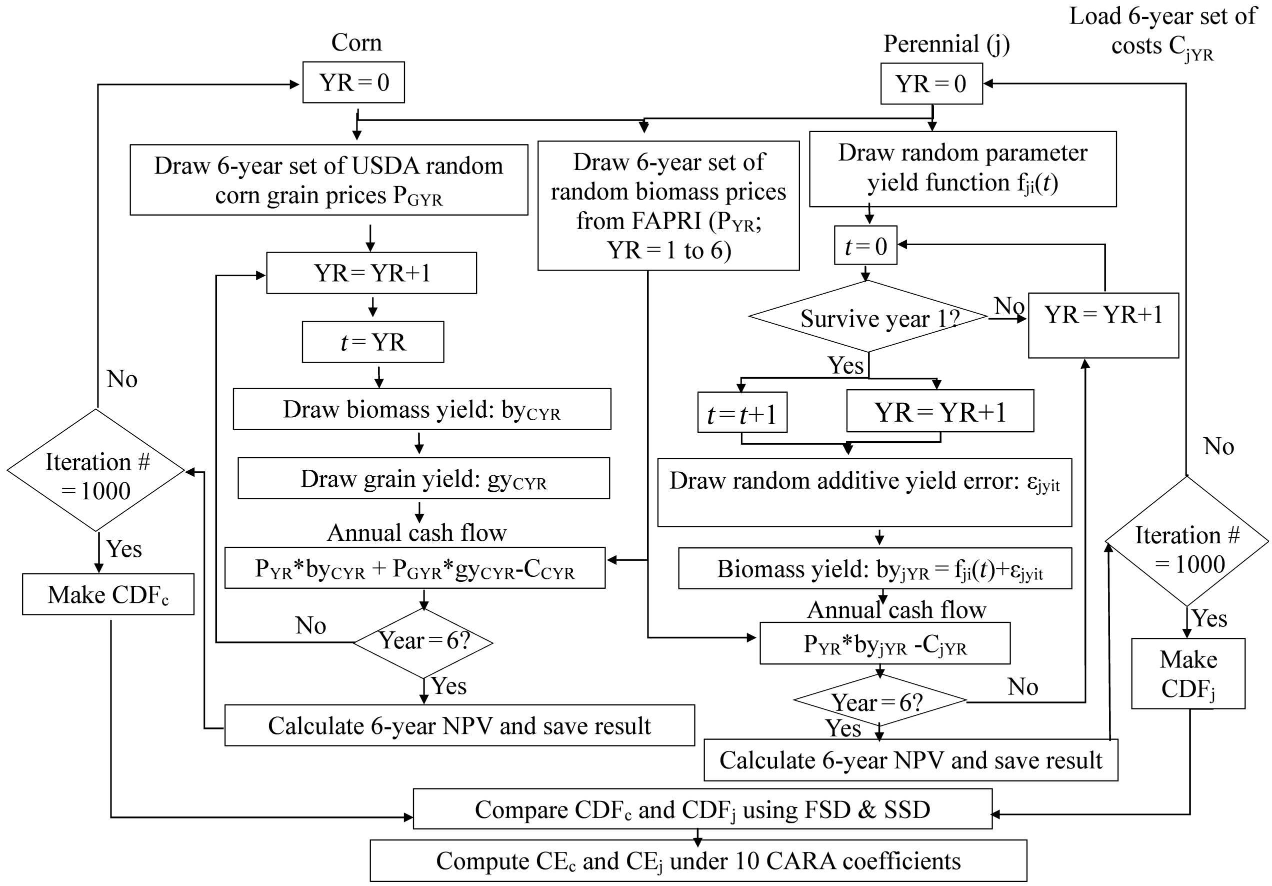

Fig. 2 Flowchart of stochastic simulation of 6-year net present values of investment returns.

year (1–6), the model first draws biomass and grain yields; then with random price and production cost, it calculates annual cash flow. After 6 years, it calculates the NPV for that period. The simulation cycle is repeated 1000 times. The simulation process for perennial bioenergy crops appears on the right side of Fig. 2. Each 6-year simulation cycle begins with drawing random biomass prices and coefficients for the random parameters yield function. If the crop fails in Year 1, it is replanted. If it survives, the biomass yield for that year is computed from the yield function plus an additive random error. Annual cash flow is the product of random biomass price and the computed yield, minus expected production cost. As with the corn model, NPV is calculated after 6 years. Upon completion of the 1000 simulation runs, cumulative distributions are constructed by ordering outcomes from smallest to largest.

Comparison of the alternative bioenergy crop NPV cumulative distributions for decision-makers who may be risk averse is performed using stochastic dominance criteria. These criteria allow ranking of investment prospects by comparing the empirical distributions of investment returns without requiring explicit knowledge of individual risk preferences. Common stochastic dominance criteria are first-degree (FSD) and second-degree stochastic dominance (SSD). FSD requires only the assumption that the decision-maker prefers higher returns to lower returns, and it covers all risk preferences. SSD requires the added assumption that the decision-maker is risk averse, so it omits risk-preferring individuals. Both approaches involve pairwise comparison of the cumulative distribution functions (CDF) of NPVs from alternative investment options. When FSD and SSD cannot identify preferred alternatives, an approach with more restrictive assumptions but stronger discriminating power is stochastic efficiency with respect to a function (SERF) (Hardaker *et al.*, 2006). Under the assumption that a decision-maker's risk preferences are known (as CARA with assumed coefficients, in this case), certainty equivalent (CE) values can be calculated as the monetary value that would leave the decision-maker indifferent between receiving the CE and the entire CDF from the risky investment. SERF ranks a set of risky alternatives in terms of CEs. Following Pratt (1964), we use the negative exponential constant absolute risk aversion (CARA) utility function: $U_{\mathrm{CARA}}(G) = -e^{-\lambda G}$. Using this function, the CE is computed as follows:

$$\mathrm{CE}_{\mathrm{CARA}}(G,\lambda) = -\ln\left(-\frac{1}{n}\sum_{i}^{n} e^{-\lambda G}\right)\Big/\lambda \quad (7)$$

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 & 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).

Data

The analyses reported here draw bioenergy crop management practices and yields from the 6-year period 2008–2013 from the Great Lakes Bioenergy Research Center (GLBRC) Biofuel Cropping System Experiment established 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, and in Sanford *et al.*, 2016). 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, 2018 FAPRI price forecasts for corn are used, while cellulosic feedstock price is assumed to be \$50 mg^{-1}. At \$159 Mg^{-1} (=\$4 $^{-1}$), the simulated mean corn grain price is lower than the observed price during 2008–2013 (\$196 Mg^{-1} (=\$5 bu^{-1}) (National Agricultural Statistics Service). The \$159 price was chosen for this analysis because 1) the observed price is an historic high that appears not to be indicative of likely future values and 2) using the same price as for the stochastic simulation analysis later in the paper allows direct comparison of results. The cellulosic feedstock 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^{-1}) 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^{-1}).

Table 3 Crop yields and prices in the southern Great Lakes area in 2008–2013 (basis for comparative breakeven investment analysis)

Crop	Location	Yield* (Mg ha^{-1}) Mean	SD	Output price† (\$ Mg^{-1})
Corn grain	ARL	12.65	1.61	159
	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	

*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.
†Corn grain price is the average (FAPRI) 2018 price forecast for corn. The respective corn grain price in \$ bu^{-1} is 4. The biomass price is derived from rounding to the nearest \$5 Mg^{-1} both the average (FAPRI) 2018 price forecast for dry biomass from warm season grass and the Michigan State University T.B. Simon power plant purchases of switchgrass and restored prairie biomass from GLBRC in 2013 (based on coal-equivalent BTU content).

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^{-1} (i.e., \$4 bu^{-1}) and \$51 Mg^{-1}, 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 postharvest. 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.

Results

Profitability by cropping system at 2008–2013 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 Figs 3 and 4. In both locations, the profitability of corn far exceeded that of any of the perennial crop systems for two primary reasons. First, corn revenues benefit from two components: the valuable grain product plus the less valuable cellulosic biomass product. Second, predicted corn prices at \$4 bushel^{-1} are strong compared to historic levels, despite being below the high levels of 2008–2013. 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 vegetation—indicating that lower

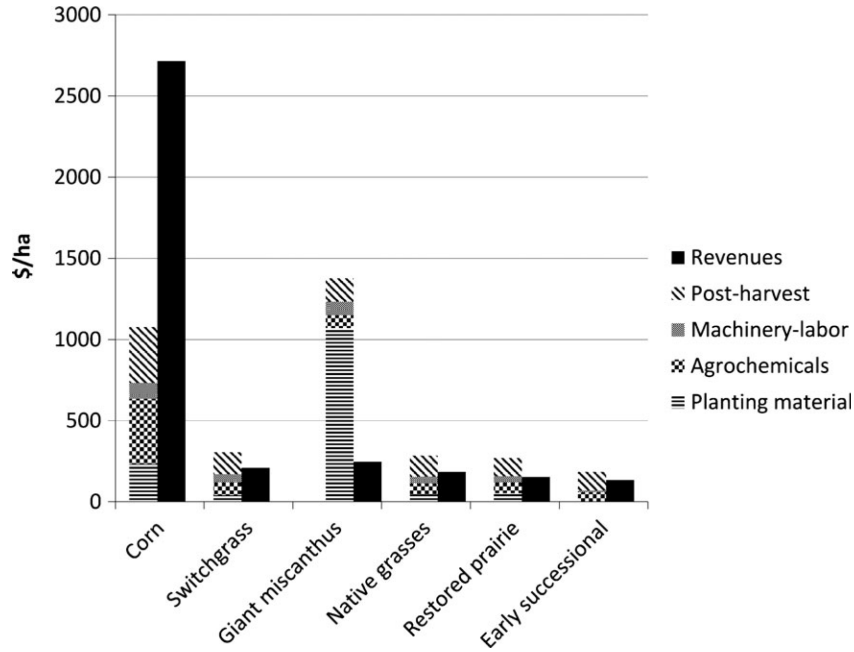

Fig. 3 Revenues and production costs (annualized NPV in $ ha^{-1}) of biomass crops, ARL, WI.

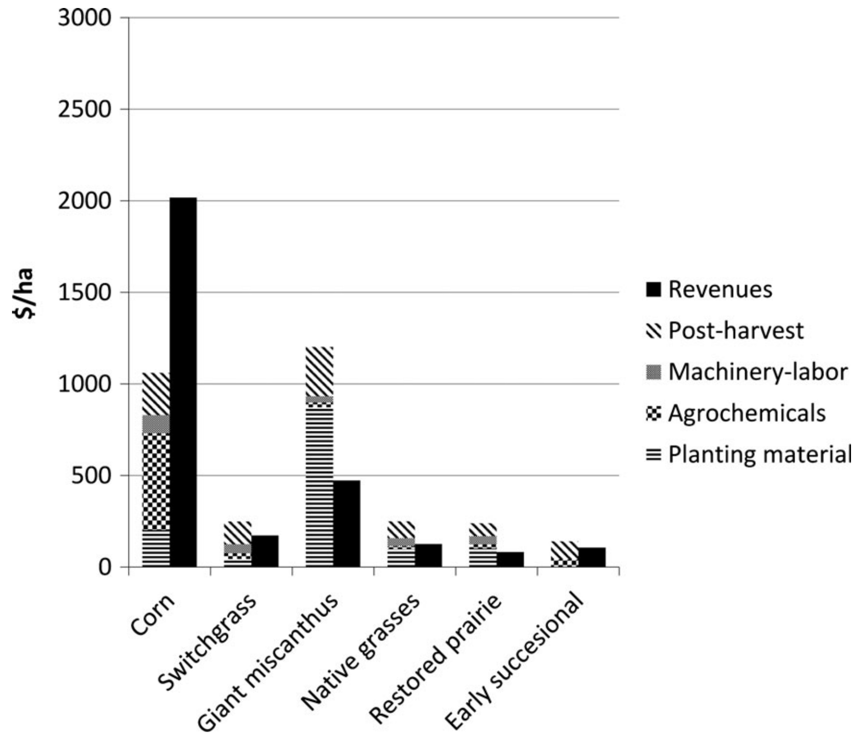

Fig. 4 Revenues and production costs (annualized NPV in $ ha^{-1}) of biomass crops, KBS, MI.

productivity at KBS is less pronounced for bioenergy perennial crops than for corn. The following breakeven analysis examines just how close each site and cropping system comes to matching the profitability of corn.

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 comparative breakeven prices for each cropping system assuming a corn grain price of \$159 Mg^{-1} (\$4 bu^{-1}). The giant miscanthus figures are underestimates, because they ignore the risk of winterkill. Even so, no system can break even at ARL because the mean corn stover yield there exceeds the mean biomass yield of any of the perennial bioenergy crops. At KBS, however, corn stover yields are 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 \$203 Mg^{-1}. Switchgrass would require \$642 Mg^{-1}, while the native grasses would require the price of a new, small car for each ton of biomass, because their mean yield barely exceeded that of corn stover. Restored prairie and early successional vegetation at KBS produce less biomass than corn stover and so cannot break even at any biomass price.

Comparative breakeven yields

Table 4 also 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 at ARL. The crop with the lowest breakeven yield at ARL is early successional vegetation, which has the lowest costs—just the cost of fertilization and biomass harvest. Next lowest are the native grasses, restored prairie, and switchgrass. At KBS, switchgrass has the lowest breakeven yield, followed by early successional vegetation, native grasses, and restored prairie. Comparing current yields (Table 3) and breakeven yields (Table 4), at the corn and biomass prices assumed, nearly all of the perennial bioenergy crops would require a tenfold yield boost to break even with corn. However, the magnitude of yield gains needed is much smaller at KBS than at ARL, due to the lower productivity of the corn reference system and the relatively better yields of switchgrass and giant miscanthus at the KBS site.

Table 4 Comparative breakeven prices (\$ Mg^{-1}), and yields ($Mg\ ha^{-1}$) of biomass feedstocks with respect to a corn grain price of \$4.00 bu^{-1} (\$159 Mg^{-1}), and biomass price of \$50 Mg^{-1} at ARL and KBS sites

	Breakeven prices (\$ Mg^{-1})		Breakeven yields ($Mg\ ha^{-1}$)		Breakeven yield as percent of current yield (%)	
Crop	ARL	KBS	ARL	KBS	ARL	KBS
Switchgrass	N/A*	\$642	56	19	1050	362
Giant miscanthus	N/A	\$203	104	67	1654	510
Native grasses	N/A	\$15 482	52	32	1119	989
Restored prairie	N/A	N/A	55	33	1513	1633
Early successional	N/A	N/A	51	23	1626	882

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

BCAP and insurance premium results

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 under 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 was the case for all bioenergy perennials except giant miscanthus in both locations. In two cases (early successional vegetation at KBS and switchgrass and early successional vegetation at ARL), individual BCAP payments such as annual rental and matching payments could also reverse the expectation of negative profitability.

Crop revenue insurance offers another potential means to avert negative profitability. Table 5 presents insurance premiums needed to insure against NPV falling below zero. Premiums are very low (i.e., \$1–2 ha^{-1}) only in the instances where among the 1000 simulations, the NPV rarely failed to be positive. That occurred only for corn at ARL and corn and switchgrass at KBS. Insurance premiums are higher at ARL for all crops except restored prairie; four bioenergy crops there frequently generated negative annualized NPVs, including giant miscanthus (100% of cases), switchgrass (98%), native grasses (88%), and early successional vegetation (75%). At KBS, only giant miscanthus (98% of cases) and restored prairie (99% of cases) generated negative annualized NPVs most of the time.

Stochastic simulation results

Up to this point, all results have been based on mean values, ignoring production and price risk. Summary statistics from the 1000 stochastic simulations of the six

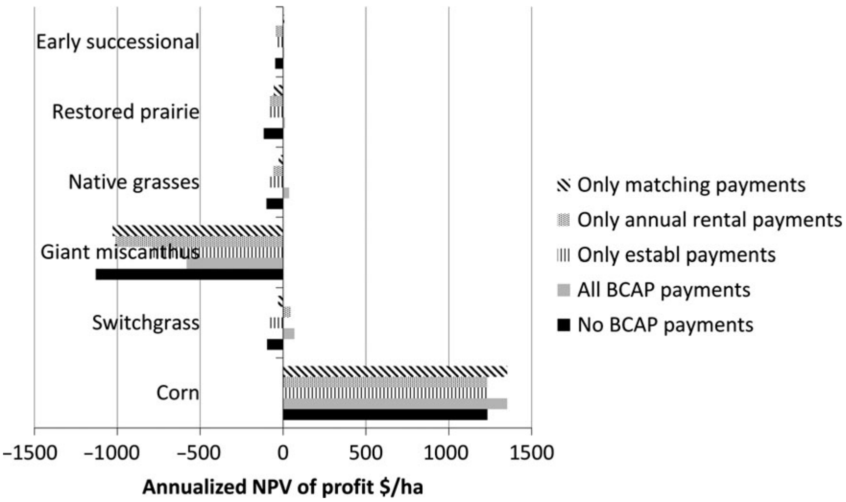

Fig. 5 BCAP scenarios: Annualized NPVs, ARL, WI.

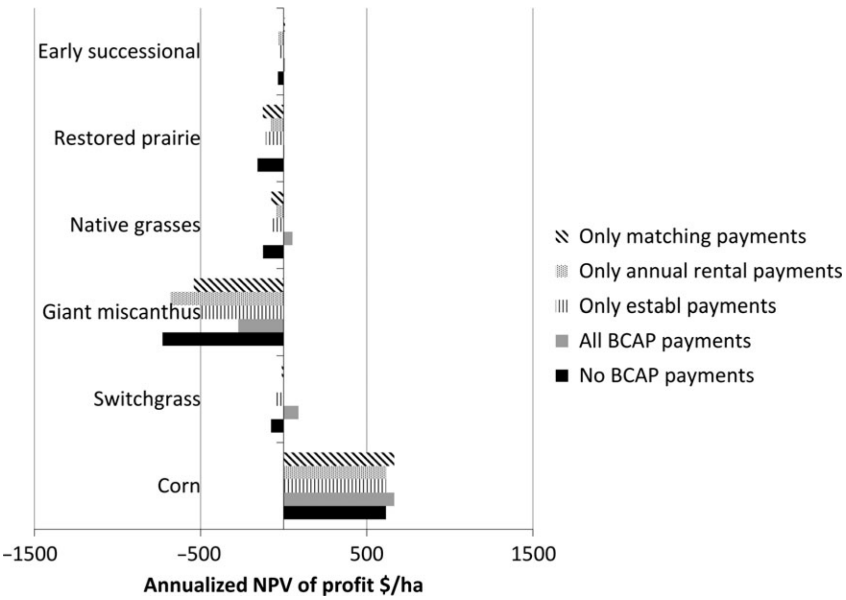

Fig. 6 BCAP scenarios: Annualized NPVs, KBS, MI.

Table 5 Insurance premiums (in \$ ha^{-1}) that would support a policy that would pay off whenever the zero threshold (in net returns) is met

	Giant miscanthus	Switchgrass	Native grasses	Restored prairie	Early successional	Corn
ARL	1032	83	45	18	49	2
KBS	626	2	42	136	32	1

bioenergy crops at KBS and ARL are presented in Table 6. Corn stands out as having the highest mean profit, as measured by annualized NPV; it also had 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

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

	ARL (Arlington, WI)					KBS (Hickory Corners, MI)				
Crop	Mean	SD	Median	Min	Max	Mean	SD	Median	Min	Max
Corn	943	439	932	−265	2527	328	168	319	−136	830
Switchgrass	−83	40	−81	−199	34	99	66	98	−113	304
Giant miscanthus	−830	145	−821	−1175	−361	−623	272	−670	−1148	311
Native grasses	−43	39	−40	−153	112	−14	85	−21	−206	276
Restored prairie	94	135	86	−278	503	−136	49	−138	−249	47
Early successional	−39	61	−43	−183	215	−16	55	−23	−130	171

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 vegetation 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, and corn and under SSD by restored prairie, native grasses, and early successional. The restored prairie treatment also fared poorly, being dominated at KBS under FSD by switchgrass, native grasses, early successional vegetation 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 vegetation and native grass treatments that were in the efficient set at ARL were dominated at KBS under FSD by switchgrass (the FSD and SSD results are not reported in full detail in this paper, but can be provided by the authors upon request).

Although corn was accompanied in the FSD and SSD risk efficient sets by switchgrass at KBS and by native grasses and early successional vegetation 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 vegetation 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 Figs 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 higher everywhere 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 between perennial crops (except giant miscanthus) are very small.

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 crop 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 vegetation ranks second in the risk neutral case in ARL, but when it comes to the risky case, it takes the third place). 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.

Discussion

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 to 2013 from two sites in the Great Lakes Region at Arlington, WI, and Kellogg Biological Station (KBS) at Hickory Corners, MI, we simulate four stochastic variables that affect investment returns to bioenergy

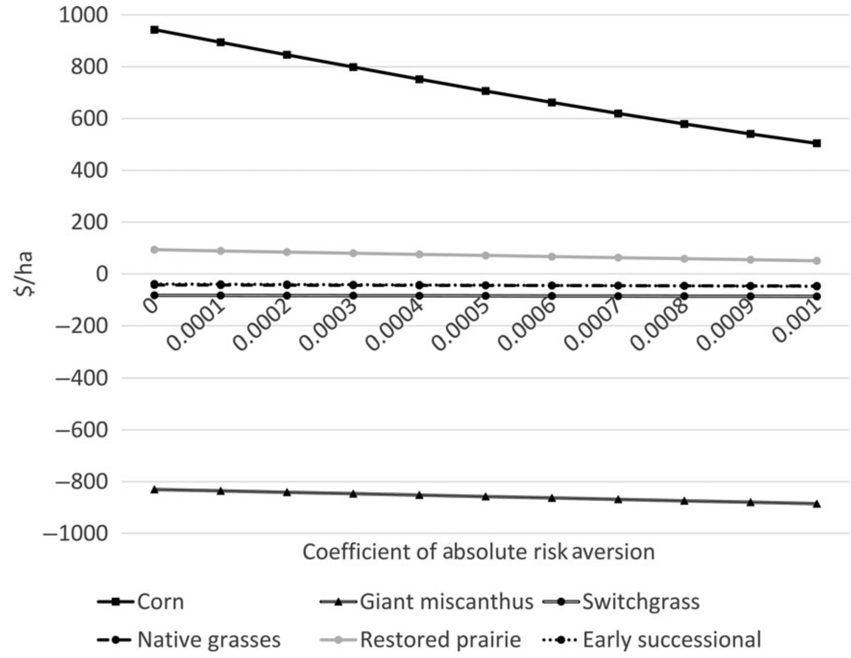

Fig. 7 Certainty equivalents for decision-makers who are risk neutral to highly risk averse with constant absolute risk aversion: stochastic efficiency with respect to a function (SERF) comparison of results from 1000 stochastic simulations of annualized net returns from bioenergy investment projects at Arlington, WI.

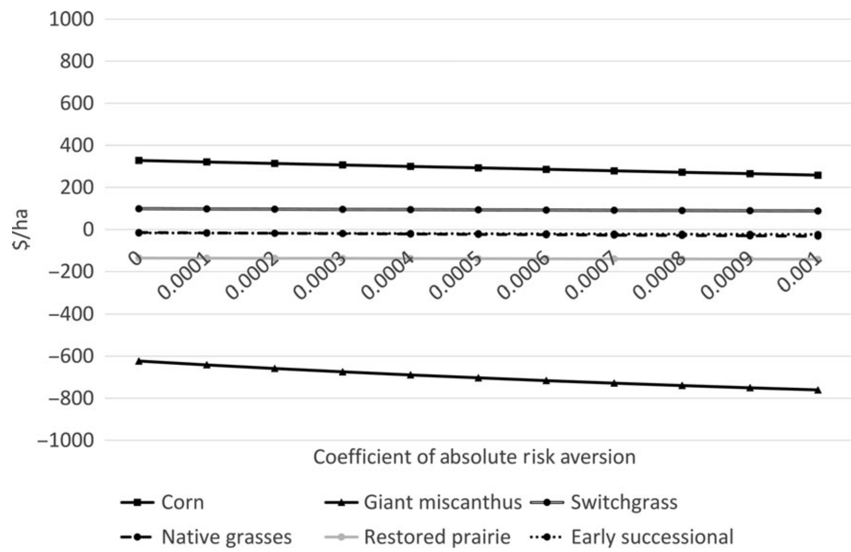

Fig. 8 Certainty equivalents for decision-makers who are risk neutral to highly risk averse with constant absolute risk aversion: stochastic efficiency with respect to a function (SERF) comparison of results from 1000 stochastic simulations of annualized net returns from bioenergy investment projects at Kellogg Biological Station (KBS), MI.

crops: crop failure risk, time to maturity risk, variability in mature yields, and price risk.

The standard, average capital budgeting analyses show that the profitability of corn dominates all other cropping systems at both sites. Corn's dominance comes from 1) providing income from both grain and cellulosic biomass, and 2) its consistently strong yields as an annual crop (unlike the slow buildup of the perennial crops). Although BCAP payments can reduce profitability losses from adopting perennial bioenergy crops, they are not sufficient to bridge the profitability gap with corn. Future research could seek to assess how much the gap could be narrowed using policies that provide farmers with payments for ecosystem benefits related to perennials.

The comparative breakeven price analysis shows that corn stover yields are so high at ARL that there is no biomass price at which perennial bioenergy crops can match the profitability of corn. Meanwhile, on the poorer soils of KBS, switchgrass, giant miscanthus, and native grasses require very high prices to break even when the price of corn is \$4 per bushel. Of the KBS bioenergy crops, giant miscanthus has the lowest breakeven price. This result is in line with previous literature that computes breakeven prices for switchgrass and miscanthus in Ontario (DeLaporte *et al.*, 2014), the Midwestern United States (Jain *et al.*, 2010), southern Michigan (James *et al.*, 2010), and Illinois (Khanna *et al.*, 2008). However, the breakeven prices for giant miscanthus and switchgrass in the current study are higher than those observed elsewhere. The differences may be due to the use of secondary yield and production cost data in those studies vs. primary data in this study. The comparative breakeven yield results find that perennial bioenergy crops require tenfold yield gains at ARL to generate net revenue equal to corn at the prices assumed, with levels at KBS also very high at three- to fivefold gains needed for switchgrass and giant miscanthus. All values are higher than the significant increases needed that were predicted by James *et al.* (2010) for southern Michigan. Both the comparative breakeven price and yield analyses demonstrate that although most perennial bioenergy crops are far from achieving average profitability comparable to corn at either site, the potential for bioenergy crops eventually to compete with corn is greater at KBS, where corn productivity is lower.

Results of the investment risk analysis were largely similar. Stochastic efficiency analysis of the investment returns shows annual corn to be an even more resilient benchmark than prior profitability studies that ignored risks 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, corn dominated all other systems over the entire range of 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 by more than half to the \$2 per bushel levels of the 1990s and early 2000s. Among the bioenergy perennials, only switchgrass generated positive profits at KBS most of the time (94%). In ARL, apart from corn, only restored 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 in the U.S. Great Lakes region, it has an extremely high probability of generating negative investment returns. Our more negative results were driven by high current rhizome costs and the high probability of winter kill in the establishment year in ARL (45%) and lower but still notable probability of winter kill at KBS (10.5%).

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 per acre at KBS to \$343–717 per acre at ARL. The bioenergy crops with the lowest subsidy requirements were switchgrass at KBS and restored prairie at ARL. One factor mitigating the cost of 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.

Overall, the results indicate that these perennial bioenergy crops are currently both less profitable and riskier than corn for farmers in the Great Lakes region. However, 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, where soils are highly productive. Like Miao & Khanna (2014), we find that while bioenergy crops remain significantly poorer investments than corn, their lower opportunity cost under more marginal crop production conditions 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. The ranking of biomass investment projects presented here offers information on the comparative riskiness of bioenergy investment projects in the southern Great Lakes region. Future research could apply this modeling approach to assess the comparative riskiness of bioenergy crops in other regions, where climatic and soil conditions may have different effects on crop establishment risk and the temporal distribution of crop yields.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Costs of production (\$ ha^{-1}) for each bioenergy feedstock, Arlington, WI.
Table S2. Cost of production (\$ ha^{-1}) for each bioenergy feedstock, KBS, MI.