Using life cycle assessment and techno-economic analysis in a real options framework to inform the design of algal biofuel production facilities

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h i g h l i g h t s

- LCA/TEA modeling of algal biofuel plants assumes static operating parameters.
- Real options analysis aids decision making about plant design under uncertainty.
- Real options analysis quantifies the value of investing in operational flexibility.
- Investment in anaerobic digestion/CHP adds operational flexibility.
- But commodity price dynamics don't currently support the additional capital cost required.

Keywords:
Algae
Biofuels
Techno-economic analysis Life cycle assessment Real options

This study investigates the use of ‘‘real options analysis" (ROA) to quantify the value of greater product flexibility at algal biofuel production facilities. A deterministic optimization framework is integrated with a combined life cycle assessment/techno-economic analysis model and subjected to an ensemble of 30-year commodity price trajectories. Profits are maximized for two competing plant configurations: 1) one that sells lipid-extracted algae as animal feed only; and 2) one that can sell lipid-extracted algae as feed or use it to recover nutrients and energy, due to an up-front investment in anaerobic digestion/combined heat and power. Results show that added investment in plant flexibility does not result in an improve-ment in net present value, because current feed meal prices discourage use of lipid-extracted algae for nutrient and energy recovery. However, this study demonstrates that ROA provides many useful insights regarding plant design that cannot be captured via traditional techno-economic modeling.

The production of algal biofuel lends itself to vertically inte-grated ‘‘closed loop" production pathways, encompassing biomass cultivation, harvesting, and conversion to fuels (Brennan and Owende, 2009; Quinn and Davis, 2014). This allows for potentially high levels of water, nutrient, and energy recycling, a necessary component for sustainable, commercial-scale biofuel production (Chowdhury et al., 2011).

There is also tremendous design flexibil-ity in creating algal biofuel production pathways (Bennion et al., 2014; Brennan and Owende, 2009; Gardner et al., 2013; Jones et al., 2014; Lopez Barreiro et al., 2013; Richardson et al., 2012, 2014); as well as potential at each step of the cultivation-to-conversion process for research and development to yield effi-ciency gains and cost reductions (Collet et al., 2013; Quinn and Davis, 2014). Algal biofuel production can also be paired with (and economically supported by) the co-production of other high value products (Subhadra, 2011), including: animal feed (Beal et al., 2015; Gerber et al., 2016), nutraceuticals (Stephens et al.,

2010) and chemicals (Pittman et al., 2011), as well as valuable industrial processes such as wastewater treatment (Pittman et al., 2011) and combined heat and power (Gerber et al., 2016).

Yet, uncertainties in input and product prices, plant configuration and plant performances result in a wide range of algal biofuel cost-benefit estimates (Beal et al., 2015; Gerber et al., 2016; Sills et al., 2013). In recent years, a number of studies have used techno-economic analysis (TEA) and life-cycle assessment (LCA) to explore an array of potential algal biofuel production pathways (Quinn and Davis, 2014). Collectively, and in few cases individually (Gerber et al., 2016; Sills et al., 2013), these previous studies have been useful in bounding the principal sources of uncertainty impacting the economic value of algal biofuel projects—a critical step in identifying future research and development needs.

However, even when uncertainty analysis is used to explore the sensitivity of a plant's net present value (NPV), an underlying assumption common to LCA/TEA modeling of algal biofuel plants is that operating parameters (e.g., input and product prices) remain constant over a plant's lifetime (Gerber et al., 2016; Sills et al., 2013). The potential for substantial year-to-year changes in input and/or product prices, combined with the need to make up-front, potentially "irreversible" decisions about system design and configuration, create a high-risk environment for both investors and plant operators (E2 Environmental Entrepreneurs, 2014; McCarty and Sesmero, 2015; Miller et al., 2013; Stock, 2015). As algal biofuel becomes more cost competitive, there is a growing need for decision support tools that can help identify robust plant designs (i.e., those that maintain financial viability over time, despite operating under regulatory, technological and market uncertainty).

One approach that has been used extensively in other sectors to help navigate market uncertainty, as well as the path dependency associated with making irreversible infrastructure decisions, is "real options analysis" (ROA). ROA applies the theory behind financial options to situations in which uncertainty in future input and/or product prices affects cash flow projections and the NPV of capital projects (Miller and Waller, 2003). Specifically, ROA identifies decisions that may decrease profitability in certain future scenarios, but overall help investors realize a higher expected NPV or minimize the risk of substantial losses. Hence, ROA assumes, and is designed to address, a stochastic decision-making environment. A number of previous studies have addressed the potential for ROA to guide decision-making in the biofuels industry (Pederson and Zhou, 2009; Schmit et al., 2009, 2011; Sharma et al., 2011; Sharma et al., 2013a,b; McCarty and Sesmero, 2015). To the authors' knowledge, however, no previous study has addressed the integrated use of LCA/TEA and ROA to inform decision-making surrounding algal biofuel production.

This study explores the use of ROA to help identify algal biofuel production pathways that remain viable even when key parameters (e.g., product prices) driving economic competitiveness are highly uncertain. To do this, an existing LCA/TEA model is paired with a mixed integer linear program (MILP) and subjected to time-varying data for key operational parameters (e.g., prices for electricity, natural gas, nutrients, biodiesel, algal meal, etc.) The plant's NPV is optimized over an ensemble of 30-year price scenarios, and then the "real option" value of specific plant designs is identified.

Initial use of ROA focuses on addressing a key design question that has important implications for the economic and environmental sustainability of algal biofuel facilities. Within the context of a conventional, transesterification (TE)-based oil extraction process, this study evaluates tradeoffs between: 1) the sale of lipid-extracted algae (LEA) as animal feed replacement; and 2) the use of a more "closed loop" process that relies on anaerobic digestion of LEA to recover nutrients and produce biogas for use in on-site combined heat and power (CHP). Specifically, this study quantifies the added value of an up-front investment in anaerobic digestion/CHP, which allows switching between selling LEA as algal meal and recovering nutrients and producing energy on-site on a year-to-year basis, depending on market prices.

This study provides an important demonstration of how LCA/TEA can be incorporated in a more dynamic, decision focused modeling framework. Results establish the utility of ROA as a tool for addressing design challenges unique to algal biofuel production pathways and promoting the economic and environmental sustainability of these systems under market uncertainty.

2. Methods

The general approach taken for integrating LCA/TEA within a real options analysis (ROA) framework is illustrated in Fig. 1. First, an existing LCA/TEA model for an algal biofuel production facility was adapted to accept stochastic price data for energy and agricultural commodities. Then, for two competing plant configurations, operational decisions were optimized (profits were maximized) via a mixed integer linear program (MILP) over an ensemble of 30-year scenarios. Finally, resultant distributions of environmental and financial performance metrics were compared for the competing plant configurations to identify the "real option" value of decisions that offer plant operators more flexibility in responding to dynamic prices.

2.1. LCA/TEA model

The foundation of the modeling framework used was an existing LCA/TEA model of an algal biofuel facility. The model, developed by Hise et al. (2016), has been used in the past to assess the relative impacts of novel processing techniques (Gardner et al., 2013; Lohman et al., 2015; Vadlamani, 2014; Zhao, 2015) and financing parameters on algal biofuel costs. The LCA/TEA model simulates life cycle system performance for a range of potential plant configurations and produces estimates of minimum fuel selling prices and global warming potential within acceptable ranges (Jones et al., 2014; Quinn and Davis, 2014).

In this study, it was assumed that algal cultivation takes place in open raceway ponds and the facility produces a functional unit of 10 million gallons of biodiesel fuel annually. Fig. 2 shows the different plant configurations explored herein. Within the context of a conventional transesterification (TE) conversion pathway, this study quantifies the added value of an investment in anaerobic digestion and combined heat and power (CHP). This added capability requires a significant up-front capital cost, but it gives the plant operator the flexibility to decide each year, based on market prices for energy and agricultural commodities, whether to: 1) recover nutrients and use biogas from digested LEA to produce on-site heat and power; or 2) sell lipid extracted algae (LEA) as feed meal.

In both plant configurations, the system boundary included the combustion of produced biofuel (i.e. a "well-to-wheels" scope) in order to facilitate comparisons with conventional fuel life cycles (Frank et al., 2011). However, similar to previous analyses (Bennion et al., 2014; van Boxtel et al., 2015), characterization of each plant configuration's global warming potential and energetic balance excluded the energy and emissions associated with system construction (i.e., it assumed to be small for all plant configurations considered) (Frank et al., 2011). Global warming potential (GWP) was calculated by converting emissions (i.e. CO_2, N_2O, and CH_4) from the production and use of energy and material into grams of CO_2 equivalents, and comparing this value to life cycle emissions of conventional diesel fuel. The emissions and energy associated with individual process inputs were obtained from GREET (Frank et al., 2011), other analyses, and industrial sources. GWP in this

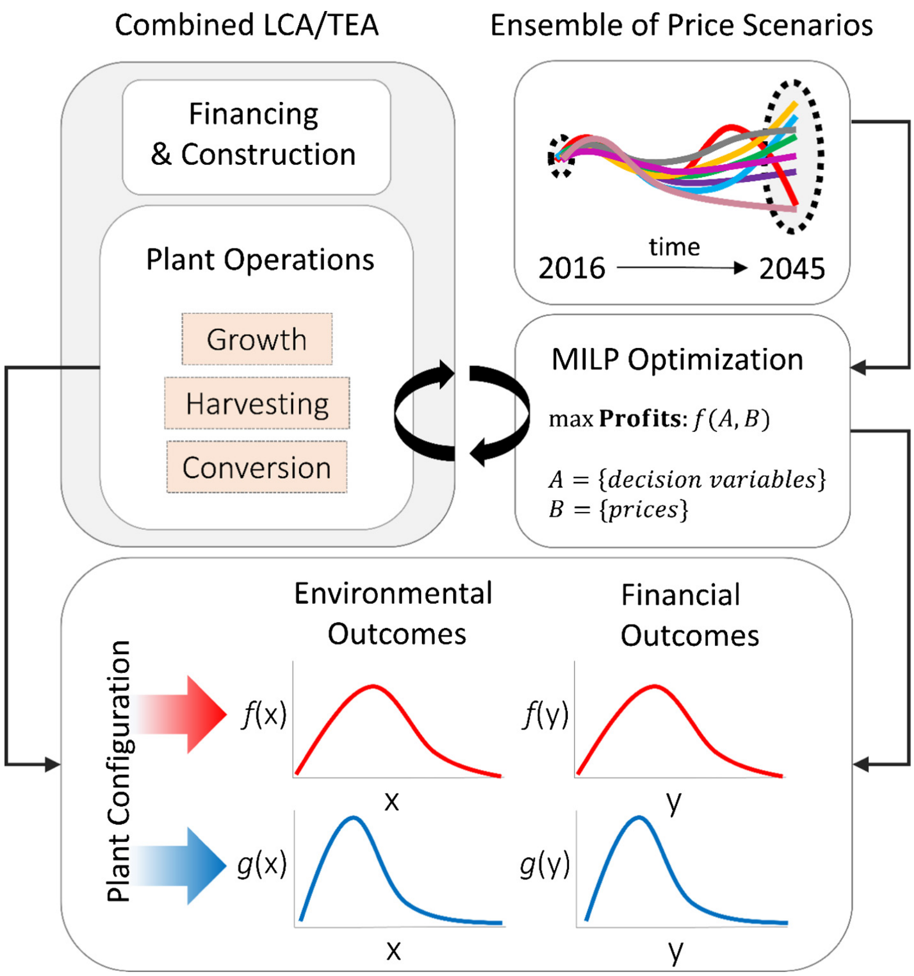

Fig. 1. A LCA/TEA model is adapted to incorporate an ensemble of stochastic price data, then plant operational decisions are optimized (profits are maximized) via a mixed integer linear program (MILP). We then compare probability distributions of relevant environmental and financial performance metrics for two competing plant configurations (blue vs. red) to identify the real option value. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

paper is reported as a percentage relative to emissions from convention diesel, with percentages less than 100% equating to a life cycle greenhouse gas reduction, and percentages above 100% equating to a greenhouse gas increase.

The LCA/TEA model assumed a three-year construction period and a 30-year project lifetime. Most economic analysis and financing parameters were taken from Jones et al. (2014). A complete summary of all model parameters and sources can be found in Hise et al. (2016).

Under current technology readiness levels, the theoretical "minimum fuel selling price" reported by most algal biofuel studies is significantly higher than the market price of biodiesel—meaning modeled projects are not currently cost competitive. Although this should not discourage the development of more decision oriented tools in anticipation of increased cost competitiveness of algal biofuel, it did motivate use of generous financing parameters (i.e., low interest rates) and optimistic algal cultivation characteristics. This study assumed a very low cost of capital (4%) and an algae areal productivity rate of 32 $g\ m^{-2}\ d^{-1}$ with 45% lipid content; these represent substantial technical and financing improvements that, if realized in the near future, would help make algal biofuel cost competitive. As a reference, in other work published by the authors, baseline conditions were characterized by an 8% interest rate (reflective of a riskier investment), along with 13.2 $g\ m^{-2}\ d^{-1}$ areal productivity and 25% lipid content.

2.2. Deterministic optimization

In order to use the LCA/TEA model in a ROA framework, it was paired with a deterministic optimization program that uses stochastic commodity prices to make decisions about how best to operate the algal biofuel plant. The optimization program then passes these decisions back to the LCA/TEA model, which calculates associated environmental and financial outcomes. Specifically, the program optimizes the use of a TE-based pathway in which the plant operator can dynamically switch between using LEA to: 1) recover nutrients and produce energy on-site; and 2) produce algal meal (see Fig. 2). A goal of this research was to understand how frequently commodity price dynamics incentivize a plant operator to switch between these two options, and whether the value of that operational flexibility justifies the associated increase in up-front capital costs.

The plant operator's decision process was represented via a mixed integer linear program (MILP) coded in the AMPL mathematical programming language and solved with a CPLEX solver, whose objective was to maximize profits (or minimize costs) (Eq. (1)). The MILP pulled parameters from the LCA/TEA model relevant to nutrient recovery and on-site energy production via anaerobic digestion/CHP, and algal meal production (see Table 1). In each discretized annual time period, the MILP used these parameters, along with commodity price data, to find the optimal use of the plant

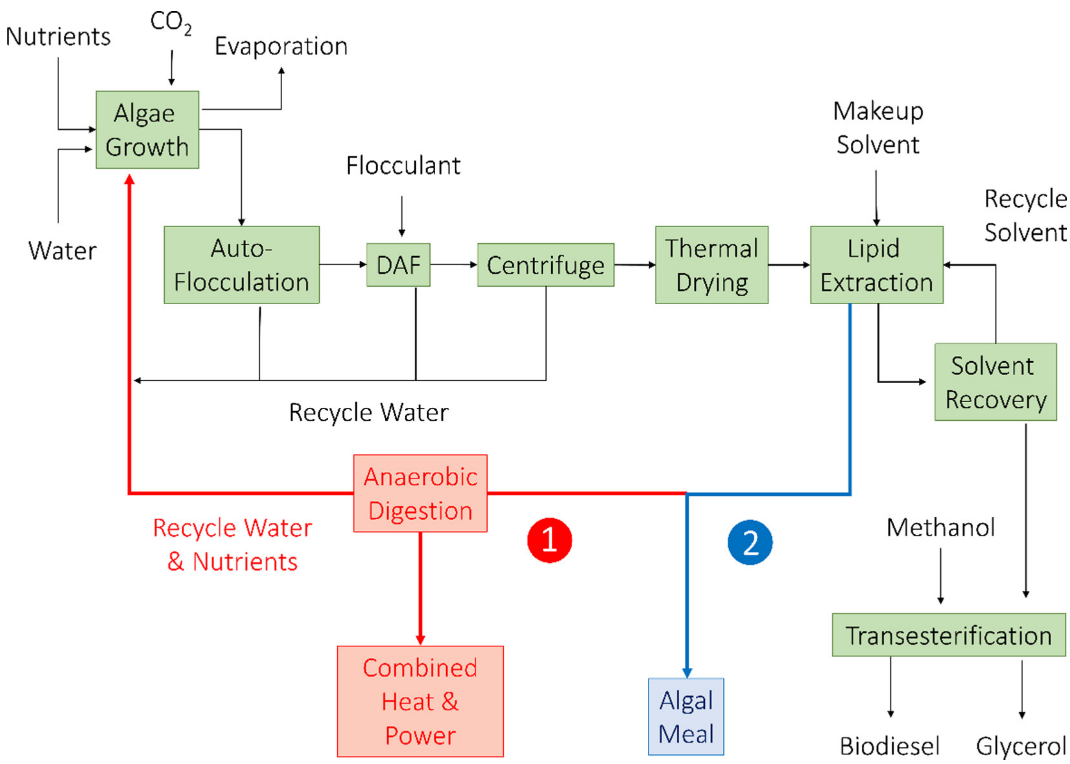

Fig. 2. The two plant configurations explored in this study, based around a conventional transesterification (TE) production pathway in which a plant operator can decide to use lipid extracted algae to recover nutrients and produce energy onsite (option 1) or sell algal meal (option 2).

Table 1
LCA/TEA parameters used in the MILP describing the transesterification-based system (Fig. 2). Inputs are indicated by a minus sign (−) and outputs are positive. We differentiate here between a system that sells LEA as algal meal and one that uses anaerobic digestion/CHP to partially recover nutrients and energy. Even for the "closed loop" system, there are net input requirements for energy and nutrients (far right column). These are calculated as the sum of each row.

	Open loop		Closed loop		
	Inputs	Production	Anaerobic digestion	CHP	Net inputs
Electricity (kWh)	−2.14E+08		−6.04E+03	7.48E+07	−1.39E+08
Natural gas (MMBtu)	−1.63E+06		−5.33E+01	2.41E+05	−1.39E+06
Nitrogen (kg)	−8.58E+06		6.52E+06		−2.06E+06
Phosphorus (kg)	−8.58E+05		4.29E+05		−4.29E+05
Algal meal (tons)		7.83E+04			

(i.e., choosing option #1 or #2, as described above), and represented this decision using binary variables. In the MILP, the plant owner can toggle back and forth on an annual basis, without restriction—i.e., the choice to sell algal meal one year does not constrain or otherwise impact the decision to do so again the following year, or switch to nutrient recovery and on-site energy production. The objective function of the 30-year MILP was expressed as follows, with all production values associated with one functional unit (ten million gallons annually) of algal biofuel:

$$\textbf{Maximize Z}: \sum_{t=1}^{30} MealON_t * (Meal * PriceMeal_t) + RecoverON_t * (Elec * PriceElec_t + NatGas * PriceGas_t + Nitrogen * PriceNitr_t + Phosphorus * PricePhos_t) \quad (1)$$

Where

$MealON_t$ = binary (0,1) variable that triggers algal meal production in year t
$Meal$ = mass of algal meal produced by one functional unit
$PriceMeal_t$ = price of algal meal in year t
$RecoverON_t$ = binary (0,1) variable that triggers anaerobic digestion/CHP in year t
$Elec$ = net electricity production from anaerobic digestion/CHP
$PriceElec_t$ = price of electricity in year t
$NatGas$ = net heat from anaerobic digestion/CHP (in natural gas MMBtu)
$Nitrogen$ = nitrogen recovery from anaerobic digestion
$PriceNitr_t$ = price of nitrogen fertilizer in year t
$Phosphorus$ = phosphorus recovery from anaerobic digestion
$PricePhos_t$ = price of phosphorus fertilizer in year t

It is important to note that the sale of biodiesel (the primary function of the plant) was not incorporated in the MILP, because decisions regarding the fate of LEA were assumed not to impact the volume of biodiesel (or any other product) produced via TE. The single constraint on this optimization was that the choice between nutrient recovery and on-site energy production, and the sale of algal meal, be mutually exclusive. To enact this simple constraint, the solution of the MILP was subjected to:

$$MealON_t + RecoverON_t \leqslant 1 \qquad \forall t \quad (2)$$

Note that the solution of this optimization problem is relatively straightforward and, in its current form, may not require the use of a specialized language and solver to integrate with the LCA/TEA model. However, this was done in anticipation of further developing this modeling framework to explore more complex decision-making problems related to algal biofuel facility design and operations.

2.3. Commodity price modeling

After pairing the LCA/TEA model with the MILP, it was subjected to an ensemble of 30-year commodity price trajectories to gain a probabilistic understanding of plant decision-making and associated environmental and financial metrics. In generating stochastic time series of commodity prices, the focus was on replicating observed price dynamics for several energy and agricultural commodities. Annual prices were modeled for the following key system inputs: nitrogen and phosphorus fertilizer (anhydrous ammonia and diammonium phosphate), electricity, and natural gas; and outputs: biodiesel fuel (B99) and the price of algal meal, which we assumed to be equivalent to the market price of soybean meal. Note that in cases where the plant operator chooses to recover nutrients and produce energy on-site via anaerobic digestion/CHP, these technically become system outputs as well.

Historical biofuel price data were taken from the U.S. Department of Energy's Alternative Fuels Data Center (Alternative Fuels Data Center, 2016); natural gas and crude oil prices were acquired from the U.S. Energy Information Administration (Internet, 2016); electricity prices were obtained from PJM Interconnection Data Miner, 2016); nitrogen (anhydrous ammonia) fertilizer prices were acquired from the U.S. Department of Agriculture's Economic Research Service (Fertilizer Use and Price, 2016); and phosphorus (diammonium phosphate) and soybean meal prices were obtained from an online industry source (Agricultural Chemical Companies, 2016; Soybean Meal, 2016). Historical commodity prices were adjusted for inflation using CPI data available from the U.S. Bureau of Labor and Statistics. (Consumer Price Index, 2016). All historical price data used in this study can be found in the Supplemental Information section.

Table 2 shows a Pearson correlation matrix of average annual prices for these commodities over the period 2000–2015 (the relationship among these commodities and crude oil is also shown). Values close to 1 or −1 indicate strong relationships between prices for two commodities, while values close to 0 indicate weak relationships; positive values indicate direct relationships, while negative values indicate indirect relationships. Due to the significant statistical dependencies among the prices for these commodities, a combination of vector autoregressive (VAR) and linear regression models was used to generate synthetic ensembles of future prices. VAR models are a standard econometric approach for describing multivariate time series of energy and agricultural commodity prices in cases where significant linear dependency exists among variables (Gutierrez et al., 2014; Harri et al., 2009; Nazlioglu, 2011).

VAR models describe the behavior of a set of $\mathbf{k}$ variables over a given time period as a linear function of only their past values. Simulated values of each variable are stored in a $\mathbf{k} \times \mathbf{1}$ vector $\mathbf{y_t}$, which has as its $\mathbf{i}$th element, $\mathbf{y_{i,t}}$, the value of the $\mathbf{i}$th variable at time $\mathbf{t}$. The "lag" of the model (i.e., the number of previous time steps that are accounted for when estimating values in $\mathbf{y_t}$) is denoted by the parameter $\mathbf{p}$. Formally, VAR models are written as follows:

$$y_t = C + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t \tag{3}$$

Where
C = $k \times 1$ vector of constants
A_i = $k \times k$ matrix of coefficients
$\varepsilon_t = k \times 1$ vector of error terms
t = time period
p = model "lag"

Multiplying every matrix $\mathbf{A_i}$ by its corresponding vector $\mathbf{y_{t-i}}$ yields an equation for each of the $\mathbf{k}$ variables in $\mathbf{y_t}$ that is a linear function of all variables' previous values back through period ($\mathbf{t}-\mathbf{p}$). For example, a VAR model considering only two variables ($\mathbf{a}$ and $\mathbf{b}$) and a lag of one period can be written equivalently as:

$$y_t = C + A_1 y_{t-1} + \varepsilon_t \tag{4}$$

$$\begin{bmatrix} y_{a,t} \\ y_{b,t} \end{bmatrix} = \begin{bmatrix} C_a \\ C_b \end{bmatrix} + \begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{bmatrix} \begin{bmatrix} y_{a,t-1} \\ y_{b,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{a,t} \\ \varepsilon_{b,t} \end{bmatrix} \tag{5}$$

$$y_{a,t} = C_a + A_{1,1} y_{a,t-1} + A_{1,2} y_{b,t-1} + \varepsilon_{a,t} \tag{6}$$

$$y_{b,t} = C_b + A_{2,1} y_{a,t-1} + A_{2,2} y_{b,t-1} + \varepsilon_{b,t} \tag{7}$$

Linear equations for each individual variable in $\mathbf{y_t}$ (Eqs. (6) and (7)) are distinguished by different $\mathbf{A}$-coefficients. The simulation evolves as a result of random sampling of error terms ($\boldsymbol{\varepsilon_t}$) from a multivariate probability distribution with mean zero and covariance $\mathbf{cov}(\boldsymbol{\varepsilon_a}, \boldsymbol{\varepsilon_b})$, that describes the linear dependency among each variable. Both the regression parameters ($\mathbf{A}$- coefficients) and covariance matrix were fitted via maximum likelihood estimation. The number of lags considered was determined via Akaike Information Criteria.

Since a fairly limited overlapping historical record of annual commodity prices is available (2000–2015), the number of individual variables that could be represented simultaneously using a VAR model was restricted, in this case to three variables. Strong correlations are known to exist between natural gas electricity prices (Linn et al., 2014), as well as between soybean meal and fertilizer prices (see Table 2) (Jones et al., 2014). Thus, the VAR model was used to model natural gas prices, soybean meal, and B99, and then linear regression was used to capture relationships between prices for these three commodities and the three others considered (anhydrous ammonia, diammonium phosphate, and electricity). All time series model specifications are listed in the SI.

Table 2
Pearson correlation matrix for the six energy and agricultural commodities considered in this study, plus crude oil. Many of these commodities show strong linear dependency, which has to be accounted for when developing stochastic price models.

	Crude Oil (WTI)	B99	Electricity	Natural gas	Soybean meal	Anhydrous ammonia
B99	0.93					
Electricity	0.09	0.03				
Natural gas	0.03	−0.03	0.94			
Soybean meal	0.73	0.72	−0.41	−0.51		
Anhydrous ammonia	0.81	0.79	−0.20	−0.20	0.79	
Diammonium phosphate	0.80	0.85	0.25	0.10	0.60	0.71

2.4. Real options analysis

A primary goal of this study was to determine the "real option" value of up-front investment in algal biofuel plant features that provide added operational flexibility under price uncertainty. Specifically, within the context of a conventional transesterification (TE) conversion pathway (Fig. 2), the real options value of an up-front investment in anaerobic digestion/CHP was assessed. This added capability comes at a significant cost, but it gives the plant operator an ability to switch between recovering nutrients and energy and selling lipid extracted algae (LEA) as algal meal.

Essentially, use of real options analysis (ROA) involved two steps: 1) simulating the NPV of two different plant designs under a range of potential future price scenarios; and 2) determining whether the added NPV benefits of investment in plant flexibility outweigh the higher up-front capital costs.

Typically, ROA relies on the discretization of a stochastic time series of prices into a multi-stage uncertainty tree, whose branches emanate (up or down) from a starting condition based on estimated probabilities (Sharma et al., 2013a) (see Fig. S1 in the Supplemental Information section). Each node in the uncertainty tree is associated with a commodity price (or set of prices), and each node also represents a discrete decision point where a plant operator must choose how best to operate the plant. Operational decisions are optimized along every possible price trajectory, and for each trajectory an associated net present value (NPV) is calculated. Given the probability of each individual price trajectory, a mean NPV is estimated for each plant design under consideration. If investment in added flexibility results in an increase in mean NPV that outweighs the additional capital cost requirements, investment in plant flexibility is said to possess real option value.

In this study, due to the high dimensionality of modeled price data (six different commodities were considered), stochastic time series of price data were not discretized into an uncertainty tree. Rather, the MILP previously described was used to optimize plant operations on an annual basis for an ensemble of 1000 separate 30-year commodity price trajectories. For each plant design under consideration, this yielded a distribution of possible NPVs. The mean and variance of these distributions were then compared to assess the real option value of different plant designs.

3. Results and discussion

3.1. Validation of commodity price models

The primary consideration when generating the ensemble of commodity prices was maintaining historically accurate statistical moments (mean, variance) and annual time series characteristics (autocorrelation for individual commodities and cross-correlations among multiple commodities). Fig. 3 shows validation of our commodity price modeling. The top panels show histograms of simulated prices for each commodity alongside their historical means. The bottom panels show the autocorrelation functions of historical (2000–2015) and simulated prices for all six commodities. The time series models also reproduced cross-correlations among commodity prices with relatively minor errors. Overall, it was found that the commodity price models demonstrated a reasonable ability to reproduce key characteristics of the historical record in the simulated prices that are fed to the MILP. However, it is important to note that a fundamental assumption of the modeling approach, and a potential limitation of this work, was that prices are not subject to any long term changes in mean, variance, or cross correlation among commodities (i.e., they are stationary).

3.2. Valuing product flexibility as a real option

As a test of the ROA framework, the added value of an initial investment in anaerobic digestion/CHP was assessed. Of particular interest were: 1) how often movements in market prices for different commodities incentivize a plant operator to switch between nutrient and energy recovery and algal meal production; and 2) whether the financial benefits from operating the plant in such a flexible manner outweigh the annualized capital cost of adding anaerobic digestion/CHP. To test this, 1000 independent 30-year model runs were performed.

Results suggest that commodity price dynamics rarely create sufficient conditions to incentivize an algal biofuel plant to switch between the two modes of operation. For a plant with added up-front investment in anaerobic digestion/CHP, in only 122 (0.4%) of the total 30,000 simulation years did the plant actually decide to forego the sale of LEA as algal meal in order to recover nutrients and energy. In these 122 years, nutrient and energy recovery provided an average of $990,000 in added value. In all other years, the average financial margin (difference) between the two operational pathways was $11.09 million, in favor of producing algal meal only.

Table 3 lists the annual financial benefits associated with different sub processes under a range of price conditions. Under mean price conditions for all commodities, annual revenues from the sale of algal meal ($24.43 million) far outweighed the combined benefits associated of nutrient recovery and energy production ($13.42 million). It was found that avoided electricity costs ($5.39 million) were the largest cost recovery mechanism for anaerobic digestion/CHP, followed by avoided anhydrous ammonia costs ($5.37 million), natural gas heating costs ($1.64 million) and diammonium phosphate costs ($1.02 million).

The range of benefits that exists for different sub-processes suggests that, if prices for each commodity were independent random variables, the net benefits associated with anaerobic digestion/CHP might outweigh those associated with selling algal meal with greater regularity. However, strong correlations between algal meal and nutrient prices prevented this from occurring. It was common in the ensemble of price data for algal meal prices and natural gas and electricity prices to move in opposite directions, since historically prices for these commodities have been negatively correlated (see Table 2). But, prices for nutrients and algal meal generally moved in tandem, meaning there was very rarely a year in which algal meal prices were low while nutrient prices were high. For the most part, the 122 years in which a financial incentive existed to forego production of algal meal in favor of nutrient and energy recovery all had in common low algal meal prices and high prices for electricity and gas.

Overall, the benefits from investing in a flexible plant design, which only accrued in a handful of years in which algal meal prices decreased dramatically and energy prices rose, were not enough to offset the combined up-front capital cost of $33.6 million for anaerobic digestion ($9.06 million) and CHP ($24.30 million). As a consequence, nearly the entire distribution of NPVs associated with an up-front investment in greater plant flexibility fell below the distribution of NPVs associated with a plant that did not invest in these technologies and simply sold LEA as algal meal (Fig. 4, top panel).

These results have important implications for the design of algal biofuel facilities. First, they indicate that the real option value of operational flexibility at algal biofuel plants—an often cited, potential advantage of fully engineered systems—may be nullified if it is associated with a significant increase in capital costs. Results also suggest that a more sustainable "closed-loop" approach (another widely cited advantage of fully engineered systems) may be a less cost-effective production route. Direct tradeoffs were found

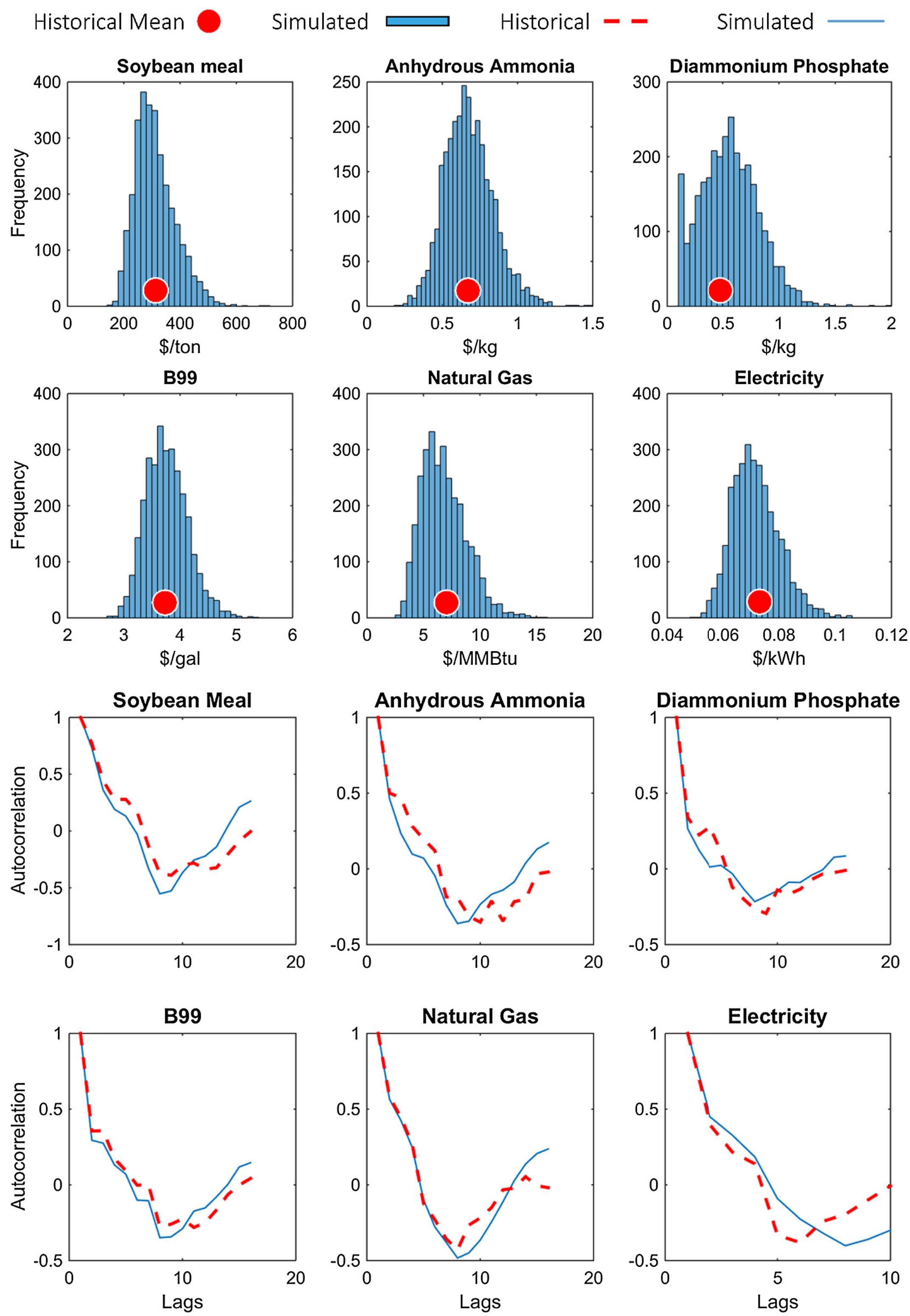

Fig. 3. Top panels: frequency histograms of simulated price data from 1000-run ensemble, with historical means (2000–2015) indicated by red circles. Bottom: Comparison of time series autocorrelation for historical annual commodity prices (dotted red line) and prices simulated by the VAR and regression models (solid blue line). In general, the models accurately reproduce historical price dynamics. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

between resource consumption, global warming potential (GWP) and financial viability. In particular, a more closed loop system that recovered nutrients and energy and never sold algal meal was associated with both a significantly lower GWP (121.4%) and NPV (−$144 million) than a plant that only sold algal meal (GWP: 216.5%; NPV: −$105 million).

Table 3
Annual financial benefits associated with anaerobic digestion/CHP and the sale of algal meal under different price conditions. In general, the sale of algal meal far outweighs the combined benefits associated of nutrient and energy production.

	Production		Prices ($/unit)			Annual value ($ millions)		
	Algal meal	Nutrient & energy recovery	Low	Mean	High	Low	Mean	High
Electricity (kWh)		7.48E+07	0.047	0.072	0.12	3.52	5.39	8.98
Natural gas (MMBtu)		2.41E+05	2.05	6.83	17.54	0.49	1.64	4.22
Anhydrous ammonia (kg)		7.89E+06	0.12	0.68	1.49	0.95	5.37	11.76
Diammonium phosphate (kg)		1.82E+06	0.1	0.56	1.91	0.18	1.02	3.47
Algal meal (tons)	7.83E+04		132	312	713	10.34	24.43	55.83

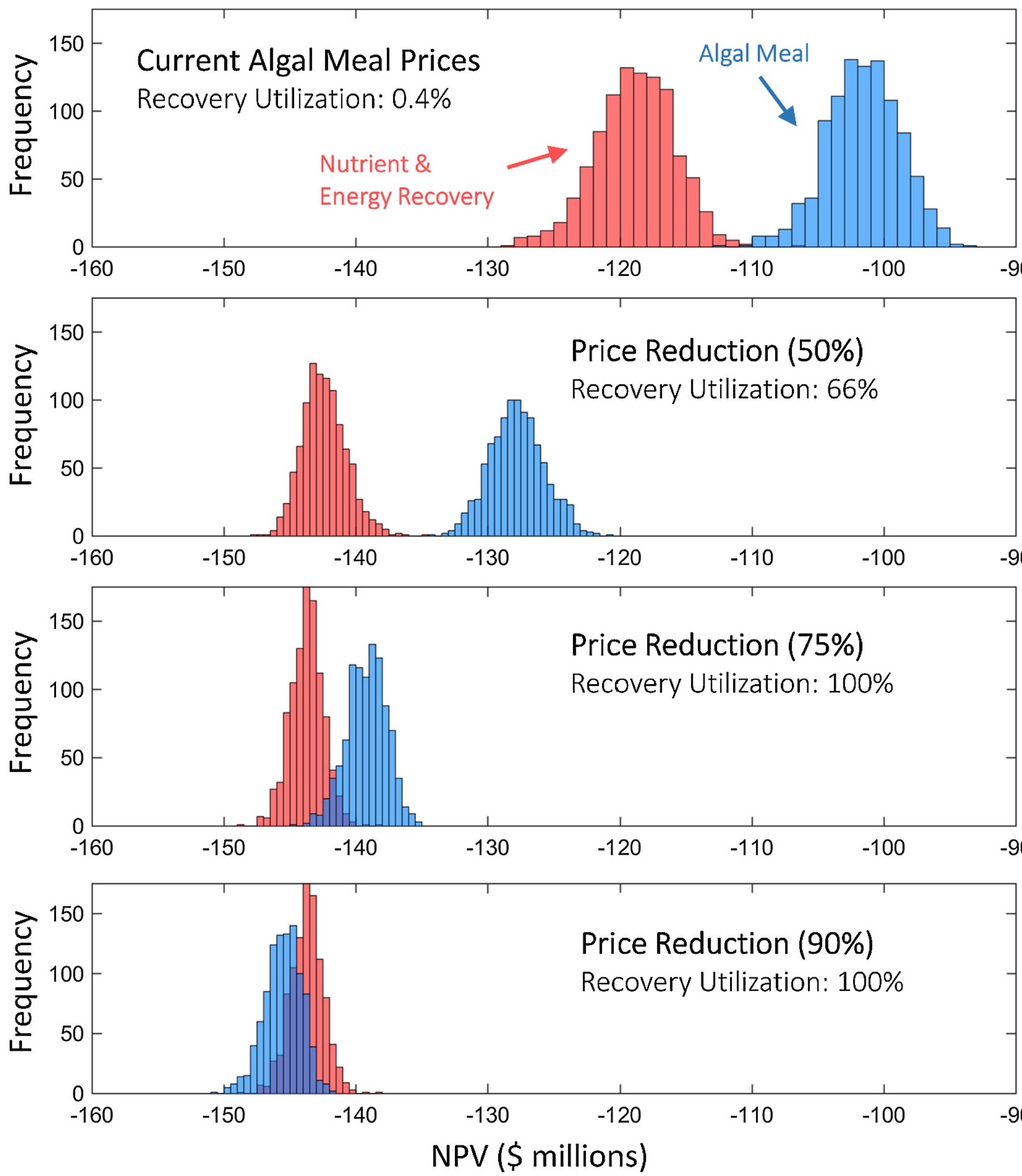

Fig. 4. NPV distributions for: 1) a plant that invests in anaerobic digestion/CHP and has the ability to recover nutrients and energy (red); and 2) a plant that does not invest in additional infrastructure and only sells LEA as algal meal (blue). Recovery utilization indicates the fraction of years over the ensemble simulation in which the flexible plant forgoes the sale of algal meal in order to recover nutrients and energy. Algal meal prices have to fall roughly 90% to justify investment in anaerobic digestion/CHP. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. Sensitivity analysis

There are a number of important caveats to this study's use of ROA to value operational flexibility at algal biofuel plants and explore financial tradeoffs between investment in anaerobic digestion/CHP and algal meal production. Key assumptions were that commodity prices are not subject to any permanent changes in mean or variance (e.g., a gradual increase or decrease in the inflation adjusted price of energy, nutrients, and/or algal meal); nor were prices of different commodities subject to changes in cross-correlation. Such changes are difficult to predict, hence their exclusion from our initial commodity price modeling. However, in an energy industry increasingly subject to technological and regulatory disruption, price non-stationarity is a distinct possibility.

Another downside of the assumption of price stationarity was that it precluded any potential for prices to change in response to market feedbacks. For example, if, through a combination of process improvements and the sale of LEA as algal meal, algal biofuel plants became financially viable, it is conceivable that economy wide production would scale relatively quickly. Especially in markets with low volume, this could put downward pressure on prices. Several previous studies have noted the potential for this type of saturation in markets for high value co-products of algal biofuel plants, including algal meal (Beal et al., 2015; Gerber et al., 2016; Stephens et al., 2010).

The potential for future price declines in algal meal as a function of market saturation motivated the use of sensitivity analysis to evaluate associated impacts on the real option value of anaerobic digestion/CHP. Fig. 4 shows the impact of a gradual decline in the price of algal meal on the distribution of NPVs for both plant configurations considered (i.e., one that invests in anaerobic digestion/CHP (red), and one that only sells LEA as algal meal (blue)). At current algal meal prices, the anaerobic digestion/CHP facilities were only used in 122 (0.4%) of the 30,000 total simulation years. As the price of algal meal fell, utilization of nutrient and energy recovery increased; at a 50% reduction in algal meal prices, utilization of recovery facilities occurred in roughly 66% of simulation years. But, NPV distributions for both plants shifted downward, because a substantial source of plant income- selling algal meal-had become less lucrative. At a 75% reduction in algal meal prices, nutrient and energy recovery occurred in 100% of simulation years. Note that, at this point, even though the plant switched completely away from selling algal meal due to price incentives, the mean NPV for the plant with anaerobic digestion/CHP was still considerably lower. This was due to the additional up-front capital costs associated with an investment in plant flexibility.

As the utilization of nutrient and energy recovery increased in response to falling algal meal prices, the NPV distributions converged. The bottom panel of Fig. 4 shows that at a 90% reduction in algal meal prices, the mean NPV for the plant with anaerobic digestion/CHP finally eclipsed the mean NPV for the plant using LEA to produce algal meal only. Overall, this sensitivity analysis suggests that relatively small decreases in the price of algal meal are required to incentivize a plant *with existing anaerobic digestion/CHP facilities* to recover nutrients and energy. However, a nearly complete collapse in the market for algal meal is required to actually incentivize up-front investment in this added flexibility, due to the substantial capital costs required. Note as well, that in no case did either plant appear cost competitive (have a positive NPV), even incorporating generous assumptions regarding project financing, algal growth rates and lipid content. However, it is acknowledged that the plant design considered here might not be state-of-the-art and may leave out a number of process improvements (Vadlamani, 2014; Zhao, 2015) that have been shown to improve project economics. This study represented the first attempt to bring ROA into the technical knowledge base surrounding the design and operations of algal biofuel facilities. Thus, there are number of other plant configurations that warrant further consideration. The modeling framework could also be used to assess: alternative conversion processes (i.e., hydrothermal liquefaction); plant siting (e.g., co-location with wastewater treatment plants); and the implications of gradual technical improvements over a plant's lifetime (e.g., increasing algal growth rates and lipid content).

3.4. LCA/TEA for a dynamic system

Even though current commodity price dynamics did not appear to support investment in anaerobic digestion/CHP, there was still considerable interest in demonstrating how the ROA approach can improve understanding of system dynamics, especially with regard to environmental performance.

Fig. 5 shows how algal meal prices, and the corresponding utilization of nutrient recovery and on-site energy production, affected the GWP of an algal biofuel plant that invested in anaerobic digestion/CHP. At current algal meal prices, the plant effectively used LEA only to sell algal meal. As a consequence, it was associated with a nearly static annual GWP of 216.5%. As the price of algal meal prices declined, the plant began to switch more frequently between modes of operation. This had two effects—first, it lowered the plant's mean GWP; but it also widened the uncertainty around this value. The plant's mean value continued to decrease, while its distribution widened, until utilization of nutrient recovery and on-site energy production reached a threshold of more than 50% of the total 30,000 simulation years. Beyond this point, the plant's GWP continued to decrease, but its distribution narrowed, ultimately collapsing to a single static value (121.4%) when utilization of recovery facilities reached 100%.

There was also interest in understanding how year-to-year changes in price dynamics could create alternating, extended periods of low and high environmental impacts in cases where commodity prices encourage frequent operational switching (i.e., where algal meal prices fall 30–60%). This motivated more detailed exploration of a scenario in which mean algal meal prices fall 45%. For a plant with added investment in anaerobic digestion/CHP, this fall in algal meal prices precipitated much more frequent recovery of nutrients and energy, with utilization climbing to roughly 50% (i.e., 15,000 out of 30,000 years).

Fig. 6 illustrates the dynamic operation of this algal biofuel facility in response to fluctuations in market prices for energy and agricultural commodities over a single 30-year simulation run in which algal meal prices were on average 45% lower. Beige bars indicate periods in which the plant operator was incentivized to recover nutrients and produce energy on-site via anaerobic digestion/CHP. During these periods, which are typically associated with high energy prices and low algal meal prices, the environmental footprint of the plant was lower (biodiesel production has a GWP of 121.4%). White bars indicate periods in which the plant operator was incentivized to use LEA to sell algal meal. During these periods, which were usually associated with low energy prices and high algal meal prices, the plant had a GWP of 216.5%. Thus, under frequent operational switching, the associated greenhouse gas benefits of operating the algal biofuel facility were dynamic, depending directly on fluctuations in commodity prices. This has interesting implications for the operation of algal biofuel plants in order to reduce life cycle emissions. For example, if plant operators were eligible to receive government incentives (e.g., production tax credits) for meeting greenhouse gas emissions criteria, it could incentivize a plant operator to switch to anaerobic digestion/CHP for a certain number of months per year. However, the timing of this switch should be optimized to take advantage of favorable price conditions (i.e., low algal meal prices and/or high nutrient and energy prices).

3.5. Future research

Based on the results of this study, a number of topic areas for future research are suggested. First, ROA should be used in a similar manner to assess the potential of alternative thermochemical conversion pathways, namely hydrothermal liquefaction. ROA should also be used to perform a more in-depth investigation of

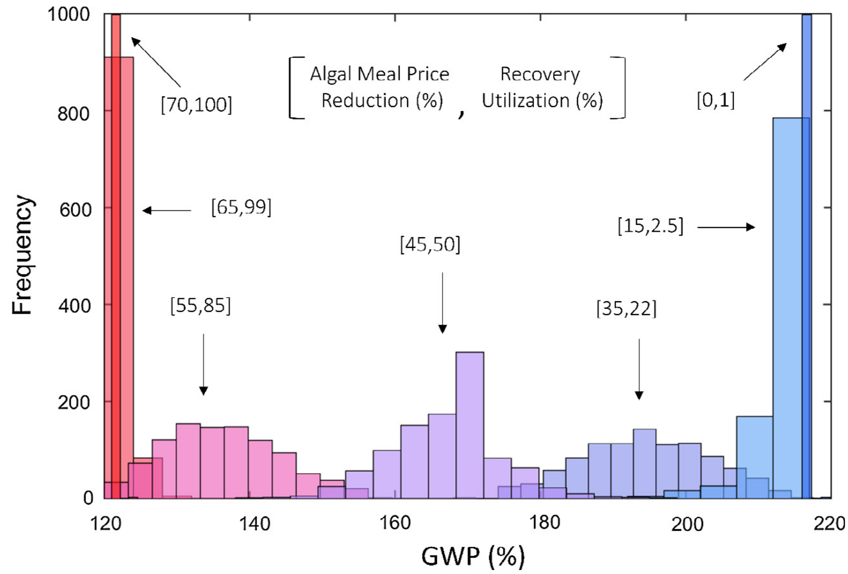

Fig. 5. GWP distributions for a plant that invests in anaerobic digestion/CHP and has the ability to recover nutrients and energy. As the price of algal meal falls, the plant's utilization of nutrient and energy recovery increases and its GWP falls. Initially, GWP distributions become wider (more variable) until the plant begins to employ anaerobic digestion/CHP a majority of the time.

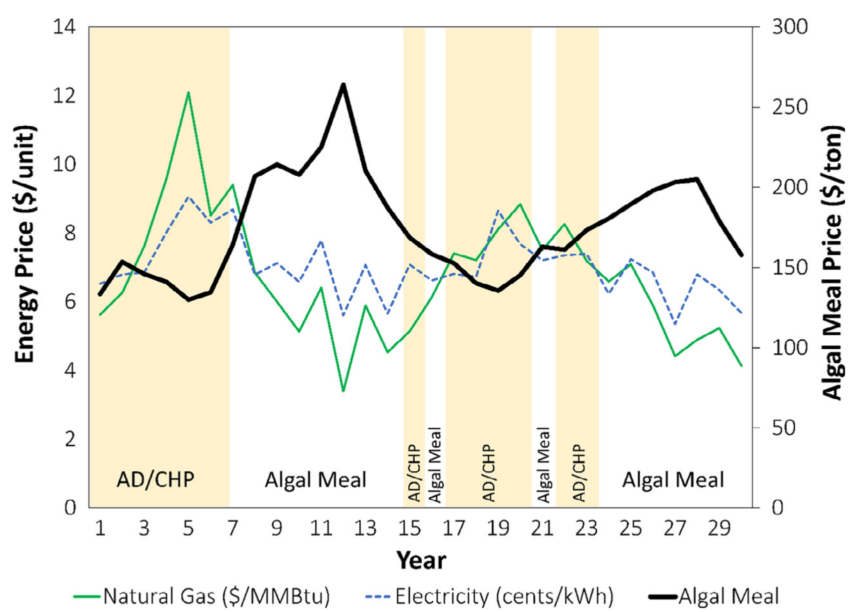

Fig. 6. Dynamic operation of an algal biofuel facility in response to changes in market prices. Beige bars (typically associated with high energy prices and low algal meal prices) indicate periods in which the plant operator is incentivized to recover nutrients and produce energy on-site via anaerobic digestion/CHP. These periods are associated with lower resource consumption and GWP. White bars (typically associated with low energy prices and high algal meal prices) indicate periods in which the plant operator is incentivized to use LEA to sell algal meal. These periods are associated with higher resource consumption and GWP.

how non-stationarity in commodity prices could impact plant design and operations. Areas of particular interest are: the potential for increased regulation of greenhouse gas emissions (e.g., a carbon tax); fertilizer (phosphorous) shortages; and disruptive market forces that temporarily or permanently alter correlations among prices for energy and agricultural commodities.

4. Conclusions

This study demonstrated the utility of integrating real options analysis (ROA) and traditional LCA/TEA modeling in the design of cost-competitive algal biofuel production pathways. Our analysis examined the value of an up-front investment in anaerobic digestion and combined heat and power (CHP), which gives plant owners additional flexibility in using lipid-extracted algae (LEA). Results suggest that this particular added investment does not improve plant NPV, due to current commodity price dynamics. Nonetheless, this study establishes ROA as a valuable approach for algal biofuel plant design, one that may become increasingly useful in the future as the technology nears commercial viability.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.biortech.2016.11.116.

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