Beyond life cycle analysis: Using an agent-based approach to model the emerging bio-energy industry

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Abstract—**Life cycle analysis (LCA) provides a methodology to quantify the environmental impacts of a product or process throughout its entire supply chain. However when used alone, this approach fails to account for the local variability in non-homogeneous systems. Agent-based modeling (ABM) can be used to supplement life cycle analysis to account for these variances. Using spatially-explicit input parameters, a hybrid LCA / agent-based emission modeling framework was built for a theoretical farm region. Using market and policy input parameters, the development of the switchgrass biofuel and bio-electricity markets were analyzed at the local level. Though this research is currently in an early stage of development, this hybrid LCA/ABM approach has been shown to be a useful tool for assessing small scale variability and interaction amongst variables.**

***Index Terms*—Agent-Based Modeling, Life Cycle Analysis, Decision Making, Biofuels**

I. Introduction

DUE in part to concerns regarding anthropogenic climate change and resource scarcity, scientists have developed methods to more fully assess a product's impacts on society and the environment [1, 2]. Life Cycle Analysis (LCA) is a process that quantifies the impacts associated with a product over its entire lifetime (material extraction, fabrication, use and disposal) [3]. This methodology can quantify hidden impacts in a supply chain that wouldn't be considered in a traditional use-phase analytical approach. LCA allows an individual to compare two or more products based on the environmental impacts of each; allowing them to make an informed sustainable choice [4, 5].

One criticism of life cycle analysis is that it fails to account for variability in data values that may result in an inaccurate representation of a particular study area [6]. For example, to conduct a LCA for the production of one bushel of corn, one may choose to specify a representative soil type and an average crop yield for a particular region. While these assumptions simplify the assessment process, they may lead to an inaccurate representation of the system being analyzed. Some soils in the study region may drain better than others, resulting in varying crop yields across the study area. Variances in crop yields affect production costs, which in turn affect the impacts of subsidies and market allocations.

Another example would be to model the impacts of fertilizer runoff from a study area with average values for nitrogen application rates and soil properties. However, the specific characteristics of the land cover and soil properties at buffer areas closest to the rivers may have a larger impact on overall river nutrient loading than an estimate of average fertilizer and soil values for the entire study region. It is difficult to incorporate these important spatially-explicit factors within a conventional life cycle analysis, thus a modified approach that can account for these variances may be appropriate.

II. Agent–Based Modeling

Researchers in many disciplines have begun supplementing LCA with agent-based modeling (ABM) [7, 8]. Agent-based models are constructed by building entities that represent the individual actors in a system (agents). Each agent is programmed with its own parameters, variables, and rules. Model scenarios are then executed, and the interactions among agents are monitored. Interestingly, these interactions often give rise to emergent phenomena that can't be predicted by observing the behavior of each agent individually [9]. This process can be repeated with all possible iterations of the input parameters to assess the sensitivity of system development under various conditions. ABM-enhanced LCA can produce system-wide results much like traditional LCA, but the agent-based analysis does so from a "bottom-up" approach as opposed to a "top-down" approach. By capturing the nuanced variability in data at the individual scale, ABM-enhanced analysis can more accurately represent a system.

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III. CASE STUDY: SWITCHGRASS BIOENERGY

In 2007, the United States Congress passed the Energy Independence and Security Act (EISA) which mandates the production of 36 billion gallons of bio-derived ethanol by 2022 [10]. Though this mandate will be met largely with corn ethanol production, 16 billion gallons of that total must come from cellulosic sources. Switchgrass is one popular candidate crop for the cellulosic portion of the EISA mandate [11], and can also displace coal in electricity generation through co-fired combustion. Biomass co-fired generation is already occurring on a utility scale, but cellulosic ethanol production is still in an early phase of development [12].

Because the infrastructure for cellulosic ethanol has not yet been established, it is difficult to assess the environmental impacts of this system with conventional life cycle analysis. However, "what if" scenarios can be analyzed with ABM-enhanced LCA and can help inform the decision-making process associated with infrastructure construction. Additionally, policy and market parameters can be introduced into the ABM-enhanced model, and system performance can be evaluated under these extrinsic factors. Policy impact analysis has already been used to study natural systems [13], and would be beneficial if applied to the developing biofuel industry. Data from real world agent-based model scenarios can provide feedback for decision makers preemptively, instead of employing a costly "trial and error" approach.

IV. THE MODEL

A. Overview

Currently, our model is in the proof of concept phase. At the time of this publication, the scale of our agent-based modeling framework focuses on the interactions between farmers, bio-fuel refineries, and co-fired electric generators (Fig. 1). However, as the model develops, full life cycle impacts will be assessed. Also, it is important to note that the eventual results from this model will need to be compared to data collected from real farming systems to verify applicability.

To demonstrate the proof-of concept, a theoretical study region was constructed. The region consists of agents assigned to one of three classes: farmers, bio-refineries, or electricity generators. Agents in each class have variables unique to their class (farmers have crop yields, generators have heat rates, etc.). It is important to note that each agent within a class can have a unique set of values for each of the variables (not all farmers have the same yields, and generators may have different heat rates based on the technology employed, etc.). The values assigned to each particular agent will eventually be derived from agent-specific real-world data. However, for the proof-of-concept model, the values were normally distributed around values collected from external sources (the data used are thus placeholders for real data after further model development).

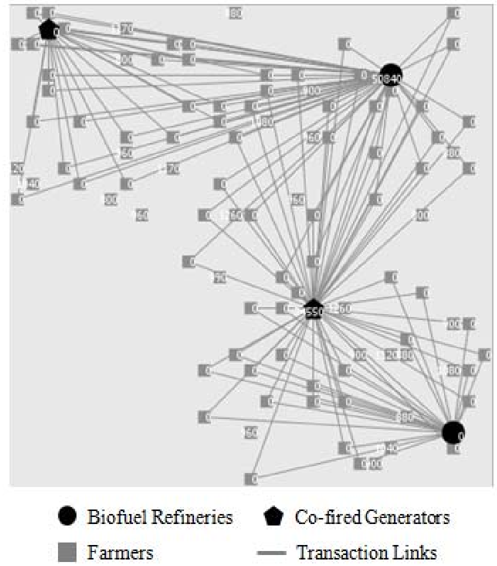

Figure 1: Agent-based switchgrass supply chain model

B. Farmers

The farmers are the most important agent class in this model. Their land allocation strategies, farming practices, risk tolerance, social influence, soil type farmed, proximity to waterways, and other parameters dramatically influence environmental performance and market development for the study region. For the proof of concept model, each farmer was randomly assigned a farm size, crop land-use allocation, fertilizer application rate, and location. Farmers were also assigned risk tolerance (willingness to change from current annual crops to perennial energy crops) and a social acceptance threshold (the minimum number of farmers in their network that must adopt switchgrass before they take action). Farmers were also programed to seek maximum profits by selling their harvested switchgrass (if any), to the refinery or electric generator bidding the highest price.

Environmental parameters (soil type, drainage properties, etc) were assigned to each farmer by extracting these values from theoretical geographic information system (GIS) data layers at the location of each farm (Fig. 2). Through further model development, these parameters will be used to weight each farm's impact when determining overall system performance. For example, farmers situated on uncultivated land may decide to convert this native land for switchgrass production under high price incentive scenarios. The resulting loss of native carbon sequestration can be incorporated into the model. The land conversion practices of farmers located near water bodies may be weighted stronger than others when assessing system nutrient loading. Many other calculations can be done with these ABM-enhanced LCA data.

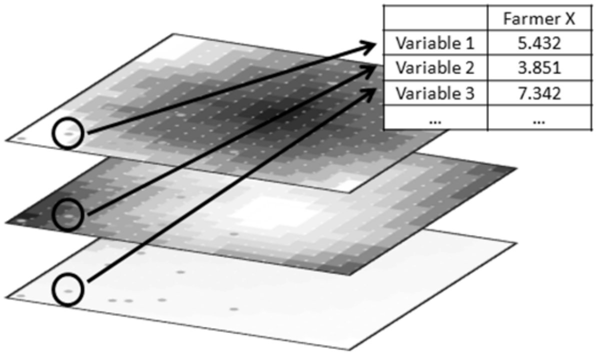

Figure 2: GIS data layer extraction for farmer environmental parameters.

C. *Biofuel Refineries*

Refineries are assigned to a geographic location in the study area which impacts feedstock transportation emissions. Each refinery was assigned a conversion efficiency (liters of ethanol per tonne of switchgrass) and process energy intensity. Future versions of the model will include a time dependency for these parameters to analyze the impacts of learned efficiency and technology development. Refineries set a maximum feedstock purchase price based on current market conditions including the price of gasoline and ethanol subsidies. Because the study area is assumed to be small relative to the national market (and thus an individual refinery can't dramatically affect market prices by altering production), they will continue to produce ethanol as long as they are able to purchase feedstock.

D. *Co-fired Electric Generators (Utilities)*

Electricity generating agents are assigned a geographic location in the model, which affects biomass transportation emissions. They are individually assigned a heat rate (BTUs of fuel energy per kilowatt-hour of electricity) and a process energy intensity which can also improve with time (as in the refinery agent class). Generators set a maximum feedstock purchase price based on market conditions including the price of coal and biomass subsidies. Because the study area is assumed to be small relative to the national market, they will convert all purchased biomass into electricity.

E. *Global Variables*

System parameters that are not agent-specific are also included in the model. These include transportation emissions per cargo ton-mile, market prices, policies and incentives. Actors that control these parameters are not modeled as agents, but their decisions shape the model by controlling other agent interactions. A table of global variables and their qualitative effects on the model are listed in Table 1.

F. *Agent Interactions*

Farmer agents decide at the beginning of each growing season whether to continue their previous year's crop land allocation or to adjust based on risk tolerance, market conditions and incentives. The growing season is simulated and switchgrass carbon sequestration is calculated. At the end of the growing season, the model simulates transactions between farmers, and refineries/utilities based on market conditions. As transactions are made, switchgrass transportation emissions are modeled based on the distance between the farmer and the customer. After distribution, the utilities combust the switchgrass to produce electricity and these emissions are recorded. Bio-refineries make ethanol and process emissions are recorded. Finally, the carbon content of the fuel is calculated to account for the tailpipe emissions when the fuel is eventually used. An outline of this process is shown in Fig. 3. Further versions of the model will assess

TABLE 1

Domain	Variable	Units	Impact
Markets			
	Price - Gasoline	$ / liter	As the price of gasoline increases, biofuel refineries can sell ethanol at a higher price and will purchase more switchgrass at a higher price.
	Price - Coal	$ / tonne	As the price of coal increases, co-fired generator operators will purchase more switchgrass at a higher price to displace more coal.
Physical			
	Heat Content - Coal	GJ / tonne	As the heat content of coal increases, fewer tons of coal are displaced by switchgrass due to the increased fossil fuel energy density
Policy			
	Coal Subsidy	$ / tonne	As the subsidy for coal increases it becomes less economical to purchase switchgrass for electricity generation.
	Gasoline Subsidy	$ / liter	As the subsidy for gasoline increases, ethanol becomes less cost competitive and biofuel refineries will offer lower prices for feedstock switchgrass.
	Farmer Annual Crop Subsidies	$ / hectare or $ / tonne	As the subsidies for various annual crops (corn, soybeans, etc) increase, farmers are less likely to plant switchgrass.
	Ethanol Production Subsidy	$ / liter	As the subsidy to produce ethanol increases, biofuel refineries are able to offer higher feedstock prices to famers.
	Biomass Electricity Subsidy	$ / MWh	As the subsidy to produce biomass-derived electricity increases, utilities are able to offer higher feedstock prices to famers.
	Farmer Switchgrass Subsidy	$ / hectare or $ / tonne	As the subsidy to plant switchgrass increases, farmers will plant more switchgrass as it becomes cost competitive with other crops.

emissions beyond carbon dioxide, and will also model nutrient loading and annual crop displacement scenarios.

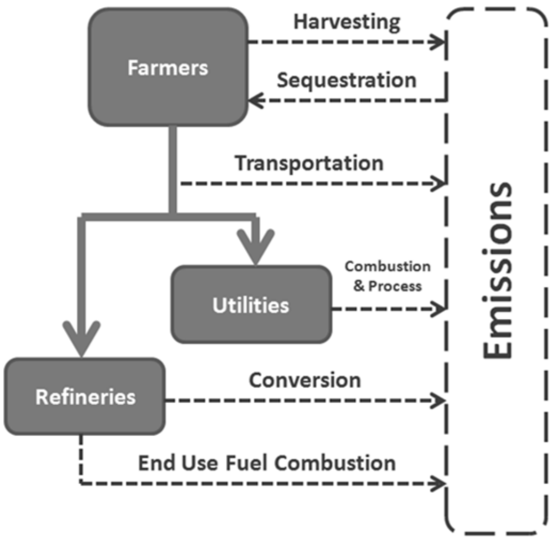

Figure 3: Schematic of switchgrass mass flow and emissions

V. RESULTS

Because this model is in a proof-of-concept phase and is applied to a theoretical case study region, definitive results cannot be produced at this point. Further work will also be required to correlate model results with "ground truth" when a real-world study region is identified. However, at this point, our ABM-enhanced LCA model already shows some distinct advantages over a traditional LCA approach. Agent-based methodology highlights the complex interactions amongst individual variables. To discuss these interactions, it is important to consider how variables are assigned. Table 2 outlines the differences between variable assignments between a traditional LCA approach and our ABM-enhanced LCA.

TABLE 2

Agent	Category	Methodology	
		LCA	LCA + ABM
Farmer			
	Sequestration	Fixed	Fixed
	Harvesting	Fixed	Depends on farming practices
Transportation			
	Miles	Fixed	Depends on farm distance
Biofuel Refineries			
	Process Emissions	Fixed	Depends on efficiency and technology
	Fuel Combustion	Fixed	Fixed
Electric Generators			
	Process Emissions	Fixed	Depends on technology
	Combustion	Fixed	Depends on heat rate and technology

Many variable interactions can be noted from the ABM-enhanced approach. For example, subsidies can indirectly impact feedstock transportation emissions. Refineries and generators compete for switchgrass feedstock based on subsides and prices they receive for biofuel and electricity respectively. Consequently, these subsidies and prices affect the price at which each refinery or generator is willing to purchase switchgrass. A strong biofuel subsidy will allow bio-refineries to purchase switchgrass at a higher price than what is offered by the electric generators. Consequently, farmers will sell (and transport) their switchgrass to the refinery despite the fact that a generator may be geographically closer. Thus, the strong subsidy will increase the feedstock transportation emissions due to longer distribution trips. ABM-enhanced LCA captures this parameter interaction by adjusting the feedstock ton-miles associated with the scenario automatically.

Many complicated variable interactions like the previous example can be explored with the ABM-enhanced approach. However, it is incredibly important to note that these interactions are scenario-specific. An identical variable change can produce different results in different scenarios. Consequently, our work will not seek to provide overarching policy recommendations or market incentives for switchgrass bioenergy development. However, decision makers will be able to use this modeling tool to determine appropriate actions for the development of bio-energy systems within their particular jurisdictions. This bottom-up approach to constructing bio-energy supply chains will hopefully allow for sustainably optimal bioenergy development.

VI. ACKNOWLEDGMENT

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