Potential Development of a Second-Generation Ethanol Industry in Alberta: Product Prices, Land Use Change, and Co-production Opportunities

by

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Abstract

Alberta holds a vast supply of lands that could be suitable for growing energy crops for biofuels; yet the cellulosic ethanol industry remains in its infancy. This thesis presents two studies that investigate the factors influencing the potential future of the industry. To provide insights into possible future prices, the first study investigates historic price movements of ethanol and two of its potential co-products: electricity and lignin pellets. Time series analyses focus on characterizing the underlying processes driving the series, and exploring seasonal effects and volatility. Each bioenergy commodity is found to evolve according to a mean reverting process. Ethanol and electricity exhibit non-constant volatility over time, while pellet prices vary according to season. These price models are applied in simulating stochastic prices that feed into the land use change analysis of the second study. The second study assesses the conditions under which private landowners might convert land from agriculture to switchgrass or hybrid poplar energy crops. A real options modeling approach is taken; offering landowners the option to switch between land uses and product markets, along with the option to defer the harvest of trees. The model is unique with its focus on co-production of bioenergy commodities and inclusion of two energy crops that deliver feedstocks which are managed and harvested over different time scales. Results suggest that substantial subsidies would be necessary to see the proliferation of energy crops on the landscape. In addition, hybrid poplar appears to dominate switchgrass as a bioenergy feedstock, while co-production of ethanol alongside electricity appears as financially preferred over co-production of ethanol with pellets. This preference for hybrid poplar feedstocks creates a challenge in providing biorefineries with an initial supply of feedstocks. The results of this thesis inform the feedstocks and co-products that may encourage the growth of the cellulosic ethanol industry.

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Chapter 1: Introduction

Renewable fuels could play a key role in the diversification of Canada's energy profile. Ethanol has central applications in the transportation sector, and holds the potential to contribute to energy security and stimulate economic development (Slating and Kesan, 2014). Recently, focus has shifted from first-generation ethanol, which utilizes sugar and starch feedstocks, to second-generation ethanol, based on cellulosic feedstocks (i.e. Naik et al., 2010; Carriquiry et al., 2011; Eggert and Greaker, 2014). This shift is the result of criticisms over potential competition between food and fuel production (Pimental et al., 2009), and uncertainties around possible negative environmental impacts from the first-generation fuels (Mohr and Raman, 2013). Second-generation ethanol may reduce greenhouse gas emissions, improve net energy output (Wiloso et al., 2012), and offer carbon sequestration benefits (Slating and Kesan, 2014). However, the financial viability of this prospective industry remains uncertain, and, despite its potential, this industry remains in its infancy in Canada.

When considering the potential future of a Canadian second-generation ethanol industry, it is essential to consider feedstock supply. There are a multitude of cellulosic feedstocks that could be used to produce ethanol, including crops, woody plantations, and residual materials from existing forestry and agriculture operations. Optimal feedstock selection will depend on both environmental concerns and costs (DiPardo, 2000), and, to efficiently produce large quantities of ethanol, the industry is likely going to rely on a mix of feedstocks (Vadas et al., 2008). To date, there remains uncertainty regarding which feedstocks are the most biophysically and economically viable. This study evaluates switchgrass and hybrid poplar, given that they can be grown on marginal lands, and may contribute to improving soil quality (Blanco-Canqui, 2010).

Second-generation ethanol is derived from the cellulose component of plants, leaving hemicellulose and lignin as residuals that can be utilized in co-production. Products derived from these residuals could have significant impacts on the profitability of biofuel operations, as the structural composition of hemicellulose and lignin makes up 40-50% of switchgrass plants (Howard et al., 2003), and approximately 35-49% of poplar wood (Torget and Hsu, 1994). To maximize the input efficiency of cellulosic feedstocks, co-production possibilities are highlighted in this study. Specifically, co-production combinations of ethanol with electricity, or ethanol with lignin pellets are explored. Accounting for these co-production opportunities is expected to improve the economic performance of second-generation ethanol (Lynd et al., 2005).

The goal of this thesis is to investigate bioenergy commodity prices, land use changes, and co-production opportunities as key factors that might influence the development of a second-generation ethanol industry in Alberta, Canada. Two studies are conducted that contribute to this investigation. First, to capture historic price behaviour for the projection of potential future price paths, Chapter 2 investigates historic ethanol, electricity, and pellet price series. The objectives of Chapter 2 are to assess the underlying processes driving the price series, and to test for the presence of seasonal effects and non-constant variance. Incorporating the results of this time series analysis, Chapter 3 applies a land use change model, based on real options analysis, to estimate landowner returns under different co-production scenarios. The objectives of Chapter 3 are to make three comparisons of financial competitiveness: of energy crops versus agriculture land use allocations; of hybrid poplar versus switchgrass feedstocks; and of ethanol with electricity versus ethanol with pellets co-production combinations. Sensitivity analyses on market conditions and energy crop productivity levels are also conducted to assess the conditions under which energy crops might be able to compete with agriculture in Alberta.

Chapter 2: Characterizing Historic Ethanol, Electricity, and Pellet Price Series for Second Generation Biofuels

2. 1 Introduction

Growing cellulosic energy crops holds the potential to improve the environmental performance of ethanol production, relative to starch-based systems, and may provide a large quantity of feedstocks. However, there remains a great deal of uncertainty over whether bioenergy crops can financially compete with other industries, such as agriculture, for land (Work, 2014; Liu et al., 2012).

One way to improve the financial competitiveness of this industry could be to engage in co-production of value-added products alongside ethanol (i.e. Barta et al., 2013; Dong et al., 2011; Cotana et al., 2014). This thesis explores the potential for electricity and pellets as co-products to ethanol, given potential cost-effectiveness benefits, sustainability advantages (Kazi, 2010), and reductions in greenhouse gases associated with these bioenergy commodities (McKechnie et al., 2011). Johnston and van Kooten (2015) also note that Canada is emerging as a significant pellet supplier to Europe, given EU policies that incentivize biomass burning in thermal power plants.

Assessing financial preferences for co-production of ethanol and electricity or ethanol and pellets involves a comparison of the price behaviour and potential profitability of the two scenarios. Understanding historic price movements can offer insights into possible future prices, variance, and confidence intervals; elements that are essential for landowner decision-making and risk management (Yang et al., 2012).

The price models estimated in this chapter form the basis of the stochastic bioenergy commodity price simulations applied in the land use change analysis in Chapter 3. The land use change model also requires stochastic agricultural land values, which are simulated based on the model estimated in Chapter 3.

The objectives of this chapter are to characterize the underlying processes, seasonal effects, and volatilities associated with historic ethanol, electricity, and pellet price series. This understanding of past price movements may provide insight into future market behaviour of these products; products that could support the emerging bioethanol industry in Alberta. This chapter is organized as follows: first, price series literature is reviewed, and the methods are described. An overview of the data is then provided, followed by the results of the ethanol, electricity, and pellet price series analysis.

2.2 Literature Review

This section provides a review of the means of analyzing underlying processes, seasonal effects, and volatilities associated with price behaviour, and presents the results of previous bioenergy commodity price series analysis studies.

2.2.1 Price Processes

Evaluating the stochastic process that best characterizes a historic price series is a key step in understanding price behaviour. The characterization of a price series has significant implications for investment decisions, since applying the incorrect price process in financial analyses could lead to errors in assumed returns (Isik, 2006).

Two common processes that are investigated in modeling price series are random walks and mean reversion (Leuthold, 1972; Schwartz, 1997). Under random walks, price changes operate as independent random variables (Leuthold, 1972). Conversely, for series characterized by mean reversion, estimates of future prices are expected to return to their long-run historic mean. Where these mean reverting series have both a fixed mean and variance, they are further characterized as being stationary (Stigler, 2011).

Conventional price theory suggests that commodity prices are expected to be mean reverting in competitive markets (Schwartz, 1997). Yang et al. (2012) offer empirical evidence supporting this expectation, identifying 17 mean reverting and stationary series out of the 24 commodities analyzed. Wang and Tomek (2007) and Andersson (2007) find contradictory results, where commodity price series have unit roots and are best characterized under a random walk process. Andersson (2007) identifies unit roots in 85% of the 280 commodities considered in their study. These conflicting results make it clear that no overarching assumptions as to underlying commodity price processes can be claimed, and that price processes may vary on a commodity-specific basis.

Given that the Canadian cellulosic ethanol industry is in its infancy, there are no price series available for analysis. However, price series are available in the US and Brazil, where ethanol industries are established. Ethanol prices in the United States have been characterized both as following a mean reverting process (Work et al., 2016; Gradebroek and Hernandez, 2013) as well as a random walk (Schmit et al., 2009). Price process analyses also reveal conflicting results in the case of Brazilian ethanol prices, where Bastien-Pinto et al. (2009) characterize prices under a mean reverting process, while Serra et al. (2011) find that prices follow a random walk. Schmit et al. (2009) explain that the results of these unit root test can vary with the inclusion of drift and/ or trend terms in the regressions.

Unlike ethanol, there are vast records of historical electricity price data. Studies have investigated the behaviour of hourly electricity prices in Alberta[1], the region of focus in this thesis. Gogas and Serletis (2009) find that logged prices are mean reverting and stationary, while Uritskaya and Uritsky (2015) instead characterize prices as following a random walk. Uritskaya and Uritsky (2015) highlight challenges in definitively characterizing price processes, and note that the electricity price series in Alberta may also be fit to a mean reverting model, given negative correlations in price increments.

Despite the fact that wood has long been burned for fuel, and that an established wood pellet market exists, few analyses of pellet price series were identified in the literature. Kristoefel et al. (2014) and Hillring (2014) find that Austrian and Danish wood pellet prices, respectively, follow a random walk process. Xian et al. (2015) analyze pellet prices in the US and find mixed signals in their unit root tests, where results depend on whether or not a time trend is included. The authors note that when the series is classified as a mean reverting process, the mean reverting rate was slow, and therefore conclude that the series follows a random walk.

The above review of price process characterizations for ethanol, electricity, and pellets reveal highly inconsistent results. This lack of consensus regarding the underlying price process driving these bioenergy commodity prices suggests the need for further analysis, which is undertaken in this chapter.

2.2.2 Seasonality in Prices

Trends arising across seasons can significantly impact price behaviour in commodity markets (Milonas, 1991). Seasonal effects in prices might arise on the supply side, due to the nature of

[1] Justification for this study region is provided in Section 3.1.

planting, harvesting, and storage considerations, as well as on the demand side, with seasonal temperature variations and changing heating or cooling needs (Pareira et al., 2012).

There are multiple methods of integrating seasonal effects into price models. Seasonal dummy variables can be added to models, resulting in a shift in the intercept term (Wildt, 1977). Autoregressive Integrated Moving Average (ARIMA, described in Section 2.3.2) structures can also be applied to the seasonal components of price series, resulting in in seasonal ARIMA (SARIMA) models (Box and Jenkins, 1976). With these models, seasonal periods progress according to autoregressive and/ or moving average movements. Seasonal effects can also be introduced as periodic functions of time. Under this method, seasonal effects evolve according to a mean reverting function that can be captured with Fourier seasonal terms (Fackler and Roberts, 1999). These Fourier seasonal models are based on sine and cosine oscillations, capturing the cyclical nature of seasonal effects (Hannan et al., 1970). Capturing seasonal effects through the addition of Fourier terms is said to offer benefits in terms of flexible modeling (Sorensen, 2002). In this thesis, SARIMA and Fourier seasonal models are tested.

Seasonality in ethanol prices has not been widely explored, perhaps because of the infancy of the industry. Pareira et al. (2012) indirectly evaluate seasonal effects in the ethanol industry in Brazil through their investigation of sugarcane prices[2]. The authors identify significant seasonal effects in the price series that are captured with a sine function. In addition, Furlan et al. (2013) find there is seasonal variability in monthly ethanol prices in Brazil, based on calculations of percentage variation about the mean.

Seasonal effects in annual, weekly, and daily price levels are commonly identified in electricity price series (i.e. Janczura et al., 2013; Hambly et al., 2009; Lucia and Schwartz, 2002). These seasonal effects are said to arise given that the energy commodity is difficult to store and its use is closely linked to weather conditions (Janczura et al., 2013). In the context of electricity prices in Alberta, Uritskaya and Uritsky (2015) identify significant seasonal effects that are captured through the addition of Fourier terms.

No analyses were identified that investigate seasonal effects in pellet price series. For an alternative wood product, Mei et al. (2010) incorporate seasonal dummies into their US timber

[2] Sugarcane is a starch-based feedstock is the basis for ethanol production in Brazil.

price models, and find no significant seasonal effects.

2.2.3 Price Volatility

Price volatility relates to the risk of holding assets (Zareipour et al., 2007), or, in the context of this study, risks associated with maintaining land in alternative uses given uncertain future returns. Empirical time series analyses for price volatility involve tests for non-constant variances in price model residuals (i.e. Work et al., 2016; Efimova and Serletis, 2014; Kristoefel et al., 2014). Work et al. (2016) highlight market shocks, policy interventions, and unpredictable weather events as potential sources driving these non-constant volatilities. Where non-constant variances are identified, Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH (GARCH) models are applied to capture changes in variance. Details on ARCH and GARCH modelling are provided in Section 2.3.4.

Most studies that have investigated volatility in ethanol price series generally do so in the context of multivariate GARCH models that assess volatility interactions between biofuel, food, and energy prices (i.e. Serra, 2013; Trujillo-Barrera et al., 2012; Gardebroek and Hernandez, 2013). These studies often find significant volatility spillovers between markets. With respect to univariate models, Work et al. (2016) identify non-constant volatilities in US ethanol prices that are captured by a GARCH(1,1)[3] model for conditional variances.

Electricity price series are expected to exhibit non-constant volatilities given that the commodity is difficult to store, is associated with high transportation costs, and has a highly inelastic demand (Efimova and Serletis, 2014). Efimova and Serletis (2014) find evidence of GARCH effects in US electricity markets, and estimate a GARCH(1,1) model for conditional variances. In Alberta, electricity price series have been found to be highly volatile (Uritskaya and Uritsky, 2015; Li and Flynn, 2004). Serletis and Shahmoradi (2006) and Gogas and Serletis (2009) model the conditional variance of hourly ethanol price series according to a GARCH(1,1) process.

[3] GARCH(1,1) models apply one GARCH lag on the conditional variance and one ARCH lag on the conditional covariance of the series.

Kristoefel et al. (2014) assess price volatility of wood pellets used for energy production in Austria using a univariate GARCH model and find there is increasing volatility over time. The authors fit a GARCH(1,1) model to the conditional variance.

Each of the univariate non-constant variance models identified in the literature for ethanol, electricity, and pellet price series have been in the form of GARCH (1,1) models. These GARCH(1,1) models, proposed by Bollerslev (1986), are noted to be widely applicable in variance modeling (Hansen and Lunde, 2005).

2.3 Methods

To capture energy commodity price behaviour, the underlying price process is first assessed; characterizing the series as either mean reverting or following a random walk. Next, preliminary ARIMA models are estimated, and the significance of seasonal model extensions is assessed. Residuals from these models are then tested for time-varying conditional variances, and, if present, non-constant variance models are estimated.

2.3.1 Price Processes

The classification of the underlying process driving a series is informed by unit root tests. To formally test for unit roots, the Augmented Dickey Fuller (ADF) test is employed (Dickey and Fuller, 1979). The null hypothesis of this test is that the series contains a unit root. Lag lengths from 0 to 12 are varied in the ADF test, and the optimal lag length is selected according to Bayesian Information Criterion (BIC) values, where lower values generally indicate a better fit.

Series with unit roots are said to follow a random walk, which can be modelled as a Geometric Brownian Motion (GBM) process. Meade (2010) describes the following discrete time specification for GBM:

$$Z_t = \mu + \varepsilon_t \qquad\qquad Z_t = \ln(P_t/P_{t-1}) \qquad (2.1)$$

where:

- Z_t is a logged price return[4];

[4] Price return variables show the effect of random walk or mean reverting processes on price adjustments between two price periods.

- μ is a drift rate;
- ε_t represents a constant variance error term, and
- P_t is the commodity price in the current period, t.

Alternatively, series that reject the null of unit roots are said to follow mean reverting patterns. Meade (2010) outlines a discrete time mean reverting price model as:

$$Z_t = \kappa(\eta - \ln(P_{t-1}) + \varepsilon_t \qquad Z_t = \ln(P_t/P_{t-1}) \tag{2.2}$$

where:

- κ represents the speed of mean reversion, and
- η is the long run mean log price.

After establishing the underlying process that drives the price series, the stationarity of the series is investigated using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). Stationarity analysis reveals whether mean reverting series have a fixed mean and variance over time (Stigler, 2011).

The ADF and KPSS test are applied together to characterize the underlying processes driving price series. Unit root and stationarity tests are linked such that where the null of a unit root in the ADF test is rejected (not rejected), it is expected that the null of stationarity would not be rejected (rejected).

2.3.2 ARIMA Model Estimation

Autoregressive Integrated Moving Average (ARIMA(*p,d,q*)) models provide estimates of time series models based on autoregressive lags of the average values in a series (*p*), orders of differencing (*d*), and moving average lags of error terms (*q*). These models are applied to stationary time series, or series that can be rendered stationary by differencing and/ or applying non-linear transformations to the series. For level time series that are mean reverting, *d* is equal to 0, and models are simplified to ARMA (*p,q*). The selection of *p* and *q* is made to render the residuals white noise, while adhering to principles of parsimony and least squares (de Smith, 2014). Akaike Information Criterion (AIC) values are compared when selecting parameters for the best fitting ARIMA models, where smaller values generally indicate a better fit.

In estimating ARIMA models, a backshift operator is applied. This operator adjusts observations backwards according to:

$$B^n P_t = P_{t-n} \tag{2.3}$$

where:

- B^{n} is the backshift operator, and
- n is the number of periods being adjusted (n represents p for the number of autoregressive lags and q for the number of moving average lags).

Using the backshift operator, Box and Jenkins (1976) define ARIMA models as:

$$\phi(B)\nabla^d P_t = \mu + \theta(B)e_t \tag{2.4}$$

$$\phi(B) = 1 - \sum_{j=1}^{p} \phi_j(B^j)$$

$$\theta(B) = 1 - \sum_{j=1}^{q} \theta_j(B^j)$$

where:

- $\phi(B)$ is the moving average operator for lagged error terms;
- $\nabla^d P_t$ is a price rendered stationary through differencing;
- μ is the drift term;
- $\theta(B)$ is the autoregressive operator for lagged prices;
- e_t is the error term;
- ϕ_p are the moving average coefficients, and
- θ_q are the autoregressive coefficients.

2.3.3 Seasonality in Prices

Seasonal effects are present in series where prices evolve according to cyclical patterns. In this analysis, the significance of seasonal effects is tested through SARIMA models and with Fourier seasonal terms.

2.3.3.1 Seasonal Autoregressive Integrated Moving Average Models

SARIMA models add multiplicative seasonal terms to the classic ARIMA model structure (Equation 2.4). The significance of the seasonal effects in SARIMA models is assessed through a likelihood ratio test against the base ARIMA model estimated. SARIMA models are classified as ARIMA(p,d,q)x($\mathcal{P},D,Q$)H, where $\mathcal{P}$ is the number of seasonal autoregressive lags, D is the level of seasonal differencing, Q is the number of seasonal moving average lags, and H is the time span of the repeating seasonal pattern. Where no differencing is required, either in the mean model or in the seasonal model, the classification becomes ARMA(p,q)x($\mathcal{P}$,Q)H. Box and Jenkins (1976) outline SARIMA models as:

$$\Phi(B^H)\phi(B)\nabla_H^D\nabla^d P_t = \mu + \Theta(B^H)\theta(B)e_t \tag{2.5}$$

$$\Phi(B^H) = 1 - \sum_{J=1}^{\mathcal{P}} \Phi_J B^{HJ}$$

$$\Theta(B^H) = 1 - \sum_{J=1}^{Q} \Theta_J B^{HJ}$$

$$\nabla_H^D P_t = (1 - B^H)^D P_t$$

where:

- $\nabla_H^D P_t$ is a seasonally differenced price;
- $\Theta(B^H)$ is the seasonal moving average operator;
- $\Phi(B^H)$ is the seasonal autoregressive operator;
- $\mathcal{P}$ is the number of seasonal autoregressive lags, and
- Q is the number of seasonal moving average lags.

2.3.3.2 Fourier Seasonal Models

ARIMA models can incorporate Fourier seasonal terms to capture seasonality. Haidu et al. (1987) outline the modelling of Fourier periodic trends (S_t) according to:

$$S_t = \frac{1}{2}\alpha_0 + \sum_{k=1}^{k}(\alpha_k \cos\frac{2\pi}{T}kt + \beta_k \sin\frac{2\pi}{T}kt) \tag{2.6}$$

where:

- α_0, α_k, and β_k are the estimated Fourier coefficients;
- k is the number Fourier terms;
- t is the current time period;
- T is the length of the seasonal period, and
- $\frac{2\pi}{T}$ is the frequency of the seasonal oscillations.

The overall price model adds the Fourier seasonal component of Equation 2.6 to the base ARIMA model outlined in Equation 2.4, so that the price series model becomes:

$$Y_t = P_t + S_t \tag{2.7}$$

2.3.4 Autoregressive Conditional Heteroskedasticity Models

For series exhibiting non-constant variance, Engle (1982) proposes applying an autoregressive conditional herteroskedasticity (ARCH) model, where conditional variance is modeled as a function of time. Under this model, squared residuals of the current period are a factor of past squared residuals, according to:

$$e_t | \varphi_{t-1} \sim N(0, \sigma_t^2) \tag{2.8}$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j e_{t-j}^2$$

where:

- e_t is the error term, with a mean of zero and a conditional variance of σ_t^2;
- φ_t is the information set of all information through time;
- α_0 and α_p are the estimated ARCH coefficients;
- p is the number of autoregressive lags, and
- e_{t-j}^2 are the squared errors of previous time periods.

Bollerslev (1986) develops a generalized ARCH (GARCH) model that introduces past volatilities in the volatility equation according to:

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j e_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2.9}$$

where:

- q is the number of autoregressive lags, and
- σ_{t-j}^2 are the volatilities from past periods.

In the time series analyses conducted in this chapter, GARCH modelling is pursued wherever non-constant volatilities are identified. GARCH models of the error term (Equation 2.9) are then integrated into the ARIMA models outlined above in Equation 2.4.

2.3.5 Tests Applied in Estimating Price Models

A series of tests are run following model estimation. To assess model distributions, the Shapiro-Wilk and Anderson-Darling tests are run, with the null hypothesis of normally distributed residuals. Where normality is rejected and alternative distributions are tested, the Pearson Goodness of Fit test is applied. In assessing the contribution of seasonal effects to the predictive capacity of models, base ARIMA models are compared to their seasonal counterparts with likelihood-ratio tests. The ARCH Lagrange multiplier test is also applied to residuals, with the null hypothesis of no ARCH effects. Finally, under the null hypothesis of no remaining autocorrelation, the Weighted Ljung-Box test assesses autocorrelation in residuals, while the Weighted Portmanteau test evaluates GARCH residuals by testing the null hypothesis of an adequately fitted ARCH process.

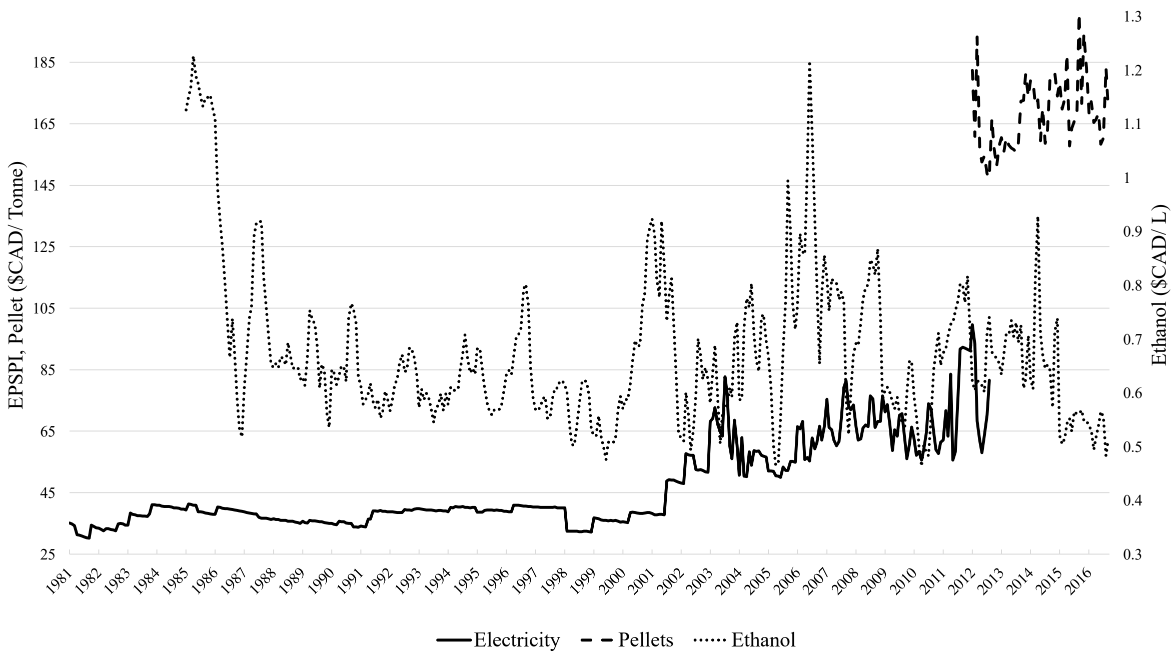
2.4 Data

Given this study's focus on the potential for a cellulosic ethanol industry in Alberta, province-specific prices are sought where available. For consistency in the level of aggregation for price behaviour comparisons of the three energy commodities, monthly data series are analyzed. All price series are inflation-adjusted to January 2016 dollars using the monthly consumer price index (CPI) from Statistics Canada's Canadian Socio-economic Information Management System (CANSIM).

2.4.1 Ethanol

The Canadian cellulosic ethanol industry remains in development, and no historic price series are available for analysis. With the expectation that Canadian prices would behave similarly to those observed in the US, a price series obtained from the US Department of Agriculture is analyzed in this study. This series is made up of 381 monthly observations extending from January 1985 to

September 2016, with prices ranging between 0.46 and 1.23 $/L. Prices are converted from US dollars to Canadian dollars using average monthly exchange rates from the Bank of Canada, and are converted from $/US gallon to $/L. The resulting price series, in real dollars, appears to be mean-reverting with non-constant volatility, as shown in Figure 2-1.



Sources:

Electricity: CANSIM Series V107792870

Pellets: CIMT 440131

Ethanol: USDA Economic Research Service U.S. Bioenergy Statistics' Website

Figure 2-1: Real price series for ethanol, electricity, and pellets

2.4.2 Electricity

Alberta's electricity price behaviour is assessed based on CANSIM's Electric Power Selling Price Index[5] (EPSPI). This is a monthly series tracking the sale of electricity from distributors to commercial and industrial users in Alberta. The series contains observations dating back to January 1981, but observations are missing for September 2012-December 2013. The 32 observations that extend from January 2014 to August 2016 are too few to conduct a robust time

[5] The index for annual production of over 5000 kw is selected, given expectations that electricity production in excess of plant use in the proposed co-production facilities of at least 8747 KW (McAloon et al., 2000).

series analysis. Therefore, price behaviour before the missing data is analyzed.

A visual inspection of the series, presented in Figure 2-1, suggests that a structural break might exist in the data, with the switch point occurring sometime between the years 2000-2002. After this point, both the mean and variance of the series appear to change. A Chow test[6] confirms that a structural break takes place in February 2002. Therefore, to estimate future price behaviour based on current price patterns, index movements following this break are analyzed. The structural break observed in the series is likely the result of Alberta's electricity market deregulation (Zareipour et al., 2007). Legislation supporting this shift came into effect January 1, 1996 (Alberta Energy, 2003). However, the retail market did not fully open to competition until 2001 (Borden Ladner Gervais, 2016). The formal structural break point in 2002 could reflect the time required for the market to adjust to the market change.

Because of both the missing data, and the structural break, this time series analysis is conducted on the 127 data points of the index spanning from February 2002 to September 2012.

2.4.3 Pellets

Like ethanol, the lignin pellet industry is not yet established in Canada. Canadian wood pellet prices are therefore selected for analysis as a proxy for lignin pellet prices. Still, despite the existence of the wood pellet market, a price series could not be obtained. Instead, a price series is estimated as a function of total wood pellet export revenues and quantities[7]. The wood pellet export data are obtained from Statistics Canada's Canadian International Merchandise Trade Database (CIMT), where monthly export revenues are recorded as Free on Board at the port of departure. Revenues are reported in Canadian dollars, while quantities are reported in kilograms. There are 57 monthly observations with a minimum value of 147.41 $/tonne, and a maximum value of 200.97 $/tonne. The derived series appears to exhibit non-constant volatility and is displayed in Figure 2-1.

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[6] The Chow test returned an F score of 11.894 with a corresponding p value of 9.814 e-06, supporting the notion that a structural break occurred at this point.

[7] Canada is a key pellet exporter to Europe and Asia (US Department of Commerce, 2016).

2.5 Results

For each of the ethanol, electricity, and pellet price series, the underlying process is assessed, the significance of seasonal effects is explored, and ARIMA/ARMA models are estimated; either under the assumption of constant volatility, or with GARCH effects.

2.5.1 Ethanol

As the first step in analyzing the ethanol price series, the ADF test is run under the null hypothesis of a unit root. Results in Table 2-1 indicate that the null hypothesis is rejected, suggesting the series is mean reverting and may be stationarity. The stationarity of the series is further examined with the KPSS test. Table 2-1 shows that the null hypothesis of stationarity is not rejected. Ethanol price model estimation therefore proceeds under the assumption of mean reversion and stationarity.

Table 2-1: Ethanol unit root and stationarity test results

Test	Test Statistic
ADF, 2 lags (5% CV = -2.8694)	-4.8180***
KPSS, 12 lags (5% CV = 0.4630)	0.2903

***** and ** indicate significance at the 1% and 5% levels of significance, respectively**

Table 2-2 outlines the parameters of the ARMA(2,1) model that is estimated for the ethanol price series. Both the Shapiro-Wilk and Anderson-Darling tests reject the null hypothesis of normally distributed residuals. The ARCH LM test rejects the null hypothesis of no ARCH effects. Accordingly, a GARCH model under a non-normal distribution is estimated below.

Table 2-2: Ethanol ARMA model results

Component	Lag	ARMA Model, Normal Distribution
Autoregressive	Constant	0.6804*** (0.0316)
	1	0.5960*** (0.1233)
	2	0.2643** (0.1198)
Moving Average	1	0.6412*** (0.1198)
AIC		-1135.73
Shapiro-Wilk Test Statistic		0.9638***
P-value		4.301 e-08
Anderson-Darling Test Statistic		3.7019***
P-value		2.99 e-09
ARCH LM Chi-squared Value		55.705***
P-value		1.352 e-07

***** indicates significance at the 1% level of significance.**

Seasonal effects are tested both under SARMA modelling and with Fourier regressors. Table 2-3 outlines the best fitting SARMA model as ARMA(2,1)(1,1). However, the likelihood ratio test for this seasonal model against the pure ARMA(2,1) model indicates that adding seasonal autoregressive terms does not significantly improve the model's fit. When applying external Fourier regressors, the Fourier coefficients are not significant at the 10% level of significance. Results of the likelihood ratio test confirm that adding these seasonal parameters do not improve the predictive capacity model. Overall, the ethanol price series is not found to be significantly impacted by seasonal effects.

An ARMA-GARCH model with non-constant volatility is estimated under non-normal distributions. Skew-normal, student-t, skew-student-t, skewed generalized error, and generalized hyperbolic distributions are tested. The Pearson Goodness-of-fit test indicates that the skewed generalized error distribution provides the best fit. Table 2-4 outlines the parameters of the estimated ARMA(1,1)-GARCH(1,1) model. The Ljung-Box test reveals that autocorrelation has been sufficiently accounted for in the ARMA mean model. In addition, the weighted Protmanteau test indicates that non-constant volatilities are captured in the GARCH model.

Table 2-3: Ethanol seasonal model results

		Model	
Component	**Lag**	**SARMA, Normal Distribution**	**Fourier, Normal Distribution**
Autoregressive	Constant	0.6801*** (0.0319)	0.6809*** (0.0323)
	1	0.6148*** (0.1313)	0.5788*** (0.1228)
	2	0.2447* (0.1273)	0.2842** (0.1195)
Moving Average	1	0.6209*** (0.1111)	0.6521*** (0.1010)
Seasonal Autoregressive 12	1	-0.7347*** (0.1662)	
Seasonal Moving Average12	1	0.7896*** (0.1488)	
Sine 12	1		-0.0154 (0.0096)
Cosine 12	1		-0.0090 (0.0096)
AIC		-1134.06	-1135.11
LR Chi-squared Value		2.3327	2.2806
Shapiro-Wilk Test Statistic		0.9637***	0.9634***
P-value		4.136 e-08	3.745 e-08
Anderson- Darling Test Statistic		3.7266***	3.7892***
P-value		2.609 e-09	1.839 e-09
ARCH LM Chi-squared Value		57.305***	57.297***
P-value		6.962 e-08	6.986 e-08

*****, **, and * indicate significance at the 1%, 5% and 10% levels of significance, respectively**

Table 2-4: Ethanol GARCH model results

Component	Lag	GARCH Model, SGED Distribution
Autoregressive	Constant	0.6589*** (0.1894)
	1	0.8621*** (0.1144)
Moving Average	1	0.3583*** (0.1146)
ARCH	Constant	0.000187*** (0.000072)
	1	0.1507*** (0.0178)
GARCH	1	0.7892*** (0.1187)
AIC		-3.1654
Weighted Ljung-Box Test Statistic		0.6514
P-Value		0.4196
Weighted Portmanteau Test Statistic		0.2031
P-value		0.6523

*****, ** and * indicate significance at the 1%, 5% and 10% levels of significance, respectively.**

2.5.2 Electricity

For the electricity series, the ADF test rejects the null hypothesis of a unit root, suggesting a mean reverting process (Table 2-5). With the KPSS test, the null hypothesis of stationarity is rejected. These conflicting results may be a result of the series length, where stationarity tests can suffer from a loss of power with smaller sample sizes (Joensson, 2011). Based on the results of the ADF test, ARIMA model estimation proceeds under the assumption of a stationary series.

Table 2-5: Electricity unit root and stationarity test results

Test	Test Statistic
ADF, 0 lags (5% CV = -2.8842)	-4.1181***
KPSS, 12 lags (5% CV = 0.4630)	0.5942**

***** and ** indicate significance at the 1% and 5% levels of significance, respectively**

Table 2-6 outlines the parameter estimates of the ARMA(1,0) model fit to the electricity series. Post-estimation tests reveal that residuals are non-normally distributed and that ARCH effects are present. As such, a GARCH model under an alternative distribution is estimated below.

Table 2-6: Electricity ARMA model results

Component	Lag	ARMA Model, Normal Distribution
Autoregressive	Constant	64.3488*** (2.5561)
	1	0.7663*** (0.0582)
AIC		858.2
Shapiro-Wilk Test Statistic		0.9650***
P-value		0.0023
Anderson-Darling Test Statistic		1.5406***
P-value		0.0005
ARCH LM Chi-squared Value		20.383*
P-value		0.0602

*****, ** and * indicate significance at the 1%, 5% and 10% levels of significance, respectively**

The best fitting SARIMA model for the electricity price series is classified as ARMA(1,0)(0,1) (Table 2-7). However, the seasonal moving average term is not significant at the 10% level of significance. For the ARMA model estimated with external Fourier regressors, the coefficients on the Fourier terms are not significant at the 5% level. Based on these results, the electricity series is assumed to not be significantly affected by seasonal effects.

Table 2-7: Electricity seasonal model results

		Model	
Component	**Lag**	**Seasonal ARMA, Normal Distribution**	**Fourier, Normal Distribution**
Autoregressive	Constant	65.2816*** (2.8608)	
	1	0.7602*** (0.0584)	0.6740*** (0.0891)
Moving Average	1		-0.9425*** (0.0437)
Seasonal Moving Average 12	1	0.1778* (0.1058)	
Sine 12	1		-2.6013* (1.5656)
Cosine 12	1		0.3815 (1.5565)
AIC		857.09	852.89
Shapiro-Wilk Test Statistic		0.9664***	0.9642***
P-value		0.0030	0.0019
Anderson-Darling Test Statistic		1.4553***	1.6235***
P-value		0.0009	0.0003
ARCH LM Chi-squared Value		21.559**	17.487
P-value		0.0428	0.1322

*****, ** and * indicate significance at the 1%, 5% and 10% levels of significance, respectively**

An ARMA(1,0)-GARCH(1,1) model of non-constant variance under a skewed generalized error distribution is estimated for the electricity series. The estimated model parameters are outlined in Table 2-8. Residuals testing reveals that there are no remaining autocorrelations or ARCH effects.

Table 2-8: Electricity GARCH model results

Component	Lag	GARCH Model, SGED Distribution
Autoregressive	Constant	61.3699*** (0.0000)
	1	0.7390*** (0.0000)
ARCH	Constant	6.7281*** (0.0000)
	1	0.2207*** (0.0000)
GARCH	1	0.6263*** (0.0000)
AIC		6.6076
Weighted Ljung-Box Test Statistic		0.4470
P-value		0.5038
Pearson Goodness-of-Fit Test Statistic (group 20)		15.20
P-value		0.7095
Weighted ARCH LM Test Statistic (3 lags)		0.1669
P-value		0.6829

*****, ** and * indicate significance at the 1%, 5% and 10% levels of significance, respectively.**

2.5.3 Pellets

The ADF test rejects the null hypothesis of unit roots in the pellet series, suggesting mean reversion (Table 2-9). Meanwhile, the null hypothesis of stationarity is not rejected with the KPSS test. The pellet price series is therefore assumed to be mean reverting and stationary.

Table 2-9: Pellet unit root and stationarity tests

Test	Test Statistic
ADF, 3 lags (5% CV = -1.95)	-4.1525**
KPSS, 12 lags (5% CV = 0.4630)	0.3196

***** and ** indicate significance at the 1% and 5% levels of significance, respectively**

An ARMA(1,1) model is fit to the pellet price series, as outlined in Table 2-10. Both the Shapiro-Wilk and Anderson-Darling indicate that the residuals are not normally distributed. The ARCH LM test provides evidence that estimating a constant variance model is appropriate, with no need to estimate a GARCH model.

Table 2-10: Pellet ARMA model results

Component	Lag	ARMA Model, Normal Distribution
Autoregressive	Constant	168.6642*** (3.1833)
	1	0.7690*** (0.1391)
Moving Average	1	-0.4503** (0.1849)
AIC		438.1
Shapiro-Wilk Test Statistic		0.9590*
P-value		0.0509
Anderson-Darling Test Statistic		0.7383*
P-value		0.0513
ARCH LM Chi-squared Value		6.5592
P-value		0.8853

*****, ** and * indicate significance at the 1%, 5% and 10% levels of significance, respectively**

Table 2-11 outlines the best fitting SARIMA model as SARIMA(3,0,0)(0,1,1), with one level of seasonal differencing. Seasonal differencing stabilizes the seasonal effect mean, but in doing so eliminates 12 observations. Given that the original pellet series is comprised of only 57 observations, further restricting the sample size could lead to issues in the robustness of model estimation results. Because of these sample size limitations, the SARIMA model is not selected as the best fitting model.

An ARMA model with external Fourier regressors is estimated, where one sine and two cosine oscillations are significant at the 5% level of significance (Table 2-11). The likelihood-ratio test indicates that the seasonal regressors significantly contribute to the predictive capacity of model. In residuals testing, both the Anderson-Darling and the Shapiro-Wilk test indicate that applying a normal distribution is appropriate. Finally, with the ARCH LM test, no ARCH effects were observed. The pellet price series is therefore represented as an ARMA(2,1) with K=2 external Fourier series, falling under a normal distribution, with constant variance.

Table 2-11: Pellet seasonal model results

		Model	
Component	**Lag**	**SARMA, Normal Distribution**	**Fourier, Normal Distribution**
Autoregressive	Constant		169.4968*** (3.7217)
	1	-0.0123 (0.1401)	0.4045** (0.1619)
	2	0.3465** (0.1452)	0.4439*** (0.1321)
	3	0.4373*** (0.1547)	
Moving Average	1		-0.4254*** (0.1456)
Seasonal Moving Average 12	1	-0.5244** (0.2214)	
Sine 12	1		-1.2673 (1.442)
	2		-2.2017** (1.0940)
Cosine 12	1		7.7095*** (1.4552)
	2		-3.3313*** (1.0869)
AIC		347.91	421.48
LR Chi-squared Value			24.473***
Shapiro-Wilk Test Statistic		0.9654	0.9767
P-value		0.1021	0.3359
Anderson-Darling Test Statistic		0.9858**	0.42621
P-value		0.0124	0.3045
ARCH LM Chi-squared Value		6.6099	8.2071
P-value		0.8823	0.7687

***** and ** indicate significance at the 1% and 5% levels of significance, respectively**

2.6 Summary, Discussion and Conclusions

This chapter investigates historic price series to estimate models of ethanol, electricity, and pellet prices. The underlying processes driving the series are assessed, and potential seasonality and non-constant volatility effects are explored. Table 2-12 summarizes the results of the bioenergy commodity price analyses.

Table 2-12: Ethanol, electricity, and pellet summary price characteristics

Bioenergy Commodity	Process Characterization	Seasonal Effects	Volatility Analysis
Ethanol	Mean reverting, stationary	Not significant	Significant GARCH effects
Electricity	Mean reverting, stationary	Not significant	Significant GARCH effects
Pellets	Mean reverting, stationary	Significant Fourier seasonal effects	Constant volatility

As a first step in assessing historic price behaviour, unit root and stationarity tests are conducted. A review of the literature reveals variable results for bioenergy commodity price process analyses, where some studies characterize the ethanol, electricity, and pellet series as mean reverting, while others characterize the series as random walks. Based on the ADF unit root tests conducted in this study, each of the ethanol, electricity, and pellet series are found to be driven by mean reverting processes. KPSS test results support stationarity in the ethanol and pellet price series, while revealing conflicting stationarity findings for the case of electricity, which may be the result of the small series sample size.

Conventional price series analysis suggests that where the ADF test's null hypothesis of unit roots is rejected in favor of the stationarity alternative, the KPSS tests' null hypothesis of stationarity should not be rejected. However, empirical analyses often dispute this convention. In a cross-country review of GDP time series analyses, Cheung and Chinn (1996) find that the two tests are consistent in only 11% of cases, highlighting the challenges of forming definitive conclusions regarding time series properties. In addition, Caner and Kilian (2001) note that viewing the ADF and KPSS tests as complementary is likely to lead to contradictions, given that stationarity tests like the KPSS test, that are based on asymptotic critical values, do not differentiate white noise processes from persistent stationary processes. With these persistent series, the null of stationarity is expected to be rejected more often than might be the true case (Caner and Kilian, 2001). As a result of the challenges in differentiating stationarity from persistence, here, the underlying process driving the series is assessed according to the results of the ADF test, and ARMA models are estimated under the assumption of mean reverting and stationary processes for the ethanol, electricity, and pellet series.

The classification of these series as mean reverting implies more certainty for agents in future expected prices than if they were classified as random walks. For series classified as random walks, price shocks are viewed as permanent, and volatilities can grow without bound (Chaudhuri and Wu, 2003). As a result, future returns for random walk series are not easily predictable based on historic observations. In contrast, mean reverting series fluctuate around a long-term mean, allowing agents to integrate historic price trends into expectations of future returns. Laughton and Jacoby (1993) note that with mean reverting series, long-term price risk is reduced relative to random walks, thereby reducing the risk premium applied to investments. Moreover, with mean reverting series, external shocks are expected to dissipate over time.

Under the assumption of mean reversion, a constant variance ARMA model is initially estimated for the ethanol price series. This series is not found to be significantly impacted by seasonal variation. However, post-estimation tests suggest that the residuals are not normally distributed, and that ARCH effects are present. As a result, an ARMA(1,1)-GARCH(1,1) model is estimated under a skewed generalized error distribution, with one autoregressive and one moving average lag in the mean model, along with one ARCH autoregressive lag in squared errors and one GARCH moving average lag in the variance model. The estimated GARCH coefficient is larger than the ARCH coefficient, indicating that past volatilities have a greater impact on the series than past errors.

Like the model estimated for the ethanol series, the electricity series is characterized without seasonality, under a non-normal distribution, and with ARCH effects. The model is estimated as ARMA(1,0)-GARCH(1,1), under a skewed generalized error distribution, with one autoregressive lag in the mean model, along with one ARCH lag and one GARCH lag in the variance model. The GARCH coefficient is larger than the ARCH coefficient, suggesting that past volatilities have a greater impact on the current observed variance than do previous errors, which are driven by external factors. Though the ethanol and electricity ARMA models are mean reverting, the ARCH/GARCH components introduce more price risk than constant variance models.

Seasonal effects are identified for electricity price series in the literature, but are not found to be significant in this analysis. This difference may be attributed to the fact that analyses in the literature are based on hourly series, while a monthly series is analyzed in this study. Mei et al. (2010) note that differences in the level of aggregation of data can impact the results of price series characterizations. No studies have been identified that assessed electricity price series movements on a monthly basis.

Estimating the electricity model involves an investigation of structural change. A visual inspection of the data series reveals clear differences in the mean and variance of the series following a break point, which is confirmed with a Chow test. The timing of this structural break coincides with legislation changes for a deregulation of the electricity market. Therefore, in estimating models of current price behaviour aimed at projecting possible future prices, it is important to characterize the price series according to more recent price movements. A subsequent structural change in electricity series might be expected in the future as Alberta transitions towards a capacity market system. Changes in consumer preferences or market structures could similarly alter the future trajectory of other bioenergy commodity prices.

The pellet price series is found to be normally distributed, with significant seasonal effects, and with constant variance. The series is modeled as an ARMA(2,1) model with two autoregressive and one moving average lags in the mean model, alongside external seasonal regressors with two Fourier terms. With this seasonal model, prices are still expected to return to a long-run mean, but this mean varies according to the season. There has been limited focus placed on seasonality in the price analysis literature. Yet if these effects are present, capturing these periodic trends can improve the predictive capabilities of mean reverting models when forming future price expectations.

This investigation of ethanol, electricity, and pellet price behaviour is conducted as an initial comparison of the prospective price behaviour of co-production combinations for a potential future second-generation ethanol industry. Understanding the price characteristics of these bioenergy commodities, and assessing how the behaviour of the co-products fit together, may play into the financial viability of these co-production opportunities.

Further assessment of relative appeal of the two co-production combinations is presented in Chapter 3, with a real options analysis of potential land use changes. The price models estimated in this chapter form the basis of expected future price simulations.

Chapter 3: Potential Land Use Changes towards Energy Crops: A Real Options Model

3.1 Introduction

A second-generation ethanol industry would require a reliable and secure stream of cellulosic feedstocks for industry stability. Securing these feedstocks is not without challenges, however, as assessing where these feedstocks will be grown relates to land scarcity and land use allocation decisions.

This chapter covers an investigation of potential land use changes towards growing switchgrass or hybrid poplar as bioenergy crops. Fast-growing hybrid poplar shows promise for ethanol production because it can be grown on marginal soils, thus avoiding direct competition with food production on high-quality cropland (Huang et al., 2009). Switchgrass can also be grown on marginal cropland (Schmer et al., 2008) and is tolerant of cool temperatures, while being cultivated using conventional farming practices (Khanna et al., 2008).

Regulations in most provinces currently restrict the growing of exotic hybrid poplar stands on public land (e.g. Cairus, 2008). Therefore, this investigation focuses on potential conversions to energy crops from private lands that are currently allocated to growing agricultural products. A focus is placed on Alberta, which is known to hold a high prevalence of marginalized agricultural land (Anderson and Luckert, 2007) that Campbell et al. (2008) identify as a likely location for plantations.

Land use allocation decisions on private lands may be made based on a combination of economic, social, and biophysical factors. Here, it is assumed that decisions are evaluated based on the economic value or profitability of the selected land use, where the land use options are agriculture[8], switchgrass, or hybrid poplar. Land valuation estimates are influenced by product prices, short-term and long-term discount rates, energy crop yields and renewable energy policies. It is also assumed that a rational, profit-maximizing landowner will seek to maximize the expected value of their land, and therefore the highest valued use, on an expected value basis.

[8] In this study, agricultural land generally captures the crops grown in Alberta, but does not include energy crops such as switchgrass.

Risk and uncertainty play key roles in the potential development of the second-generation ethanol industry. There is risk associated with future stochastic product prices and uncertainty in future production costs, technologies, and policies. This study therefore employs a real options approach, which accounts for managerial flexibility in the face of risk, in evaluating potential land use changes towards energy crops.

This work builds on the real options land use change model developed by Hauer et al. (2017). The original model is extended to include switchgrass, in addition to hybrid poplar, as an energy crop land use option. With this modification, three land uses that are managed and harvested under different time scales are compared: annual agricultural crops, perennial switchgrass crops, and short rotation hybrid poplar plantations (harvested after approximately 20 years). This work also introduces co-production possibilities, factoring in stochastic prices for ethanol and two of its potential co-products: electricity and lignin pellets. Moreover, given the presence of seasonal effects in the pellet price series (see Chapter 2), this work adjusts the model from an annual to a semi-annual time scale. This modified time-scale allows landowners to differentiate conditions in the springtime, when planting decisions are made, from the fall, where harvesting takes place. These changes are made to better capture the information landowners consider in their land use management decisions.

Although there is uncertainty in multiple aspects of a future cellulosic ethanol industry, this study primarily focuses on risk in stochastic product prices. To capture this risk in product prices, trends from historical data are captured and applied in simulations. The models forming the basis of these simulations include mean reverting ARMA models for ethanol, electricity, and pellets, described in Chapter 2, along with a first-order differenced ARIMA model of agricultural land values, outlined in Appendix 1. The ARIMA model of agricultural land values was obtained from Hauer (personal communication, 2017). This method of focusing on stochastic product prices is similar to the approach taken by McCarty and Sesmero (2015), who note that with the establishment of biofuel markets, uncertainty in technical conversions and feedstock prices are likely to diminish, while product output price volatility is likely to remain substantial over time. Uncertainty in energy crop yields and future policies are also considered in sensitivity analyses.

Three objectives are addressed in this chapter. The first objective is to assess the potential financial competitiveness of energy crops against agriculture under status-quo conditions. The second objective is to compare the financial competitiveness of hybrid poplar versus switchgrass. The third objective is to evaluate the financial competitiveness of ethanol and electricity co-production against ethanol and pellet co-production. To meet these objectives, sensitivity analyses that modify land base assumptions, discount rates, product prices, and subsidy levels are conducted. Altogether, this study will provide an understanding of the conditions under which landowners might view growing energy crops as financially favourable. This information might assist in future policy development aimed at meeting sustainable energy production targets by encouraging the growth of the second-generation ethanol industry.

This chapter is divided into three sections: first, real options valuation is described. The land use change model is then introduced, with a description of the methods employed. Finally, the results of the model's baseline trials under both ethanol and electricity, and ethanol and pellet co-production cases, along with sensitivity trials, are presented.

3.2 Literature Review

Section 3.2.1 provides an overview of two alternative land valuation methods. Section 3.2.2 proceeds by outlining feedstock input and product output options that have been considered in previous land use change studies. Section 3.2.3 then reviews approaches that have been taken to capture stochastic prices associated with bioenergy feedstocks.

3.2.1 Comparing Net Present Value and Real Options Approaches to Land Valuation

The valuation of alternative land uses has widely been pursued through net present value (NPV) approaches (e.g. Polglase et al., 2013; Boettcher et al., 2012; Keefe et al., 2012). This method provides static, deterministic estimates of land values given a constant set of parameters over time. Yet despite its widespread use, the NPV approach omits some elements that may be relevant to land valuation. The NPV approach fails to account for risk in stochastic returns, irreversibility of decisions, and flexibility in the timing of decision-making (Dixit and Pindyck, 1994). Moreover, the value of retaining options for future consideration is not accounted for, with NPV land use decisions being made on a "now or never" basis (Reeson et al., 2015). The NPV approach also assumes that land use allocation decisions are maintained into the future, when, in reality, landowners can alter choices as market conditions change (Regan et al., 2015). These shortcomings associated with the NPV approach to land valuation can limit its applicability in land use change investigations, especially in the context of uncertain developing bioenergy product markets.

Considering the limitations of the NPV approach, valuation studies have employed real options (RO) analysis (i.e. Song et al. 2010; Regan et al., 2010; Wear et al., 2015; Reeson et al., 2015; Schatzki, 2003). Diaz et al. (2015) explain that that RO reflects the right, but not the obligation, to act on an option if conditions align in such a way that the option is financially favoured. The RO approach assigns value to having options, and to being flexible when facing uncertainties in land use management decisions. Furthermore, the RO approach allows for the careful consideration of timing in land use decisions, which is central to valuation exercises that compare land uses that are managed under differing time scales (i.e. annual crops vs. perennial crops vs. short-rotation woody plantations). However, despite the positives associated with the RO approach, Regan et al. (2017) note that its complexity, when compared to the NPV approach, has been a barrier to its use in valuation.

The present research seeks to assess potential land use changes from agriculture to bioenergy feedstocks. Regan et al. (2017), Wolbert-Haverkamp and Musshoff (2014), and Song et al. (2011) have conducted studies with similar objectives, which focus on comparing the returns required to invest in a new land use through NPV and RO approaches. Across all three studies, the expected returns required to promote land use conversions towards bioenergy feedstocks are higher under RO valuation than NPV. Regan et al. (2017) note that NPV may underestimate the true returns required to prompt land use conversions to bioenergy feedstocks, given that the approach undervalues inter-temporal opportunity costs, and does not account for price risks. For these reasons, NPV estimates may not be the best metric from which to evaluate land use conversions. The land use change model developed in this chapter is based on the RO approach to land valuation. This approach is taken in light of the multi-year model period for which inter-temporal opportunity costs are relevant, and the multiple uncertainties that exist within the emerging biofuel industry, where it will likely be important to allow for managerial flexibility to alter land use decisions with changing market conditions.

3.2.2 Selection of Input and Output Options

Studies evaluating land use changes towards purpose-grown cellulosic feedstocks for bioenergy production are varied in their selection of the type and number of options included in models. In terms of feedstock inputs, Song et al. (2010) choose to focus on conversions to switchgrass from initial land uses. Alternatively, hybrid poplar has been explored by Work (2014), Hauer et al. (2017), Yemshanov et al. (2015), and Wolbert-Haverkamp and Musshoff (2014). Eucalyptus has also been studied by Wear et al. (2015) and Regan et al. (2017). For these forest plantations, biomass can be stored on the stump, generating value in the option to defer harvesting decisions until favourable market conditions are observed (Hauer et al., 2017). These feedstock inputs vary in whether or not annual returns are initially collected (i.e. with switchgrass), or if multiple time periods must pass before harvest is possible (i.e. in coppiced or short-rotation woody plantation management regimes).

Whether based on short-rotations, coppice forest plantations, or perennial grasses, the above studies have assessed potential conversions from traditional land uses to a single bioenergy feedstock. In the land use change model developed in this study, multiple feedstock options are included to assess the potential interactions between agriculture and bioenergy feedstocks with annual and multi-year harvest returns.

Regarding product options, studies have largely been restricted to assessing a single output. Common choices are forest biomass (i.e. Wolbert-Haverkamp and Musshoff, 2014; Regan et al., 2017) and ethanol (i.e. Hauer et al., 2017; Song et al., 2011). Work (2014) deviates from this single output model by allowing for two output options. That is, where land is allocated to hybrid poplar plantations, the landowner can choose to assign feedstocks towards either ethanol or pulp production, depending on market conditions. Work (2014) finds that option values accrued to landowners increase as output options are expanded.

The land use change model developed in this study differs from previous RO studies by focusing on co-production opportunities. The model incorporates the stochastic prices of ethanol alongside either electricity or pellets, depending on the scenario.

3.2.3 Stochastic Price Modeling

The incorporation of uncertain prices with stochastic returns into RO analysis is one of the key characteristics that differentiates it from NPV approaches to land valuation (Dixit and Pindyck, 1994). In RO land use change models, stochastic returns are estimated for both the starting land use, and potential future allocations. The starting land use is often assumed to be agriculture (i.e. Work, 2014; Hauer et al., 2017; Regan et al., 2017; Song et al., 2011; Wolbert-Haverkamp and

Musshoff, 2014). Agricultural markets are well-established and often have extensive historical price series available to analyze stochastic price movements. Many RO land use change models in the literature characterize returns to agriculture according to a GBM process (i.e. Work, 2014; Hauer et al., 2017, and Regan et al., 2017). Others characterize returns to agriculture according to an arithmetic Brownian motion (ABM) process (i.e. Wolbert-Haverkamp and Musshoff, 2014), or compare mean reverting and GBM specifications in sensitivity analyses (i.e. Wear et al., 2015 and Song et al., 2011). These comparisons between alternative price processes are made when there are conflicting stationarity results in the price series analysis.

Capturing stochastic price behaviours can be challenging in developing markets because of a lack of historical data. As a result, RO land use change studies vary in the approaches taken to capture stochastic price movements in the returns from bioenergy feedstocks. Regan et al. (2015) evaluate price movements of coal as an analogue for biomass prices, characterizing prices under a GBM process. Wolbert-Haverkamp and Musshoff (2014) also evaluate traditional energy product prices as a stand-in price for biofuels, modeling a heating oil price series according to an ABM process. Work et al. (2016) look to ethanol prices in the US to represent potential price movements in the Canadian market, and characterize the price series as a mean reverting process with generalized autoregressive conditional heteroscedasticity (GARCH) effects. Wear et al. (2015) turn to historic stochastic movements of net returns from eucalyptus for pulp production. The authors compare mean reverting and GBM price specifications and discover that predicted conversion patterns are sensitive to the assumed price process. In the present study, stochastic returns from bioenergy feedstocks are assessed based on the US cellulosic ethanol price series (see Chapter 2), the Canadian Electricity Sellers' Price Index, and stand-in pellet prices calculated out of export revenues and quantities.

Dixit and Pindyck (1994) highlight the importance of accounting for volatility and uncertainty in the economic environment in investment analyses, noting that investment decisions are more sensitive to these factors than to more conventional measures such as interest rate changes. Song et al. (2011) also stress the importance of assessing volatilities in stochastic returns, noting that a comparison of volatilities can provide key insights into likely conversion patterns between land uses. Yet despite the importance of capturing volatilities in stochastic price movements, limited focus has been placed on volatility in RO land use change analyses. Work et al. (2016) serve as an exception to this trend, evaluating non-constant volatilities in the ethanol price series. Work (2014) notes that with a GARCH specification, large past volatilities may lead to large current volatilities, and, as a result, extreme price values may influence land use conversions. In the present study, time series analyses (in Chapter 2) on agricultural land values and bioenergy commodity prices are conducted to capture both the underlying processes driving historical price movements, as well as volatility behaviour.

3.3 Methods

3.3.1 Structure of the Land Use Change Model

The land use change model developed in this study is an extension of the model created by Hauer et al. (2017). The model is extended in three ways. First, an additional land use option is added to the original agriculture-hybrid poplar alternatives to accommodate perennial energy crops. Switchgrass is chosen as this third option. Second, co-production opportunities for processing feedstocks are introduced, and third, annual time steps are divided into semi-annual periods to accommodate seasonal price expectations.

In Hauer et al. (2017), ethanol is the single output for the hybrid poplar option. However, utilizing the residual lignin and hemicellulose of the feedstocks in co-production with ethanol may lead to greater profits than the single output scenario. This study considers co-production of ethanol with either electricity or lignin pellets, referred to as *Ethanol & Electricity* and *Ethanol & Pellets* in the sections that follow.

Since capital investments for separate co-production systems will be large, it is assumed that biorefineries will be configured with a single co-production output combination. In addition, the overall economies of scale will call for large facilities so biorefineries will generate a large point source demand for feedstocks (Wright and Brown, 2007). This factor, combined with significant transport costs from field to demand point, suggests that landowners will only have cost efficient access to a single buyer for bioenergy feedstocks. For this reason, the two co-production scenarios are considered separately rather than as alternative selling options.

The time series analysis conducted in Chapter 2 reveals that pellet prices vary according to season. In addition, price shocks for the ethanol price series persist for at least six months. The annual time step that is applied in the original model of Hauer et al. (2017), does not account for these price effects. The model developed in this study is therefore modified to run on a semi-annual basis, while pellet price simulations factor in seasonal effects. With this change, spring planting decisions are influenced by expectations of fall harvest prices.

In the land use change model, returns are maximized through allocations to either agriculture, switchgrass, or hybrid poplar. The net benefits to landowners with these alternative land uses is dependent both on the feedstock selected and the ethanol co-production scenario, *h*, where *h*= *ee* represents *Ethanol & Electricity*, and *h*= *ep* represents *Ethanol & Pellets*. The maximization problems for estimating land values are outlined in the sections that follow. Time (*t*) steps are six-month intervals, where even *t*'s align with spring (capturing April prices), and odd *t*'s align with fall (capturing October prices).

Land use valuations rely on estimates of the net returns from production of either *Ethanol & Electricity* or *Ethanol & Pellets* and on the feedstock input (hybrid poplar or switchgrass). Estimating net returns for the production of *Ethanol & Pellets* requires a conversion from the Electric Power Selling Price Index to a $/kwh price for the pellet series analyzed in Chapter 2. The index is multiplied by 0.145 $/kwh, a value representing the average residential electricity rate in Alberta, as reported by London Economics International LLC (2014), and is divided by the mean index value of 61.4. This adjustment preserves the stochastic price movements captured in the autoregressive moving average model with Fourier external regressors.

3.3.1.1 The Value of Land in Agriculture

The value of land in agriculture is estimated in the spring, when planting occurs (even *t*'s), and at fall harvest (odd *t*'s). These expectations of future returns are dependent on options to switch to either hybrid poplar plantations or switchgrass crops. That is, in the spring, planting decisions are made based on the maximum of expectations of future returns from alternative land uses, discounted back to the present. The maximum spring value of land in agriculture is evaluated over four alternatives:

$$W_t^a = max\left(E[W_{t+1}^a](1+i)^{-1}, \mathrm{E}\left[W_{t+1,1}^g\right](1+i)^{-1} - C^g, E\left[W_{t+m,m}^f\right](1+i)^{-m} - C^f, 0\right) \quad (3.1)$$

where[9]:

- $E[W^a_{t+1}]$ is the expected future agricultural land value in period t+1;
- i is the discount rate, which is varied in future empirics (more information on these rates is outlined in Section 3.3.2);
- $E\left[W^g_{t+1,1}\right]$ is the expected future value of land in switchgrass in period t+1, one period after seeding (seeding times will be further discussed below);
- C^g is the cost of establishing switchgrass crops;
- $E\left[W^f_{t+m,m}\right]$ is the expected future value of forestry plantations, m periods later (m represents the age for mature hybrid poplar stands, and will be further discussed below), and
- C^f is the cost of establishing a hybrid poplar plantation.

The value of agricultural land in the fall (odd t's) is equal to the rents derived from the land in the current period, plus the expected future value of the land, discounted back to the present. The fall value of land in agriculture is:

$$W^a_t = \delta X^a_t + E[W^a_{t+1}](1+i)^{-1} \tag{3.2}$$

where:

- δ is the rental rate;
- X^a_t is the stochastic agricultural land price, and
- δX^a_t represents rents from agriculture.

State-dependent land values consider stochastic agriculture returns and commodity prices. The representation of agricultural land values is suppressed to W^a_t. Similarly, as described below, land values for switchgrass and hybrid poplar are suppressed to $W^g_{t,q}$ and $W^f_{t,s}$ in the equations that follow.

Accounting for option values under different land allocations, the net contribution of energy crops (NEO) is estimated as the difference between agricultural land values with options

[9] Terms enclosed by E denote expectations, which are functions of stochastic prices.

considered, and stochastic agricultural land values without options:

$$NEO_t = W_t^a - X_t^a. \tag{3.3}$$

3.3.1.2 The Value of Land in Switchgrass

The value of land in switchgrass crops has four unique expressions that depend both on the season in which it is estimated (even or odd t's), and the time that has passed since seeding[10] (q). In the spring (even t's), the value of land in switchgrass is estimated as the maximum of expected values from the three alternative land uses, discounted back to the present:

$$W_{t,q}^g = max(E[W_{t+1,q+1}^g](1+i)^{-1}, E\left[W_{t+m,m}^f\right](1+i)^{-m} - C^f - C^{gb}, \\ E[W_{t+1}^a](1+i)^{-1} - C^{gb}) \tag{3.4}$$

where:

- $E[W_{t+1,q+1}^g]$ is the expected value of land in switchgrass in period t+1, and
- C^{gb} is the cost of converting land from switchgrass to bare land.

At the time of switchgrass re-seeding, there are additional clearing and establishment costs, and the value of land in switchgrass becomes:

$$W_{t,0}^g = max(E\left[W_{t+1,1}^g\right](1+i)^{-1} - C^g - C^{gb}, E\left[W_{t+m,m}^f\right](1+i)^{-m} - C^f - C^{gb}, \\ E[W_{t+1}^a](1+i)^{-1} - C^{gb}) \tag{3.5}$$

where:

- C^g is the cost of establishing switchgrass crops.

In the fall, at harvest, the value of land allocated to switchgrass crops is equal to the net returns of switchgrass production plus the expected future land value the following spring, discounted back one period:

$$W_{t,q}^g = v^g NR_t^{g,h} + E[W_{t+1,q+1}^g](1+i)^{-1} \tag{3.6}$$

where:

[10] Details on the agronomy of switchgrass, including seeding, are contained in Section 3.3.2.

- v^g is the switchgrass yield, and
- $NR_t^{g,h}$ is the net return[11] of co-production combination h from switchgrass.

If land remains allocated to switchgrass until the point at which re-seeding would be necessary (at q=19), the value of land in switchgrass is estimated as the net returns from switchgrass production, plus the expected value of land in switchgrass at the time of re-seeding:

$$W_{t,19}^{g} = v^g NR_t^{g,h} + E[W_{t+1,0}^{g}](1+i)^{-1} \tag{3.7}$$

where:

- $\mathrm{E}[\mathrm{W}_{t+1,0}^{g}]$ is the expected value of land in switchgrass in period t+1, at the time of re-seeding.

3.3.1.3 The Value of Land in Hybrid Poplar Plantations

The value of land in hybrid poplar plantations is a function of current returns from harvest and option values derived from the possibilities of deferring harvest and switching to agriculture or switchgrass crops in the future. Hybrid poplar plantations can be harvested in either the spring (even t's) or in the fall (odd t's). Therefore, for established hybrid poplar stands, there is no need to define separate semi-annual land values for spring and fall. The maximization function for the value of land in hybrid poplar plantations is:

$$W_{t,s}^{f} = max\left(v_s^f NR_{t,s}^{f,h} + \; W_{t,0}^{f}, E\left[W_{t+1,s+1}^{f}\right](1+i)^{-1}, 0\right) \tag{3.8}$$

where:

- v_s^f is the hybrid poplar yield at stand age s where age is defined in six-month intervals;
- $NR_{t,s}^{f,h}$ is the net return of co-production combination h, at stand age s out of hybrid poplar;
- $W_{t,0}^{f}$ is the value of bare land after harvest takes place;

[11] Net return calculations incorporate price, output yields, biorefinery costs, and growing costs of bioenergy feedstocks. These net return calculations are outlined in Sections 3.3.1.4 and 3.3.1.5.

- $E\left[W_{t+1,s+1}^{f}\right]$ is the expected value of harvest, deferred for one period, and
- 0 is included as a defer harvest option if all other options are negative when *t* is less than the maximum rotation age, and as an abandonment option if *t* is at the maximum rotation age.

The optimal economic rotation of hybrid poplar is selected according to the above maximization process with options. This harvest decision is flexible, depending on stochastic elements, but is constrained within a minimum and maximum rotation age. The minimum rotation age is set at 32 Periods (m_{min}) because of prohibitively high harvest costs associated with younger stand ages (Sidders and Keddy, 2015), while the maximum rotation age is set to 70 Periods (m_{max}) given that yields rapidly decrease after this point (Hauer et al., 2017). This constraint improves the computational efficiency of the model by reducing the number of stand ages that are considered in land valuation calculations.

Given that harvest does not take place until a minimum maturity date, *m*, the value of land that has not yet reached maturity is a function of the difference in time between *m* and *s*:

$$W_{t,s}^{f} = E\left[W_{t+m-s,m-s}^{f}\right](1+i)^{-(m-s)} \tag{3.9}$$

where:

- *m-s* is the number of time periods remaining before harvest is possible, and
- $E\left[W_{t+m-s,m-s}^{f}\right]$ is the expected value of land in hybrid poplar plantations, estimated when harvest is possible.

Equation 3.8 relies on estimates of bare land values, the value of land with stumps after harvest has taken place. The bare land value of hybrid poplar plantation land differs depending on the season. In the spring (even *t*'s), the bare land value is a maximization of expected land values for future potential land uses, discounted back to the present:

$$W_{t,0}^{f} = max\ (E\left[W_{t+m,m}^{f}\right](1+i)^{-m} - C^{f}, \\ E[W_{t+1}^{a}](1+i)^{-1} - C^{fb}, E[W_{t+1,1}^{g}] - C^{fb} - C^{g}, 0) \tag{3.10}$$

where:

- $E\left[W_{t+m,m}^{f}\right]$ is the expected value of land in hybrid poplar plantations, after re-establishing stands, m years later;
- C^{f} is the cost of establishing forestry plantations, and
- C^{fb} is the cost of converting land from forestry back to bare land.

In the fall (odd *t*'s), the value of bare land previously forested is estimated as the future expected value in the following spring, when planting decisions are made, discounted back to the present:

$$W_{t,0}^{f} = E[W_{t+1,0}^{f}](1+i)^{-1}. \qquad (3.11)$$

3.3.1.4 Net Returns from Switchgrass Feedstocks

The net returns of co-production of *Ethanol & Electricity* ($NR_t^{g,ee}$) and *Ethanol & Pellets* ($NR_t^{g,ep}$) out of switchgrass are:

$$NR_t^{g,ee} = (P_t^{eth} + d)\omega + P_t^{elec}\alpha - c^{g,\boldsymbol{ee}} - Z^{g} \qquad (3.12)$$

$$NR_t^{g,ep} = (P_t^{eth} + d)\omega + P_t^{pel}\gamma - c^{g,\boldsymbol{ep}} - Z^{g} \qquad (3.13)$$

where:

- P_t^{eth} is the stochastic ethanol price at time *t* (\$/litre);
- d is the ethanol production subsidy (\$/litre);
- ω is a conversion factor that transforms \$/litre ethanol revenues to \$/ODT values;
- P_t^{elec} is the stochastic electricity price at time *t* (\$/kwh);
- α is a conversion factor that transforms \$/kwh revenues to \$/ODT values;
- $c^{g,ee}$ is the biorefinery processing cost for switchgrass co-production of *Ethanol & Electricity* (\$/ODT input);
- Z^{g} is the cost of growing the switchgrass feedstock and bringing it to the biorefinery (accounting for fertilizer, harvest, transport, and storage) (\$/ODT);
- P_t^{pel} is the stochastic pellet price at time *t* (\$/ODT pellet produced);
- γ is a conversion factor that transforms \$/ODT revenues per pellet output, to the \$/ODT values per unit of switchgrass input, and

- $c^{g,ep}$ is the biorefinery processing cost for switchgrass co-production of *Ethanol & Pellets* ($/ODT).

From the net returns outlined above, the total rents obtained from growing switchgrass are estimated by multiplying the net returns per ODT of switchgrass by the productivity of switchgrass (v^g), to obtain a $/ hectare value ($v^g NR_t^{g,h}$). These rents are then comparable to those from agriculture (δX_t^a).

3.3.1.5 Net Returns from Hybrid Poplar Feedstocks

The calculation of net returns of co-production of bioenergy products from hybrid poplar is similar to those from switchgrass. Hybrid poplar is unique, however, in that biomass yields accumulate over multiple time periods before harvest takes place. Additionally, harvesting costs vary with stand age, *s*. The net returns from co-production of *Ethanol & Electricity* ($NR_{t,s}^{f,ee}$) and *Ethanol & Pellets* ($NR_{t,s}^{f,ep}$) out of hybrid poplar are estimated as:

$$NR_{t,s}^{f,ee} = (P_t^{eth} + d)\varphi + P_t^{elec}\zeta - c_s^{f,ee} - Z_s^f \quad (3.14)$$

$$NR_{t,s}^{f,ep} = (P_t^{eth} + d)\varphi + P_t^{pel}\psi - c_s^{f,ep} - Z_s^f \quad (3.15)$$

where:

- φ is a conversion factor that transforms $/litre ethanol revenues to $/ ODT values;
- ζ is a conversion factor that transforms $/kwh electricity revenues to $/ODT values;
- $c_s^{f,ee}$ is the biorefinery processing cost for hybrid poplar co-production of *Ethanol & Electricity*, at stand age *s* ($/ODT);
- Z_s^f is the cost of bringing hybrid poplar feedstocks to the biorefinery (accounting for harvest, chipping, felling, storage, and transport costs) ($/ODT, at stand age *s*;
- ψ is a conversion factor that transforms $/ODT revenues from pellets, to $/ODT values, and

- $c_s^{f,ep}$ is biorefinery processing cost for hybrid poplar co-production *Ethanol & Pellets*, at stand age s ($/ODT).

From these net returns, the rents derived from lands allocated to hybrid poplar plantations are obtained by multiplying $NR_{t,s}^{f,h}$, the net returns per ODT of hybrid poplar input (for either *Ethanol & Electricity* or *Ethanol & Pellets*), by v_s^f, the hybrid poplar yield, at stand age s, in ODT/ hectare ($v_s^f \, NR_{t,s}^{f,h}$), to obtain a $/hectare value.

3.3.2 Values of Model Parameters

Table 3-1 contains land use change model parameter values. Estimations of land values in alternative uses along with net return calculations rely on q, the time that has passed since switchgrass crops were seeded, s, the stand age of hybrid poplar, and *m*, the age of a mature hybrid poplar stand that is ready for harvest (a subset of s). For switchgrass, it is assumed that re-planting is required every 20 model periods (q=20) (Song et al., 2011), and that crops are harvested only one time per year (Parrish and Fike, 2007).

The estimation of annual costs for both switchgrass and hybrid poplar rely on estimates of transportation costs. The distance from the landowners' parcel of land to the biorefinery is assumed to be 10km. This conservative value is selected with the expectation that future biorefinery locations will be correspond to regions characterized as having a high likelihood of growing bioenergy feedstocks.

The valuation of agricultural land (Equation 3.2) depends on the agriculture rental rate (δ). This rate is derived by Hauer et al. (2017) by dividing average rental values by the average value of agricultural land. Four different discount rates (i) are applied in the model. The discount rates are broken down as:

$$i = \delta + g \qquad (3.16)$$

where:

- g is the growth rate of agricultural land values.

Table 3-1: Values of model parameters

Parameter Description	Parameter Value
Agriculture rental rate (δ)	3%[a]
Hybrid poplar minimum rotation age (m_{min})	32 periods[b]
Hybrid poplar maximum rotation age (m_{max})	70 periods[a]
Switchgrass maximum rotation age (q)	20 periods[c]
Baseline discount rate, with drift(i)	6.15%
Hybrid poplar discount rate, with drift (i)	7.41%
Baseline discount rate, without drift (i)	4.37%
Hybrid poplar discount rate, without drift(i)	5.63%
Ethanol conversion factor from hybrid poplar (φ)	298 L/ ODT hybrid poplar[d]
Ethanol conversion factor from switchgrass (ω)	289 L/ ODT switchgrass[d]
Electricity conversion factor from hybrid poplar (ζ)	49 kwh/ ODT hybrid poplar[d]
Electricity conversion factor from switchgrass (α)	45 kwh/ ODT switchgrass[d]
Pellet conversion factor from hybrid poplar (ψ)	0.55 ODT pellet/ ODT hybrid poplar[d]
Pellet conversion factor from switchgrass (γ)	0.55 ODT pellet/ ODT switchgrass[d]
Ethanol & Electricity biorefinery cost with hybrid poplar feedstocks ($c_s^{f,ee}$)	222.91 $/ODT hybrid poplar[e]
Ethanol & Pellets biorefinery cost with hybrid poplar feedstocks ($c_s^{f,ep}$)	362.42 $/ODT hybrid poplar[e]
Ethanol & Electricity biorefinery cost with switchgrass feedstocks ($c^{g,ee}$)	219.87 $/ODT switchgrass[e]
Ethanol & Pellets biorefinery cost with switchgrass feedstocks ($c^{g,ep}$)	354.64 $/ODT switchgrass[e]
Conversion cost: hybrid poplar to bare land (C^{fb})	354 $/ha[f]
Conversion cost: switchgrass to bare land (C^{gb})	40.77 $/ha[g]
Cost to establish hybrid poplar plantation (C^{f})	2651.40 $/ha[a]
Cost to establish switchgrass crops (C^{g})	5.98 $/ha[h]
Distance to biorefinery	10 km

Sources:

[a] *Hauer et al. (2017)*
[b] *Sidders and Keddy (2015)*
[c] *Song et al. (2011)*
[d] *Shen (2012)*
[e] *Sultana et al. (2010); Hoque et al. (2006); and Kazi et al. (2010) (see Appendix 2)*
[f] *D.A. Westworth and Associates (1994)*
[g] *Williams et al. (2009)*
[h] *Taheripour et al. (2011)*

Discount rates differ according to whether agricultural land values are modeled with or without drift, given the effect of the drift term on growth rate of agricultural land values. These discount rates are also applied to switchgrass, as returns from this crop are collected on an annual basis. For forestry, multiple years must pass between the time of initial investment and harvest. With an increase in the perceived risk associated with the wait before benefits are attained, landowners are expected to require a higher return. To compensate for this risk, an adjustment premium can be added to the discount rate applied to hybrid poplar. This premium is calculated as differences in bond rates from short and long-term investments. Using estimates from the Bank of Canada (2017), the difference in returns from long-term and short-term bonds for 2016 is found to be 1.26%[12]. As a result of these factors, 6.15% is applied as the baseline discount rate where agricultural land values are modeled with drift, then is increased to 7.41% when the discount rate premium is added to returns from hybrid poplar. Where agricultural land values are modeled without drift, 4.37% is applied as the baseline discount rate, and is increased to 5.63% for hybrid poplar with the premium applied. The differential rates apply to the 32 periods that must pass between planting and the minimum harvest age of hybrid poplar. After 32 periods, deciding whether or not to harvest becomes an annual choice, and the baseline discount rate is re-applied to plantations when compared to annual decisions regarding agriculture and switchgrass.

Net return equations (Equations 3.12-3.15) from bioenergy co-production combinations incorporate conversion factors for ethanol, electricity, and pellets from both hybrid poplar and switchgrass ($\varphi, \omega, \zeta, \alpha, \psi, \gamma$). The reported conversion factor values are based on dilute acid hydrolysis pre-treatments, one of the most promising methods in the development of lignocellulosic ethanol (Shen, 2012). These values have been converted from annual production levels, based on feedstock input levels of 2,000 ODT/ day, to a measure of product outputs/ ODT feedstock input. Net return estimations also factor in biorefinery costs ($c_s^{f,1}$, $c_s^{f,2}$, $c^{g,1}$, $c^{g,2}$). These costs differ according both to the feedstock input, and the co-production output combination selected. The reported values include cost estimates from Sultana et al. (2010), Hoque et al. (2006), and Kazi et al. (2010), and include operating (i.e. process chemicals, employee salaries, maintenance, insurance) and equipment costs. A breakdown of these costs is

[12] Long-term bonds are classified as 10+ years, while short-term bonds are 1-3 years.

outlined in Appendix 2.

3.3.3 Solving the Model

The model is solved according to the process outlined in Hauer et al. (2017), who build on the approach of Longstaff and Schwartz (2001). Least squares estimation is applied to generate expected value functions out of stochastic variables. The functions that need estimating are those enclosed by $E[\ldots]$, in the land use valuation equations in Sections 3.3.1.1- 3.3.1.3. To estimate these functions, 50,000[13] price paths are simulated for agricultural land values, along with ethanol, electricity, and pellet prices. Expected values of landowner returns ($E[W_{t+1}^{a}]$, $E[W_{t+m,m}^{f}]$, $E[W_{t+1,q+1}^{g}]$), outlined in Section 3.3.1, are then estimated using OLS.

The solution algorithm is presented in Appendix 3. The model is solved by working backwards from the end of the planning horizon to the starting time period. Though the real options model extends for 130 periods, stochastic prices are simulated out to period 200 to minimize distortions to landowner decisions at the end of the model period. Deterministic land values are also calculated for periods 131 to 200 (Steps 3-7 of the algorithm presented in Appendix 3). These base land values factor in to the first stochastic land value estimate in period 130.

The process of estimating expected values begins at the end of the 200 period time horizon by calculating standard deterministic NPVs of alternative land uses for each of the final prices in the 50,000 price paths. These NPVs are discounted to the second last price and then regressed on linear functions of second last period stochastic prices. The estimated coefficients from these regressions are used to compute expected values of the land use choices. Optimal land use choices (i.e. whether to convert land away from its current use, what to convert to, and whether to defer harvest if land is in hybrid poplar plantations) are determined by choosing the land uses with the highest expected value over 50,000 price scenarios. With these land use choices in hand, a new set of NPVs are computed which can be thought of as realized NPVs because they are dependent on the optimal choices derived from the expected values. These realized NPVs are then discounted again to the third last period, and regressed against prices for the third last period

[13] 50,000 is an approximate mid-point of the 5,000-100,000 sample sizes that Longstaff and Schwartz (2001) consider.

to estimate expected value functions. The expected value functions are again used to determine optimal land uses which are in turn used to generate new realized NPVs. This process is repeated until the beginning period is reached.

3.4 Results

The land use change model is initially run under baseline assumptions (outlined in Table 3-2). Next, these assumptions are modified to reflect lands targeted for conversion to bioenergy feedstocks. Future sensitivity analyses are set according to these initial findings. Results reveal financial preferences for hybrid poplar over switchgrass feedstocks, along with co-production of ethanol with electricity over ethanol with pellets. The first sensitivity analysis therefore increases the discount rate premium applied to hybrid poplar to evaluate where switchgrass dominates hybrid poplar. Second, pellet prices are increased to assess the price changes required to observe land conversions to bioenergy feedstocks under the ethanol and pellet co-production case.

Model trials are varied based on assumptions of increases in agricultural land values (i.e. where agricultural land values are modeled with or without drift), and in the use of baseline or differential discount rates for agriculture, switchgrass, and hybrid poplar. These variations lead to the application of the four discount rates presented in Table 3-1. Ethanol production subsidy levels are also varied across sensitivity trials to aid in assessing gaps between current conditions and the ethanol subsidy increases that would be necessary to potentially observe land conversions from agriculture to bioenergy feedstocks.

The results from the land use change model focus on option values. These are estimated by calculating the difference between agricultural land values that consider energy crop options, and agricultural land values as viewed today, without energy crop options (as expressed in Equation 3.3). The tables that follow report the proportion of the model's 50,000 trials that appear in a particular energy crop for Years 1, 10, 30, and 50. Wherever the proportions are found to be less than 0.001, proportions are reported as 0.

3.4.1 Baseline Scenario

Baseline parameters are selected as estimates of future expected yields, costs, and subsidy levels. The model's starting agricultural land value (at t=0) of 2624.59 \$/ha is equivalent to the average agricultural land values in Alberta from the land base data of Hauer et al. (2017). The baseline hybrid poplar yield of 16.14 m^3/ ha/ year represents the highest attainable mean annual increment associated with the yield curve of Joss et al. (2007) which has been adjusted according to climactic conditions of the study region by Hauer et al. (2017). The baseline switchgrass yield of 7.23 ODT/ ha/ year is taken from Min (2012), as the midpoint of the average range of Cave-in-Rock varietal trials. The baseline ethanol production subsidy level is set based on information from Alberta Environment and Parks (2017), where producer credits for second generation ethanol under the Bioenergy Producer Program are 0.14 $/L for the first 150 million litres, and 0.09$/L after that. 0.11 $/L is assumed as a midpoint.

Table 3-2: Baseline model parameters

Parameter Description	Baseline Parameter Values
Agriculture land value at t=0	2624.59 $/ ha[a]
Maximum hybrid poplar mean annual increment	16.14 m^3/ ha/ year[b]
Switchgrass yield	7.23 ODT/ ha/ year[c]
Ethanol production subsidy (d)	0.11 $/L[d]

Sources:
[a] *Hauer et al. (2017)*
[b] *Joss et al. (2007); Hauer et al. (2017)*
[c] *Min (2012)*
[d] *Alberta Environment and Parks (2017)*

Where agricultural land values are modeled with and without drift, and for baseline and differentiated discount rates for alternative land uses, neither the *Ethanol & Electricity* nor *Ethanol & Pellets* models yield positive option values. As a result, under baseline assumptions, energy crops do not appear in the expected land use schedule across the 65-year model period. With this finding, land base assumptions in future investigations are modified to consider lands targeted for conversion to energy crops.

3.4.2 Targeted Land Scenario

The baseline scenario assumes land use conversions would take place on agricultural lands that deliver mean-level returns. However, it is possible that lower-valued lands capable of producing high energy crop yields could be targeted as sites with a higher likelihood of conversion from agriculture to energy crops. These sites are likely to be located outside of urban centres, and away from the most productive agricultural lands, as these lands are likely to be higher-valued, making it more difficult for energy crops to compete. The remaining land use model trials focus on these targeted land, and apply the differential discount rates for returns from hybrid poplar and agriculture/switchgrass.

The parameter values for the targeted land scenarios (outlined in Table 3-3) include values from the land base data of Hauer et al. (2017), where agricultural land values are linked to potential hybrid poplar yields. The targeted land base is assumed to be characterized by a maximum agricultural land value of 1,000 \$/ha, with a yield curve shifted upwards to a minimum mean annual increment of 19.59 m^3/ha/year. Of the potential land base, 0.08% of the 23,876 land parcel observations reflect these selected characteristics. Lands capable of producing hybrid poplar at high yields are also assumed to produce switchgrass at high yields. These switchgrass yields are taken from Taheripour et al. (2011).

Table 3-3: Targeted land model parameters

Parameter Description	Targeted Land Parameter Values
Agriculture land value at *t*=0	1000 \$/ha[a]
Maximum hybrid poplar mean annual increment	19.59 m^3/ha/year[a]
Switchgrass yield	12.3 ODT/ha/year[b]
Ethanol production subsidy	0.21, 0.31 \$/L

Sources:
[a] *Hauer et al. (2017)*
[b] *Taheripour et al. (2011)*

For the *Ethanol & Pellet* case, no positive option values are generated where agricultural land values are modeled with or without drift. For *Ethanol & Electricity* co-production, where agricultural land values are modeled with drift, there is no option value for any ethanol production subsidy level.

For the *Ethanol & Electricity* case where agricultural land values are modeled without drift, results are dependent on the assumed ethanol production subsidy level. The current ethanol production subsidy level of 0.11 \$/L yields no positive option values. However, an increase in the subsidy level to 0.21 or 0.31 \$/L generates positive option values of 3.75 and 940.87 \$/ha, respectively. Table 3-4 shows that hybrid poplar appears in the land use schedule in proportions of 0, 0.001, 0.07, and 0.13 of the 50,000 trials for the 0.21 $/L subsidy level, and 1, 1, 0.91, and 0.81 of the 50,000 trials for the 0.31 $/L subsidy level, each at Years 1,10, 30, and 50, respectively. As expected, when the assumed ethanol production subsidy level increases from 0.21 to 0.31 $/L, both the option value and the proportion of trials that hybrid poplar appears in the land use schedules increase. Meanwhile, switchgrass does not appear in any of the 50,000 land use schedules.

Table 3-4: Targeted land base results for *Ethanol & Electricity*, without drift

Ethanol Subsidy	Option Value	Proportion of Hybrid Poplar			
		Year			
($/L)	($/ha)	1	10	30	50
0.21	3.75	0	0.001	0.07	0.13
0.31	940.87	1	1	0.91	0.81

3.4.2.1 Switchgrass Sensitivity Analysis

Given that hybrid poplar dominates switchgrass, this section investigates the conditions under which switchgrass might be selected along with or over hybrid poplar. This potential is explored by modifying the discount rate premium for hybrid poplar upwards of the base level of 1.26%. The discount rate premium is selected as the variable of focus in this sensitivity analysis given the high level of uncertainty associated with what the true premium might be. Alternatively, feedstock yields could be varied to address the objectives of this sensitivity analysis. However, hybrid poplar and switchgrass yields are expected to be correlated on lands of similar qualities, therefore trials with high switchgrass yields and low hybrid poplar yields would have limited applicability. Given the results of the initial targeted land base scenario, where option values are not generated under the drift case or for the *Ethanol & Pellet* case, focus is placed exclusively on agricultural land values modeled without drift for the *Ethanol & Electricity* co-production case.

Table 3-5 presents the results of the switchgrass sensitivity analysis. Results indicate that substantial increases in both the ethanol production subsidy level and the discount rate premium applied to hybrid poplar are required to make switchgrass more financially appealing. When a discount rate premium of 5% (in addition to the baseline rate of 4.37%) is applied to forestry investments, alongside an ethanol production subsidy level of 0.31 $/L, small option values are generated that do not lead to any expected conversions to switchgrass or hybrid poplar. Maintaining the 5% forestry discount rate premium, and with an increase in the ethanol production subsidy level to 0.41 $/L, positive option values are generated, and switchgrass enters into the land use schedule, but hybrid poplar remains in greater proportions. It is not until a discount rate premium of 6% is applied to hybrid poplar, alongside the 0.41$/L ethanol production subsidy level, that switchgrass overtakes hybrid poplar; appearing in proportions of 0.01, 0.09, and 0.09 out of the 50,000 trials in Years 10, 30, and 50, respectively. Despite the small proportions of land converting to switchgrass under these conditions, the positive option value of $72.03 suggests that there is value in considering these options with evolving market conditions.

Table 3-5: Switchgrass sensitivity analysis results for *Ethanol & Electricity*, without drift

Ethanol Subsidy	Added Rate	Option Value	Proportion of Hybrid Poplar				Proportion of Switchgrass			
			Year				Year			
($/L)	(%)	($/ha)	1	10	30	50	1	10	30	50
0.31	5	2.22	0	0	0	0	0	0	0	0
0.41	5	72.34	0	0.01	0.09	0.08	0	0.002	0.002	0.001
0.41	6	72.03	0	0	0	0	0	0.002	0.002	0.001

3.4.2.2 Pellet Sensitivity Analysis

The results of the initial targeted land scenario show that *Ethanol & Electricity* produces positive option value, while *Ethanol & Pellets* does not. This section seeks to evaluate this finding by investigating the increase in pellet prices that would be necessary to generate positive option value for *Ethanol & Pellets*. More specifically, the minimum pellet price multiplier that leads to an energy crop proportion of at least 0.01 in any year of the model period is sought. Minimum pellet price multipliers are estimated for each of the 0.11, 0.21, and 0.31 $/L ethanol production subsidy levels.

Where agricultural land values are modeled with drift, pellet price multipliers of 2.2, 1.9, and 1.6, accompanied by ethanol production subsidy levels of 0.11, 0.21, and 0.31 $/L, respectively, lead to the appearance of energy crops in the land use schedule at proportions of 0.01 or greater (Table 3-6). These results imply that at the current ethanol production subsidy level, on a parcel of land targeted for conversion, a 220% increase in the price of pellets would be required to see proportions of 0.002, 0.06, and 0.08 of the 50,000 trials appear in hybrid poplar in Years 10, 30, and 50, respectively. At the current ethanol production subsidy level, switchgrass also appears in proportions of 0.003, 0.002, and 0.001 of the 50,000 trials in Years 10, 30, and 50, respectively.

Table 3-6: Pellet sensitivity analysis for *Ethanol & Pellets*, with drift

Ethanol Subsidy	Price Multiplier	Option Value	Proportion of Hybrid Poplar				Proportion of Switchgrass			
			Year				Year			
($/L)		($/ha)	1	10	30	50	1	10	30	50
0.11	2.2	3.62	0	0.002	0.06	0.08	0	0.003	0.002	0.001
0.21	1.9	3.10	0	0.002	0.05	0.07	0	0.003	0.002	0
0.31	1.6	2.76	0	0.001	0.05	0.07	0	0.003	0.002	0.001

The results of the pellet sensitivity analysis, where agricultural land values are modeled without drift, are presented in Table 3-7. These results reveal that in order to observe energy crops in proportions greater than 0.01 in the land use schedule, pellet prices must be multiplied by 1.8, 1.4, and 1.2 for ethanol production subsidy levels of 0.11, 0.21, and 0.31 $/L, respectively. At the current ethanol production subsidy level, an 80% increase in pellet prices is necessary to observe proportions of 0.02 and 0.06 of the 50,000 trials appear in hybrid poplar in Years 30 and 50, respectively. In these results, switchgrass does not enter into the land use schedule.

Table 3-7: Pellet sensitivity analysis results for *Ethanol & Pellets*, without drift

Ethanol Subsidy	Pellet Price Multiplier	Option Value	Proportion of Hybrid Poplar			
			Year			
($/L)		($/ha)	1	10	30	50
0.11	1.8	2.33	0	0	0.02	0.06
0.21	1.4	2.47	0	0	0.02	0.06
0.31	1.2	2.37	0	0	0.03	0.08

3.5 Summary, Discussion and Conclusions

The first objective of this chapter is to generally assess the financial competitiveness of switchgrass and hybrid poplar against agriculture. Under baseline conditions, neither hybrid poplar nor switchgrass are found to compete with agriculture. However, moving forward, it is expected that specific lands will be targeted for conversion to energy crops; lands with higher energy crop yields and a lower starting agricultural land value. On these lands, with an increase in the ethanol production subsidy level from the current level of 0.11$/L to 0.21 $/L, energy crops may potentially compete with agriculture.

The second objective of this chapter is to compare the financial competitiveness of hybrid poplar and switchgrass as bioenergy feedstocks. In the targeted land base model, hybrid poplar dominates switchgrass. To assess the conditions that might be required to instead observe switchgrass dominating hybrid poplar, a sensitivity analysis is performed that modifies the discount rate premium applied to hybrid poplar. This analysis focuses on co-production of ethanol and electricity, where agricultural land values were modeled without drift, given that it is only under those cases that positive option values are generated. The results of this sensitivity analysis show that for switchgrass to dominate hybrid poplar, a 6% discount rate premium applied to hybrid poplar is required, in addition to the base rate of 4.37%, alongside an ethanol production subsidy level of 0.41 $/L. These results translate to a discount rate premium over three times the estimated value of 1.26%, with an ethanol production subsidy level nearly four times the current level of 0.11 $/L. This large gap between current or expected conditions, and those required to see switchgrass dominating hybrid poplar, supports the notion that hybrid poplar is the financially preferred bioenergy feedstock.

The setup of the land use change model likely influences the low prevalence of switchgrass in the land use schedules. When estimating the value of land allocated to switchgrass, low bioenergy commodity prices at times result in negative net returns. In contrast, returns from agriculture are always positive, given that they are calculated as a percentage of non-negative agricultural land value data. This method of calculating returns from agriculture is selected as an aggregate valuation of the variety of agricultural crops grown on private lands.

Differences in the growth and harvest of switchgrass and hybrid poplar also contribute to the low prevalence of switchgrass in the land use change schedule. Like switchgrass, the estimated value of land allocated to hybrid poplar is negative at times, due to variability in stochastic product prices. However, these negative returns can be avoided by storing woody biomass on the stump until preferable prices are reached, either at mean values or when prices rise above the mean. This option to wait for higher prices improves the prospects of selecting hybrid poplar over agriculture and switchgrass.

The third objective of this chapter is to assess financial preferences for co-production of ethanol with either electricity or pellets. For the targeted land base analysis, under an ethanol production subsidy level of 0.21 $/L, co-production of ethanol and electricity yields positive option values, but co-production of ethanol with pellets does not. This result serves as preliminary evidence that electricity is financially preferable over pellets as a co-product to ethanol.

To explore the potential to generate positive option value from co-production of ethanol with pellets, a second sensitivity analysis is conducted where pellet prices are increased until the point at which positive option values are generated and bioenergy feedstocks appear in the land use schedule. The results show that where agricultural land values are modeled with drift, with an ethanol production subsidy level of 0.21 $/L, a pellet price multiplier of 1.9 is required to generate positive option value. Maintaining the ethanol production subsidy level of 0.21 $/L, where agricultural land values were modeled without drift, a pellet price multiplier of 1.4 is required to generate positive option value. These results support the selection of electricity as a co-product to ethanol, as with an ethanol production subsidy of 0.21 $/L, positive option values are generated for the electricity co-production case under original simulated prices, whereas a 90 or 40% increase in pellet prices is required, depending on whether agricultural land values are modeled with or without drift, to generate positive option value under the pellet co-production scenario.

Overall, the results of the land use change model reveal financial preferences for co-production of electricity and ethanol over pellets and ethanol, and for hybrid poplar over switchgrass as a bioenergy feedstock. This preference for hybrid poplar is linked to challenges in providing an initial supply of feedstocks to biorefineries that is not considered in the model. During the multi-year wait before harvest of hybrid poplar plantations is possible, biorefineries will require an alternative supply of feedstocks. Switchgrass does not appear to be a financially viable option to provide for this initial supply, therefore future research might consider exploring agricultural or forestry residues as alternatives.

The assumed stochastic process underlying commodity prices influences valuation estimates (Schwartz, 1997). Returns from switchgrass and hybrid poplar are characterized as mean reverting, based on the stochastic price models estimated for ethanol, electricity, and pellets. Mean reversion is associated with a lower level of risk than random walks, thereby reducing risk discounting and increasing asset values (Laughton and Jacoby, 1993). Meanwhile, the decrease in risk in future prices with mean reversion can lead to lowered option values, given that option values increase as price volatility increases (Dixit and Pindyck, 1994). In contrast to the bioenergy commodity price models, returns from agriculture are modeled as a differenced autoregressive process (under two alternative models: with and without the drift term), representing a random walk with autocorrelated errors. Option values are increased under this differenced autoregressive price model, given higher levels of risk in future returns. These differences in the characterization of returns from energy crops and agriculture play a role in the dominance of agriculture over time in the land use change model.

The inclusion or exclusion of the drift term in the agricultural land value model is found to have an impact on the results of the land use change model. With the drift term, agricultural land values increase over time. In addition, unique discount rates are calibrated for the two models, and the model with drift has a higher discount rate. Accordingly, option values are lower where the drift term is included, and conversions towards energy crops are less common. These findings demonstrate the sensitivity of the land use change model results to the assumed price characterizations, and serve as support to explore alternative land and commodity price assumptions in future work.

The characterization of stochastic price processes for energy commodities may contribute to financial preferences for co-production of ethanol with electricity over ethanol with pellets. Ethanol prices are characterized as mean reverting with non-constant variance, and appear in both co-production scenarios. Electricity and pellet price behaviour differentiate the scenarios. Unlike the pellet series, the electricity series exhibits non-constant variance, implying that electricity prices may potentially reach greater spikes. This variance effect increases option values for the ethanol and electricity co-production scenario relative to the ethanol and pellet case. The potential to collect returns at these spikes is more pertinent to hybrid poplar than switchgrass, given that harvest decisions can be delayed until higher prices are realized.

This investigation of potential land use changes towards energy crops helps to assess whether a secure supply of bioenergy feedstocks might become available to support the development of the cellulosic ethanol industry in Alberta. As it stands, there is a significant gap between current conditions and the financial returns necessary to see the proliferation of hybrid poplar and switchgrass energy crops on the landscape. If the gap were to be closed, there appears to be financial preferences for hybrid poplar over switchgrass, alongside co-production of ethanol with electricity over ethanol with pellets. For lands targeted for conversion to energy crops, and with supporting policies or improved market conditions, landowners might have the incentive to grow these alternative energy crops in the future.

Chapter 4: Summary and Conclusions

The overarching goal of this thesis is to investigate bioenergy commodity prices, land use changes, and co-production opportunities as key factors that might influence the development of a second-generation ethanol industry in Alberta, Canada. With a focus on bioenergy commodity prices, models of ethanol, electricity, and pellet prices are estimated in Chapter 2. The first objective of this chapter is to assess the underlying processes driving the price series. Each of the three bioenergy commodity price series are found to be mean reverting, implying that over time, prices are expected to return to their long-run mean. The second and third objectives are to explore the significance of seasonal effects, and the presence of non-constant variance in the price series. The pellet price series demonstrates significant seasonal variation about its long-run mean, which was captured through the addition of external Fourier regressors. Meanwhile, both the ethanol and electricity series display autoregressive conditional heteroscedasticity effects, which are associated with higher degrees of risk in future expected prices than constant variance series. The price series models that are estimated for the ethanol, electricity, and pellet series form the basis of stochastic price simulations that underlie the real options land use change analysis conducted in Chapter 3.

Chapter 3 focuses on feedstock supply in its investigation of potential private land use conversions from agriculture to energy crops. This study relies on the development of a real-options land use change mode, that is an extension of Hauer et al. (2017). The first objective of this chapter is to assess the potential financial competitiveness of energy crops against agriculture under baseline assumptions, with "best guesses" of future yields, agricultural land values, and policies. Under these assumptions, energy crops do not financially compete with agriculture. However, one might expect that these energy crops would be grown on targeted lands that can produce high energy crop yields, yet have a lower market value. On these targeted lands, with an ethanol production subsidy of 0.21 \$/L, energy crops would have a better chance of competing against agriculture. Regarding the second objective, which is to compare the financial competitiveness of hybrid poplar versus switchgrass feedstocks; hybrid poplar is found to dominate switchgrass. Hybrid poplar enters into the land use schedule at an ethanol production subsidy level of 0.21 \$/L, while switchgrass requires a subsidy of 0.41\$/L alongside a discount rate premium of 5% on hybrid poplar plantations. The third objective of this chapter is to compare the financial competitiveness of co-production of ethanol with electricity versus ethanol with pellets. Co-production of ethanol alongside electricity leads to more expected land conversions to energy crops than co-production of ethanol and pellets. At an ethanol production subsidy level of 0.11 $/L, pellet prices would have to be 2.2 times higher in order to observe conversions to energy crops.

Financial preferences for hybrid poplar over switchgrass and co-production of ethanol and electricity over ethanol and pellets are partially the result of risk-driven option values. Chapter 2 revealed that there is a higher level of risk associated with co-production of ethanol with electricity over ethanol with pellets, due to the presence of GARCH effects in both product prices. This risk translates to higher options values for the ethanol and electricity co-production scenario, given the possibility that higher price spikes might occur, which could be captured by delaying the harvest of hybrid poplar. Overall, the results of the land use change model suggest that if market conditions adjust in favour of growing energy crops, allocating land to hybrid poplar in order to co-produce ethanol and electricity could become a financially viable scenario in the future.

Results of Chapter 3 indicate a gap between current private financial returns and those necessary to incent the planting of cellulosic energy crops. One way to close this gap is to introduce ethanol production subsidies, which could be justified on the grounds of reducing carbon. Life-cycle assessments of cellulosic ethanol reveal the potential to reduce greenhouse gas emissions by 70-90% relative to traditional fuel sources (IEA, 2006). Moreover, results indicate that land use conversions towards energy crops require an ethanol production subsidy of 0.21$ per liter of ethanol produced (i.e. approximately 0.11 $/L more than is currently offered). What is the cost to the government, on a per tonne basis, for preventing these carbon emissions? Each liter of cellulosic ethanol reduces carbon emissions, relative to fossil fuels, by 0.00051 tonnes. This works out to a price of 410.35$[14] per tonne of carbon emissions reduced. In contrast, the average costs of renewable fuel standard policies, which mandate the use of ethanol with gasoline, is estimated to be 180-185$ per tonne of greenhouse gas reduced (Canada Ecofiscal Commission, 2016). Meanwhile, the cost of emissions reduction using a carbon tax is estimated

[14] Assumes: emissions reductions of 80% as a midpoint of 70-90%; 8,887 grams of CO_2 are produced per US gallon of gasoline burned (EPA, 2014); and a conversion rate of 3.67 tonnes of CO_2 to 1 tonne of carbon (IPCC, n.d.).

to be $28.40 per tonne of carbon (Canada Ecofiscal Commission, 2016). In comparing these values, subsidies do not appear as the most cost-effective policy option to reduce carbon emissions

Regarding the price paid for ethanol at the pump, the public may be willing to pay a premium for renewable fuels that could cover the price gap between current conditions and those required to see energy crops compete with agriculture. Susaeta et al. (2010) explore public preferences for biofuel production from forest biomass and find that individuals have a positive willingness to pay for ethanol blends. Averaged across the three Southern US states in which their experiment was conducted, the public willingness to pay was an extra 0.14 $/L at the pump for gasoline blends containing 10% ethanol (E10). For E85 blends, the additional willingness to pay at the pump was 0.26 $/L. These willingness to pay estimates could support future policies that further subsidize ethanol, making conversions towards energy crops appear as more financially favorable to landowners.

There are several areas of future research that extend from this work. The dominance of hybrid poplar over switchgrass creates a challenge in delivering an initial supply of feedstocks to biorefineries, given that multiple years must pass before the harvest of hybrid poplar is possible. Therefore, studies investigating the financial feasibility of the cellulosic ethanol industry from a biorefinery perspective could consider exploring a blended feedstock supply system with hybrid poplar alongside an initial annual source such as agriculture or forestry residues.

Spatial components could also be integrated into future studies exploring the potential for a second-generation ethanol industry in Alberta. The model developed in Chapter 3 relies on the land base data from representative lands across the province, but the exact geographical locations of these targeted lands are not known. Moreover, the model does not explicitly consider the placement of future biorefineries. Instead, travel costs are calculated under the assumption that plants are located 10 kilometers from where energy crops are grown. In future analyses, one could spatially assess where lands targeted for conversion to energy crops are located across the province, to inform where biorefineries might best be placed to reduce transport costs and improve the likelihood of securing a stable supply of feedstocks. Following this investigation of biorefinery placement, a land use change model could be repeated with varied travel cost estimates.

The comparison of the alternative agricultural land value models with and without drift in Chapter 3 reveal that the assumed stochastic price process can have a substantial impact on the land use change model results. In future research, stochastic price process assumptions could be further modified to reflect uncertainty in future price paths. For example, Chapter 2 uncovers a structural break in the electricity price series, and it is possible that similar structural breaks might occur in the prices of each bioenergy commodity in the future. These potential price process changes, either as jumps to new long-term price means, or as changes from a mean reverting to a random walk process, could be factored into future real options land use change model sensitivity analyses.

One shortcoming of the land use change model that could have affected the results is the inconsistency in the methods of estimating stochastic returns from alternative land uses. Bioenergy commodity price models are estimated for each of the ethanol, electricity, and pellet series, based either on historic prices or a stand-in metric for prices. Meanwhile, stochastic returns from agriculture are estimated as a percentage of agricultural land values, instead of modelling a specific agricultural commodity. This method is selected to assess land conversions against an aggregated index of agricultural lands. Agricultural land values are characterized according to a unit root process, but it is possible that, like the bioenergy commodities, specific agricultural commodities might follow a mean reverting price pattern. In future research, conversions to switchgrass or hybrid poplar energy crops could be assessed against land currently allocated to particular agricultural crops.

The future of a second-generation ethanol industry in Alberta remains uncertain. The development of this industry would require a stable input of feedstocks for biorefineries, and, if supplied by purpose-grown energy crops, it is unlikely that under present conditions landowners will opt to grow these crops over current agricultural uses. If technical changes or market shifts lead to cellulosic ethanol being desired on the market, then this thesis provides insights into the feedstocks and co-production combinations that might assist in the development of the industry. Based on this analysis, co-production of ethanol and electricity from hybrid poplar appears as the most financially favourable production case. If there were a shift in bioenergy commodity market prices, production costs, or government subsidies, then it might be possible to see the proliferation of these energy crops on private lands.

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Appendix 1: Modeling Agricultural Land Values

The agricultural land value model applied in the real options model of Chapter 3 was estimated by Hauer as part of a work in process (personal communication, 2017). Given that there are a multitude of crops that are grown on agricultural lands across the province, agricultural land values are modeled based on an aggregate measure of agricultural land returns. Agricultural land value data comes from CANSIM Table 002-0009, a dataset of annual net farm incomes spanning from 1921 to 2015 (Statistics Canada, 2017).

Table A-1 summarizes the results of unit root and stationarity tests. In the level series, the ADF test fails to reject the null hypothesis of unit roots, while the KPSS test rejects the null of stationarity. When the series is logged and differenced, the ADF test rejects the null of unit roots, while the KPSS fails to reject the null of stationarity. With this logged series, an ARIMA model with one order of differencing can be estimated.

Table A-1: Agricultural land value unit root and stationarity test results

Series	Test	Test Statistic
Level	**ADF (5% CV = -2.895)**	3.381
	KPSS, 6 lags (5% CV = -1.091)	1.134***
Logged Differenced	**ADF (5% CV = -5.672)**	-3.162*
	KPSS, 6 lags (5% CV = -2.928)	0.238

***** and * indicate significance at the 1% and 10% levels of significance, respectively**

From the logged agricultural land value series, an ARIMA(1,1,0) model is estimated. This represents a random walk model in which the errors are autocorrelated. The drift term is not significant in this model, therefore Table A-2 reports the parameter estimates for two models: ARIMA(1,1,0) with and without drift. For the ARIMA(1,1,0) model estimated with drift, the null hypothesis of no ARCH effects in the residuals is not rejected. With this model, the constant term is not significant. As such, the series is also modeled as ARIMA(1,1,0) without drift (Table A-2). Here, ARCH effects are also not significant.

Table A-2: Agricultural land value ARIMA model results

Model	Component	Lag	ARMA Model, Normal Distribution
ARIMA (1,1,0) with drift	**Autoregressive**	Constant	0.020 (0.015)
		1	0.489*** (0.090)
	ARCH LM Chi-squared Value		15.71
	P-value		0.205
ARIMA(1,1,0) without drift	**Autoregressive**	1	0.519*** (0.088)
	ARCH LM Chi-squared Value		14.26
	P-value		0.2847

***** indicates significance at the 1% level of significance**

Appendix 2: Breakdown of Biorefinery Cost Estimates

Biorefinery costs are estimated according to both the feedstock input and co-production combination. A breakdown of the components of the biorefinery costs are outlined below in Table B-1.

Table B-1: Biorefinery cost breakdown

Product Combination	Cost Breakdown	Value ($/ tonne feedstock input)	
		Switchgrass	*Hybrid Poplar*
	Ethanol and electricity variable operating cost[a]	108.38	109.88
	Ethanol and electricity fixed cost[a]	31.79	32.23
	Capital depreciation	65.89	66.80
	Average tax	13.81	14.00
	Total	**219.87**	**222.91**
	Ethanol variable operating cost[a]	107.22	108.70
	Ethanol fixed cost[a]	31.50	31.94
	Ethanol capital depreciation	65.31	66.22
	Ethanol average tax	13.58	13.77
	Pellet variable operating cost[b]	15.10	16.15
	Pellet capital depreciation	3.00	3.21
	Pellet average tax	0.88	0.95
	Pellet train transportation cost[c]	16.79	17.96
	Pellet transfer loading cost[c]	15.94	17.04
	Process electricity cost[d]	85.31	86.49
	Total	**354.64**	**362.42**

Sources:

[a] *Kazi et al., 2010.*
[b] *Sultana et al., 2010.*
[c] *Hoque et al., 2006.*
[d] *Lorenz and Morris, 1995.*

All cost estimates have been converted to a cost per oven dried tonne feedstock input and have been inflation-adjusted to 2015 Canadian dollars. Cost estimates differed for the two co-production cases, given that cost estimates from Hoque et al. (2006) factored in ethanol and electricity co-production. Therefore, to estimate ethanol production costs for the pellet co-production scenario, electricity production-specific costs were removed. The cost estimates for switchgrass and hybrid poplar differed because they were scaled to reflect ethanol and pellets outputs that can be derived per ODT of feedstock input.

Fixed and variable operating costs were obtained from Kazi et al. (2010) and Sultana et al. (2010). These cost estimates were factored into capital depreciation and average tax calculations. Capital depreciation values were calculated using the straight-line depreciation method, assuming a 20 year plant life and interest rate of 10%. Finally, average tax values were estimated by finding the break-even price that set the per-litre profits of each co-production and feedstock combination to 0, under the assumption of a long-term competitive market. In estimating the average tax values, the combined Alberta and Federal manufacturing and processing corporate tax rates were assumed to be 27% (PWB, 2015).

Appendix 3: Algorithm for Solving the Land Use Change Model [an extension of Hauer et al. (2017)]

Preliminaries:

1. Let j= 1,...,50,000 represent trials of 100 year bi-annual simulations of ethanol prices, electricity prices, pellet prices, and agricultural land values.

2. Prices are expressed in terms of the time period, *t,* and the trial number, *j*. Thus prices for the *j*th trial, in period *t* are expressed as $p_{t,j}^{e}$ for ethanol, $p_{t,j}^{h_1}$ for electricity, and $p_{t,j}^{h_2}$ for pellets. Likewise, agricultural land values in period *t* for the *j*th trial is represented as $X_{t,j}^{a}$. The initial prices of $p_{0,j}^{e}$, $p_{0,j}^{h_1}$, $p_{0,j}^{h_2}$, and $X_{0,j}^{a}$ are set across all j=50,000 trials.

3. Let $\overline{p^{e}}$, $\overline{p^{h_1}}$, and $\overline{p^{h_2}}$ be the expected long run mean prices for ethanol, electricity, and pellets, respectively.

4. Let V^{f} be the soil expectation value for hybrid poplar plantations, which is maximized for each of *Ethanol & Electricity* and *Ethanol & Pellet* co-production combinations using the traditional Faustmann optimal economic rotation calculation for forests, as follows:

$$V^{f} = max_{s} \frac{\overline{p^{e}} v_{s}{}^{f} + \overline{p^{h_n}} v_{s}{}^{f} - C^{f}(1+i)^{s}}{(1+i)^{s}-1}$$

5. Let V_{q}^{g} be the net present value of switchgrass feedstocks, *q* periods following establishment. V_{q}^{g} is a function of long-term average prices, $\overline{P^{g,h_n}}$, which is based on the long-term average prices for ethanol, $\overline{p^{e}}$, and its co-product, $\overline{p^{h_n}}$, along with the cost of establishing switchgrass crops (C^{g}) and the cost of converting land previously in switchgrass back to agriculture (C^{ga}).

   Where *t* = odd, let $v_{t}^{g} = v^{g}$, and where *t* = even, let $v_{t}^{g} = 0$

With the initial switchgrass establishment, at q = 0, V_0^g is estimated as:

$$V_0^g = \frac{\sum_{q=1}^{19} \overline{P^{g,hn} v_q^g} * (1+i)^{20-q} - C^g (1+i)^{20} - C^{ga}}{(1+i)^{20} - 1}$$

Then, for any $q = q'$, with q' in [1,19]:

$$V_{q'}^g = \frac{\sum_{q=q'}^{19} \overline{P^{g,hn}} v^g (1+i)^{20-q} - C^{ga} + V_0^g}{(1+i)^{20-q'}}$$

This accounts for the fact that land previously held in switchgrass plantations must be converted back into its bare state to prepare for re-establishment. The net benefits from each harvest will be equivalent, given that long run expected mean prices are used.

6. For t= 131,…, 199, let $W_{t,0,j}^f = R_{t,0,j}^f = \max\left(0, V^f, X_{t,j}^a - C^{fa}, V^g - C^{fa}\right)$ be the estimated expected value and realized value for land allocated to hybrid poplar plantations, immediately after harvest, with the options to switch to agriculture or switchgrass.

7. For period t= 131, let $R_{t,j}^a = \max\left(0, V^f, X_{t,j}^a, V^g\right)$ and let $R_{t,q,j}^g = \max(0, V^f - C^{ga}, V^g, X_{t,j}^a - C^{ga})$. These are the realized values of land in agriculture and switchgrass, respectively, with the options to switch to alternative uses.

8. For j= 1,…, 50000 and t= 0,…, 130, the following stochastic price functions are computed:

    a. $L_0(P_{t,j}^e) = p_{t,j}^e / \overline{p_t^e}$

    b. $L_1(P_{t,j}^e) = {p_{t,j}^e}^2$

c. $L_0(P_{t,j}^{h_1}) = p_{t,j}^{h_1} / \overline{p_t^{h_1}}$

d. $L_1(P_{t,j}^{h_1}) = {p_{t,j}^{h_1}}^2$

e. $L_0(P_{t,j}^{h_2}) = p_{t,j}^{h_2} / \overline{p_t^{h_2}}$

f. $L_1(P_{t,j}^{h_2}) = {p_{t,j}^{h_2}}^2$

g. $L_0(X_{t,j}^{a}) = X_{t,j}^{a} / \overline{X_t^{a}}$

h. $L_1\left(X_{t,j}^{a}\right) = {X_{t,j}^{a}}^2$

i. $L_2\left(X_{t,j}^{a}\right) = (X_{t,j}^{a} - X_{t-1,j}^{a})$

j. $L_3\left(X_{t,j}^{a}\right) = |(X_{t,j}^{a} - X_{t-1,j}^{a})| * L_2\left(X_{t,j}^{a}\right)$

Algorithm

1. Set t= 130 and s= 70.

2. For j= 1,…,50,000 compute $R_{t+s,s,j}^{f} = \max(v_s^f P_{t+s,s,j}^{f,h_n} + R_{t,0,j}^{f}, 0)$, the realized value of harvest if the poplar plantation is harvested at the end of the harvesting window. Set the initial optimal rotation age for each j, that is planted at period t, to $s_j^*(t) = s$ (s=70) at the end of the harvesting age window (32-70 time periods).

3. Set $s = s - 1$

4. Using ordinary least squares, estimate the expected value of deferring harvest by 1 time period ($E[W_{t+s+1,s+1,j}^{f}](1 + i)^{-1}$) for each trial, j, with the following regression model:

$$\frac{R^{f}_{t+s+1,s+1,j}}{1+i} = \beta_0 + \beta_1 L_0\left(P^{e}_{t,j}\right) + \beta_2 L_1\left(P^{e}_{t,j}\right) + \beta_3 L_0\left(P^{h_n}_{t,j}\right) + \beta_4 L_1\left(P^{h_n}_{t,j}\right) + \beta_5 L_0\left(X^{a}_{t,j}\right) + \beta_6 L_1\left(X^{a}_{t,j}\right) + \beta_7 L_2\left(X^{a}_{t,j}\right) + \beta_8 L_3\left(X^{a}_{t,j}\right) + \varepsilon_j.$$

The co-product price used (i.e. n= 1 or n= 2) is dependent on the co-production combination. The estimated coefficients are used to compute $E[W^{f}_{t+s+1,s+1,j}](1+i)^{-1}$ for each trial j.

5. For each j, compute the expected value of harvesting immediately using the following:

$$v^{f}_{s} P^{f,h_n}_{t+s,s,j} + W^{f}_{t+s,0,j}$$

where the first term is the net-value of co-production from harvesting hybrid poplar, and the second term is the estimated bare land value (computed in *Preliminaries* Step 4, for $t+s$> 130 and in *Algorithm* Step 14 for $t+s$<= 130).

6. Where land is assigned to hybrid poplar plantations, given the state of prices, the optimal rotation decision (i.e. harvest immediately or defer harvest) is determined based on the following test:

$$\text{if} \quad v^{f}_{s} P^{f,h_n}_{t+s,s,j} + W^{f}_{t+s,0,j} \geq E\left[W^{f}_{t+s+1,s+1,j}\right](1+i)^{-1}$$

then harvest immediately and set the optimal rotation age for trial j as $s^{*}_{j}(t) = s$. In addition, set the realized value for each trial j as follows:

$$R^{f}_{t+s,s,j} = v^{f}_{s} P^{f,h_n}_{t+s,s,j} + R^{f}_{t+s,0,j}$$

Otherwise, defer harvest one period, $s^{*}_{j}(t)$ remains unchanged, and the realized value is updated to:

$$R^f_{t+s,s,j} = R^f_{t+s+1,s+1,j} / (1+i).$$

7. If $s>m$, where m is the minimum rotation period, then go to Step 3. Otherwise go to Step 8.

8. For each j, discount the realized forest value to time t and subtract the cost of planting as follows:

$$V^f_{t,0,j} = R^f_{t+m,m,j}/(1+i)^m - C^f$$

9. For each j, estimate the expected value of establishing a hybrid poplar plantation as:

$$E(V^f_{t,0,j}) = E\left[W^f_{t,0,j}\right](1+i)^{-1} - C^f$$

with the possibility of switching back to agriculture or switchgrass in the future, using the following regression model:

$$V^f_{t,0,j} = \beta_0 + \beta_1 L_0\left(P^e_{t,j}\right) + \beta_2 L_1\left(P^e_{t,j}\right) + \beta_3 L_0\left(P^{h_n}_{t,j}\right) + \beta_4 L_1\left(P^{h_n}_{t,j}\right) + \beta_5 L_0\left(X^a_{t,j}\right) + \beta_6 L_1\left(X^a_{t,j}\right) + \beta_7 L_2\left(X^a_{t,j}\right) + \beta_8 L_3\left(X^a_{t,j}\right) + \varepsilon_j$$

and then use the estimated coefficients to compute $E(V^f_{t,0,j})$.

10. For each j, compute the realized value of land in agriculture, with the option to later switch to either hybrid poplar plantations or switchgrass, as follows:

$$V^a_{t,j} = \frac{\delta X^a_{t,j} + R^a_{t+1,j}}{(1+i)}$$

11. For each j, estimate the expected value of land allocated to agriculture, $E(V^a_t)$, with the option to later to switch to either hybrid poplar plantations or switchgrass, by first estimating the following regression model:

$$V_{t,j}^{a} = \beta_0 + \beta_1 L_0\left(P_{t,j}^{e}\right) + \beta_2 L_1\left(P_{t,j}^{e}\right) + \beta_3 L_0\left(P_{t,j}^{h_n}\right) + \beta_4 L_1\left(P_{t,j}^{h_n}\right) + \beta_5 L_0\left(X_{t,j}^{a}\right) + \beta_6 L_1\left(X_{t,j}^{a}\right) + \beta_7 L_2\left(X_{t,j}^{a}\right) + \beta_8 L_3\left(X_{t,j}^{a}\right) + \varepsilon_j$$

and then using the estimated coefficients to compute $E(V_{t,j}^{a})$.

12. For each j, compute the realized value of switchgrass, with the option to later switch to either agriculture or hybrid poplar plantations, as follows:

$$V_{t,q,j}^{g} = \frac{v^g P_t^{a,h_n} + R_{t+1,q+1,j}^{g}}{(1+i)}$$

13. For each j, estimate the expected value of switchgrass, $E(V_{t,q}^{g})$, with the option to later to switch to either agriculture or hybrid poplar plantations, by first estimating the following regression model:

$$V_{t,q,j}^{g} = \beta_0 + \beta_1 L_0\left(P_{t,j}^{e}\right) + \beta_2 L_1\left(P_{t,j}^{e}\right) + \beta_3 L_0\left(P_{t,j}^{h_n}\right) + \beta_4 L_1\left(P_{t,j}^{h_n}\right) + \beta_5 L_0\left(X_{t,j}^{a}\right) + \beta_6 L_1\left(X_{t,j}^{a}\right) + \beta_7 L_2\left(X_{t,j}^{a}\right) + \beta_8 L_3\left(X_{t,j}^{a}\right) + \varepsilon_j$$

and then using the estimated coefficients to compute $E(V_{t,j}^{g})$.

14. Estimate $W_{t,j}^{a}$ as:

$$W_{t,j}^{a} = \max(E\left(V_{t,j}^{a}\right), E\left(V_{t,0,j}^{f}\right), E\left(V_{t,q,j}^{g}\right), 0)$$

15. Estimate $W_{t,q,0}^{g}$ as:

$$W_{t,q,0}^{g} = \max(E\left(V_{t,q,j}^{g}\right), E\left(V_{t,j}^{a}\right) - C^{ga}, E\left(V_{t,0,j}^{f}\right) - C^{ga}, 0)$$

16. Estimate $W^f_{t,0,j}$ as:

$$W^f_{t,0,j} = \max(E(V^f_{t,0,j}), E(V^a_{t,j}) - C^{fa}, E(V^g_{t,q,j}) - C^{fa}, 0)$$

17. For each j, first set $R^a_{t,j} = 0$ as the minimum realized value of agriculture land, and then compute the realized value of agriculture land equal to the land option yielding the highest returns, according to:

$$R^a_{t,j} = \begin{cases} V^a_{t,j} \; if \; W^a_{t,j} = E(V^a_{t,j}) \\ V^g_{t,q,j} \; if \; W^a_{t,j} = E(V^g_{t,q,j}) \\ V^f_{t,0,j} \; if \; W^a_{t,j} = E\left(V^f_{t,0,j}\right) \end{cases}$$

where the value of land in agriculture, $W^a_{t,j}$, was determined in Step 14. The realized value of land allocated to agriculture is set to one of the following three possibilities: the value of agriculture, the value of switchgrass, or the value of hybrid poplar.

18. For each j, first set $R^g_{t,q,j} = 0$ as the minimum realized value of land allocated to switchgrass, and then set the realized value of land in switchgrass equal to the land option yielding the highest returns, according to:

$$R^g_{t,j} = \begin{cases} V^g_{t,q,j} \; if \; W^a_{t,j} = E(V^g_{t,q,j}) \\ V^a_{t,j} - C^{ga} \; if \; W^a_{t,j} = E(V^a_{t,j}) - C^{ga} \\ V^f_{t,0,j} - C^{ga} \; if \; W^a_{t,j} = E\left(V^f_{t,0,j}\right) - C^{ga} \end{cases}$$

where the value of land in switchgrass, $W^g_{t,q,0}$, was determined in Step 15. The realized value of land allocated to switchgrass is set to one of the following three possibilities: the value of switchgrass crops, the value of agriculture minus conversion costs, or the value of hybrid poplar minus conversion costs.

19. For each j, first set $R^f_{t,0,j} = 0$ as the minimum realized value of land currently allocated to hybrid poplar plantations, and then set the realized value of forest land equal to the land option yielding the highest returns, according to:

$$R^f_{t,0,j} = \begin{cases} V^f_{t,0,j} \; if \; W^f_{t,0,j} = E\left(V^f_{t,0,j}\right) \\ V^a_{t,j} - C^{fa} \; if \; W^f_{t,0,j} = E\left(V^a_{t,j}\right) - C^{fa} \\ V^g_{t,q,j} - C^{fa} \; if \; W^f_{t,0,j} = E\left(V^g_{t,q,j}\right) - C^{fa} \end{cases}$$

where the value of land in forestry, $W^f_{t,0,j}$, was determined in Step 16. The realized value of land allocated to hybrid poplar is set to one of the following three possibilities: the value of hybrid poplar plantations, the value of agriculture minus the conversion costs, or the value of switchgrass minus the conversion costs.

20. If t>0, then set t= t-1 and go to step 1. If t=0, stop.