A Spatial-Dynamic Model of Bioenergy Crop Introduction in Illinois

Jürgen Scheffran

Adjunct Associate Professor
Program in Arms Control, Disarmament and International Security (ACDIS) and
Center for Advanced Bioenergy Research (CABER)
University of Illinois at Urbana-Champaign, Champaign, IL 61820
scheffra@uiuc.edu

Todd BenDor*

Assistant Professor
Department of City and Regional Planning
University of North Carolina, Chapel Hill, NC 27599
bendor@unc.edu

Yun Wang

Ph.D. Candidate
Department of Geography
University of Illinois at Urbana-Champaign, Urbana, IL 61801
yunwang@uiuc.edu

Bruce Hannon

Professor
Department of Geography
University of Illinois at Urbana-Champaign, Urbana, IL 61801
yunwang@uiuc.edu

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*Corresponding author: Department of City and Regional Planning, University of North Carolina at Chapel Hill, New East Building CB #3140, Chapel Hill, NC 27599. Email: bendor@unc.edu, Ph: 919-962-4760, fax: 919-962-5206

Abstract

Growing concern about climate change and energy security has led to increasing interest in developing renewable, domestic energy sources for meeting electricity, heating and fuel needs in the United States. Illinois has significant potential to produce bioenergy crops, including corn, soybeans, miscanthus (*Miscanthus giganteus*), and switchgrass (*Panicum virgatum*). However, land requirements for bioenergy crops place them in competition with more traditional agricultural uses, in particular food production. Additionally, environmental and economic conditions, including soil quality, climate, and variable agricultural costs, vary significantly across Illinois. The intent of this study is to examine the spatial and economic conditions necessary for introducing bioenergy crops into the Illinois landscape. In this paper, we develop a spatial dynamic model to explore the process by which individual farmer agents optimize profits through crop selection and cost minimization. This dynamic agent-based modeling approach will allow us to determine the optimal spatial arrangement of crops throughout Illinois as it is influenced by several factors, including the use of subsidies, changes in travel costs and crop demand, and the introduction of new ethanol production plants. This article discusses model development and specification, and outlines future calibration procedures and scenario tests that will be formalized in future work.

Keywords: Land use change, bioenergy crops, renewable energy, spatial dynamic modeling, geographic information systems (GIS), agent-based modeling

Introduction

Biomass can contribute to a variety of energy uses, including electricity production through incineration and refinement into biogas biofuels, including ethanol and biodiesel (Rosillo-Calle et al. 2006). On the global level, about 79% of all renewable energy is generated from biomass, corresponding to 10.4% of global energy use (in comparison, nuclear power provides 6.5%; The Economist 2007). Bioenergy is intended to be climate-neutral since the carbon emitted during energy use has been initially sequestered by plants from the atmosphere.

Our study examines the feasibility of introducing alternative biomass energy sources in Illinois. In particular, we examine two promising high-yield perennial grasses, miscanthus (*Miscanthus giganteus*) and switchgrass (*Panicum virgatum*), both of which are expected to play major roles as energy crops in the Midwestern United States. In order to examine patterns of land allocation among competing agricultural uses, we create and implement a spatially extended agent-based model that simulates the decisions of individual farmer agents throughout Illinois. Here, we intend to simulate the cultivation of four crops: miscanthus and switchgrass, which are harvested exclusively for bioenergy production, and corn and soybeans, which are used for both traditional and bioenergy purposes.

To provide a tool for decision-making in multi-actor environments, the project builds on an agent-based modeling approach developed for applications in economic and environmental management (Scheffran 2000; Scheffran and Pickl 2000; Ipsen et al. 2001; Scheffran 2002; Billari et al. 2006; Scheffran and Leimbach 2006). Additionally, this agent-based perspective on markets for biomass crops can simulate the boom and bust associated with changing agricultural prices and the over- or under-supply that often ensues.

We begin with a discussion of the bioenergy potential in Illinois and background information on the proposed bioenergy crops. Next, we discuss our data collection and processing efforts, followed by the creation, implementation, and testing of the farmer agent model. Future work will outline a series of policy tests, and will include a section detailing our conclusions and the implications of this research.

Bioenergy in Illinois

A study by Bournakis et al. (2005) analyzed economic impacts of 1% annual increases in the fraction of electricity generated from renewable resources, reaching at least 8% in 2012 and 16% in 2020. This study concluded that meeting these targets by 2020 would require construction of renewable energy facilities capable of delivering about 12.5 Terawatt hours (TWh) in 2012 and about 28 TWh in 2020. While these figures are quite high, Bournakis et al. (2005) noted that Illinois has considerable wind energy, biomass, and biowaste resources that could potentially be used to meet these targets. Brower et al. (1993) has also concluded that "homegrown biomass energy could create jobs in Illinois, keep energy dollars in state, reduce air pollution and soil erosion, and provide many other environmental benefits, all at competitive costs." Bioenergy crops also have the potential to not only displace coal in power plants and thereby reduce carbon emissions, but they also have a significant potential to sequester carbon in the soil in Illinois (Dhungana 2007). One popular method of bioenergy usage is the conversion of biomass into ethanol, an option that carries considerable economic and political weight within Illinois and is likely to experience rapid future growth. By the end of 2006, there were 110 ethanol refineries in operation and 73 under construction in the U.S. (Renewable Fuels

Association 2006). By end of 2008, the ethanol production capacity will be an estimated 42 billion liters per year and by 2030, it is estimated that ethanol may replace 30% of the current total petroleum consumption (Perlack et al. 2005).

Energy crops comprise a variety of perennial grasses and trees and are often produced using conventional agricultural practices. Perennial crops have the potential to improve environmental quality due to lower fertilizer requirements than corn and soybeans farmed under traditional practices. Additionally, extensive perennial root systems and winter harvest may also improve water quality, decrease soil erosion and increase soil organic matter. Here, we discuss two potential bioenergy sources that have been proposed to augment the use of corn in ethanol production, switchgrass and miscanthus.

Switchgrass (*Panicum virgatum*), also known as tall panic grass, Wobsqua grass, wild redtop, or thatchgrass, is a warm season grass that has historically been a dominant species of the central North American prairie. Switchgrass was determined to be a strong candidate crop for bioenergy production based on its resilience in poor soil and climate conditions, rapid growth characteristics and low fertilization and herbicide requirements (McLaughlin and Kszos 2005). According to a recent review, biomass productivity of switchgrass ranges from 9.9-23.0 t ha^{-1} in research trials, with an average of 13.4 t ha^{-1}. Several studies (McLaughlin and Kszos 2005; Perlack et al. 2005) assume that the rapid increases in switchgrass yields will continue, with innovative breeding efforts generating 20 t ha^{-1} switchgrass yields, an increase of 60 percent, by 2030.

Miscanthus (*Miscanthus giganteus*) is a perennial grass from East Asia that is genetically similar to sugar cane. The crop can photosynthesize well at low temperatures and attain high yields with low amounts of nitrogen input. Like switchgrass, miscanthus has been shown to be effective at carbon sequestration and soil quality improvement. Its utility for energy production has been explored in extensive test trials (Heaton et al. 2006) which indicate harvestable miscanthus yields range from 10-40 t ha^{-1} throughout Europe. In 2004 and 2005 miscanthus tests trials in Illinois, dry matter per unit area was significantly greater than for switchgrass. Peak dry biomass production of Miscanthus was highest in central Illinois (60.8 t ha^{-1} average), and decreasing to an average of 48.5 t ha^{-1} in southern Illinois, and 38.1 t ha^{-1} average in northern Illinois (Heaton et al. 2006). Earlier trials with miscanthus demonstrated little nitrogen contribution to runoff water and an overall decrease in water use (Beale and Long 1997; Beale et al. 1999).

The considerable variation in miscanthus yields is largely due to Illinois' North-South orientation, which leads to high levels of heterogeneity in soil quality, climatic conditions, and precipitation. For example, high soil temperatures and soil moisture coupled with few frost days, make southern and central Illinois generally more suitable to biomass crop production than northern Illinois (Heaton et al. 2006). Although it may be environmentally suitable, the attractiveness of biomass crops may be lower in central Illinois since the region produces corn and soybean yields that are much higher than in southern Illinois. This leads to land competition within the region. Additionally, the cost of transporting biomass from production regions to local power or ethanol plants may be significant and needs to be considered. Therefore, the production of biomass is more likely to be profitable (and therefore successful) in areas closer to the demand centers.

The profitability of cultivating specific crops varies significantly throughout space. Given this spatial heterogeneity, any study examining the viability of bioenergy sources must recognize that choosing among the alternatives is not an "either/or" alternative, but rather a matter of finding a mix of biomass crops that can be successfully harvested in a given area. Finding this mix means determining the spatial pattern of land that should be allocated to traditional agriculture and to biomass crops. Our study examines the feasibility and dynamics of introducing alternative biomass energy sources in Illinois using an agent-based, spatially explicit, model of farmer decisions to produce and harvest bioenergy crops.

Using geographic information systems (GIS) data on crop yields, agricultural land availability, and agricultural costs, we simulate the profitability of farmers based on their selected mix of crops. This mix generates revenue based on crop prices (determined by the relative supply from all other farmers simulated in the model), as well as costs associated with cultivating certain crops within different regions in Illinois. Farmers can then optimize their profit potential by changing their crop mix on a yearly basis in order to take advantage of more profitable crops. This model allows us to identify areas where it may be profitable to switch from conventional agriculture to bioenergy crop production. We focus our attention on the potential for cultivating miscanthus, as previous work has shown that it can be grown productively throughout Illinois and that it would be cost-effective to transport miscanthus yields to local processing plants. Our goal is to assess the conditions under which this may be the case, including an analysis of the role of market price and critical transportation distance to the next power or ethanol plant. We begin by discussing the data used to inform and parameterize our model.

Data Collection and Processing

Geographically referenced agricultural data were collected for the State of Illinois using a variety of sources. We begin by selecting an analysis unit size that facilitates the simulation of farmer behavior while maintaining computational tractability. Ideally, this would involve the collection of high resolution geographic data on individually controlled farms. However, data delineating farms or farm ownership is not available for the entire state of Illinois.

Given the resolution of several of our datasets, we select a unit of analysis corresponding to the size of one township. A township is a land unit originally created by the Public Land Survey System under Thomas Jefferson and is commonly established as a 6 x 6 mile area.[1] Although this unit size (which becomes our model cell size as described in the next section) is somewhat large, it stands as an important starting point for modeling farmer behavior.

Agricultural Land Use Data

We began by generating a land use map for the State of Illinois using U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Cropland Data Layer. Like most land use and land cover information, this data is collected annually using satellite imagery, specifically from the Thematic Mapper instrument on Landsat 5 and the Enhanced Thematic Mapper on Landsat 7 (Jensen 2000). The layer is aggregated to 13 standardized categories with an emphasis on agricultural land cover. Classification decisions are based on extensive field observations collected during the annual NASS June Agricultural Survey (NASS 2006). NASS uses broad land use categories to define land that is not under cultivation, such as non-

[1] Townships can be divided into 1 by 1 mile sections, which can be further subdivided into quarter sections and quarter-quarter sections. This is commonly the basis of legal definitions of land delineation throughout the Midwest and parts of the Western United States.

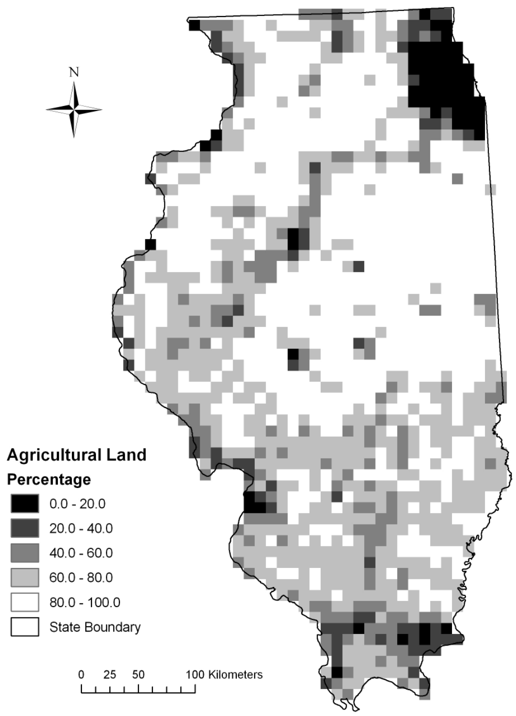
agricultural, pasture/rangeland, waste, wooded, and farmstead lands. Here, the classification accuracy has been found to be approximately 85% to 95% correct for agricultural-related land cover categories. The reference list of the categorization codes and land covers for IL is shown in Table 1. Although this data contains accurate information on land cover, no data identifying the land holdings of individual farmers is reported or derivable from this data layer.

Table 1: Land classification of USDA-NASS Cropland Data Layer for Illinois

Classification Code	Land Cover	Potential Land for Energy Crops
0	No Data	
1	Corn	X
4	Sorghum	X
5	Soybeans	X
24	Winter Wheat	X
25	Other Small Grains & Hay	X
26	Double-Cropped Win Wheat/Soybean	X
28	Oats	X
36	Alfalfa	X
43	Potatoes	X
44	Other Crops	X
54	State Code 564, Other Crops	X
61	Idle Cropland/Fallow	X
62	Pasture/range/ Non Agriculture	
63	Woodland	
81	Clouds	
82	Urban	
83	Water	
87	Wetlands	
88	Grassland	

Due to the discrepancy of the ground resolution of this base agricultural land use map (30 by 30 meters) and the resolution selected for this project (6 by 6 miles), the land cells on the base map were aggregated using the ESRI ArcToolbox GIS software (ESRI 2006). Here, the fraction of the agricultural land that can be used for growing bioenergy crops (marked with 'x' in Table 1) is estimated for each 36 square mile aggregate cell. Figure 1 reveals the heavy row crop agriculture in Central Illinois.

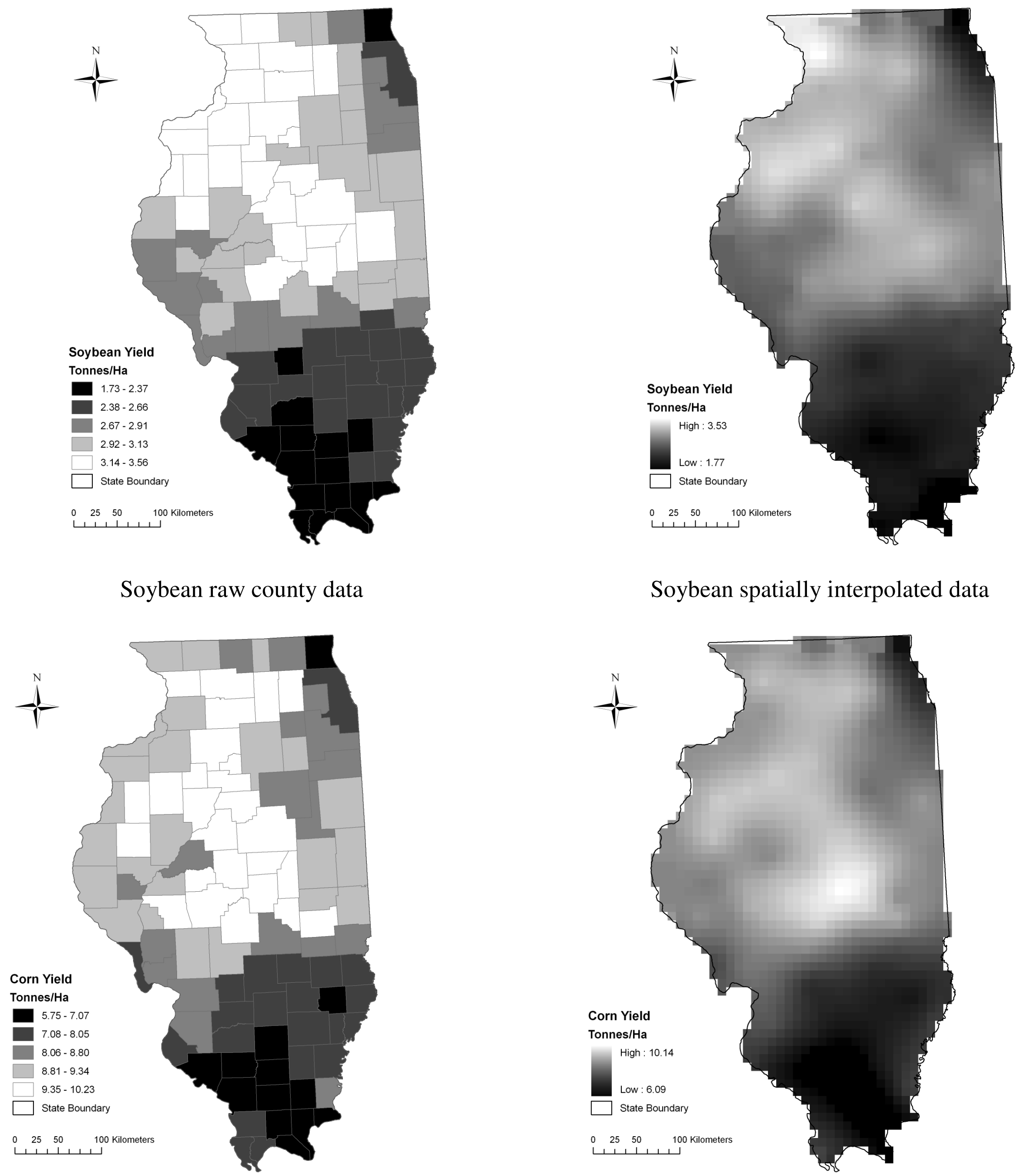
Figure 1: Agricultural Land in Illinois



Illinois Crop Yield Data

Soybean and corn production data were taken from the Illinois Crop Yields Historical NASS Database, which lists wheat, corn, and soybean yields for each county in Illinois between 1972 and 2004 (Sherrick 2005). A geographical distribution of yields was taken by taking a five year average of yields during a representative period between 1997 and 2001. This data was converted from bushels per acre measurements to metric tonnes per hectare using conversion constants from the Canada Grains Council 1999 Statistical Handbook (Canada Grains Council 1999). Since this data was collected at the County level, which is a lower resolution than our analysis, we performed a GIS spatial interpolation through a geostatistical analysis known as Kriging (spherical model; O'Sullivan and Unwin 2003). This technique interpolates the value of a variable at unobserved locations from values at nearby known locations, thereby allowing us to create a fairly accurate and continuous map of soybean and corn yields throughout Illinois at the township resolution (Figure 2).

Figure 2: Illinois Corn and Soybean Yields (1997-2001 Avg.)



Soybean raw county data

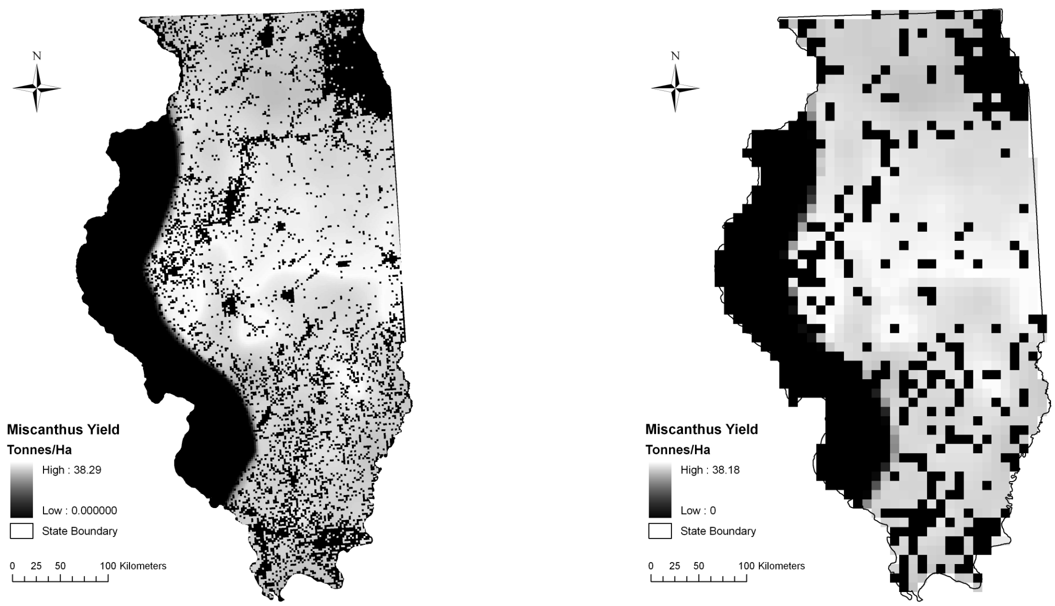
Soybean spatially interpolated data

Corn raw county level data

Corn spatially interpolated data

Given that switchgrass and miscanthus have not been planted extensively in Illinois (or elsewhere in the United States, for that matter), information on their growth patterns and harvesting costs is still relatively sparse. Potential miscanthus and switchgrass yield estimates, based on soil quality, climate, and other environmental conditions, were obtained from recent work by Khanna et al. (2005), and were aggregated to the township resolution. Likewise, estimates of the harvested biomass fraction actually taken off the field (rather than left to enhance soil quality) are 67% for miscanthus, 80% for switchgrass, and 98% for both corn and soybeans.

Figure 3: Miscanthus and Switchgrass Yields



Original miscanthus/switchgrass data | Aggregated miscanthus/switchgrass data

Source: Khanna et al. (2005)

Harvest Production and Cost Data

The value of production of corn and soybeans is estimated from the Illinois Crop Yields Historical NASS Database (NASS 2007), from which the average ‘value of production,’ the average amount of soy and corn sold multiplied by the average selling price, was calculated for 2000 through 2006. During this period, Illinois produced an average $2.604 billion worth of soybeans $4.072 billion worth of corn.

Harvest cost data for corn and soybeans were collected from the Illinois Farm Business Farm Management Association through the University of Illinois Farm Decision Outreach Council (FARMDOC 2007), which maintains cost records for corn and soybean back to 2001. These costs were divided into direct (fertilizer, pesticides, seed, storage, drying, crop insurance), power (machine use/lease/depreciation, utilities, fuel), and overhead (labor, building repair/rent/depreciation, insurance) costs. Here, harvest costs within Illinois vary by region, with the data being separated into northern, central (high and low productivity), and southern regions within Illinois (Figure 4). A six year average for each region was taken using 2001-2006 cost data, while high and low productivity areas were averaged in central Illinois.

Figure 4: Illinois Harvest Cost Regions

Source: FARMDOC (2007)

Miscanthus and switchgrass costs were estimated from the Illinois Interactive Agronomy Handbook (Hoeft and Nafziger 2006) based on similar, well established crops and were broken into capital, labor, and material cost categories.

This data collection and adjustment process yields four GIS maps showing expected yields for miscanthus, corn, switchgrass, and soybean crops throughout the State of Illinois. These maps are then used as geographically contextual input into the dynamic bioenergy model.

Model Design and Structure

System Dynamics and Agent-Based Modeling Frameworks

Understanding the dynamics of biofuel crop growth in Illinois is hindered by several factors. First, heterogeneous environmental factors across the State create a non-uniform environment for growing and cultivating crops of all types. Second, farmers are responsive to market signals that depend heavily on the ability and willingness of other farmers within the State to plant and cultivate biofuel crops. As a result, farmers act as agents, within a network of other agents, whose aggregate decisions can significantly alter the chances of biofuel crop success. These decisions are beholden to systemic delays, as well as complex spatial feedback effects due to strong environmental heterogeneity. In order to understand the complicated structure of this system, it is important to simulate the system as it is rendered spatially and dynamically. Moreover, it is important to understand how the individual decisions of farmer agents can impact the behavior of agriculture in the State as a whole.

Although they are empirically useful, long-term studies or experiments are often difficult to perform when observing complex ecological and economic systems, particularly when attempting to understand the possible future behavior of systems for which limited information is available. Here, representative models can help to fill knowledge gaps and assist in decision-making and policy-forming activities (Costanza and Voinov 2001).

While there are a variety of methods for addressing these questions, agent-based approaches have been shown to be particularly useful in understanding the behavior of a large number of agents as they make decisions and take actions on multiple levels (Billari et al. 2006). Moreover, multi-agent modeling techniques are also valuable for explaining how individual actors can adapt to system constraints through learning and negotiation processes (Kaitala and Munro 1995; Dockner et al. 2000; Scheffran et al. 2006). Although this type of modeling is quite advantageous, many agent-based modeling techniques tend to be quite technical and somewhat difficult to communicate to non-modelers. Here, we turn to system dynamics modeling techniques, a set of powerful simulation modeling tools that are effective at exploring systems as well as communicating research results. The approach facilitates involvement of stakeholders in model development, criteria setting and validation (mediated modeling, van den Belt 2004)

Over the last fifty years, the system dynamics modeling methodology has grown into a robust approach of simulation modeling that explicitly considers the information feedbacks governing interactions within systems. The capabilities of this particular technique have proven to be very useful in aiding policy decisions in industrial, social, and scientific systems (Forrester 1961, 1969, 1972; Ford 1999; Sterman 2000; Guo et al. 2001).

One advantage of this simulation modeling paradigm is that models can be easily communicated to a diverse audience. System dynamics models are commonly created and analyzed using an easily-understandable graphical programming language, thereby abstracting away many highly technical and mathematical aspects of the underlying differential equation models (see Ford 1999 and Sterman 2000 for more information on system dynamics).

As a result, using system dynamics as an educational tool has increased significantly (Costanza and Voinov 2001). This facet of the system dynamics methodology differentiates it from the technical rules of spatially arrayed Cellular Automata (CA) models, as well as other types of mathematical approaches to simulation modeling (see Wolfram 1994 for more on CA modeling). Although there have been several studies over the last several decades that incorporated spatial issues into system dynamics models, only recently have techniques been developed for explicitly representing dynamics as they occur in spatially extended systems (Maxwell and Costanza 1997; Deal and Schunk 2004).

We base our modeling technique on the structural framework of the Spatial Modeling Environment (SME), a software package created at the University of Maryland intended to bridge dynamic and spatial modeling (Maxwell and Costanza 1997; Voinov et al. 1999). In SME, a system dynamics model is replicated and embedded in spatial array of uniform grid cells, each of which are locally parameterized by GIS data in order to create a matrix of spatially relevant system dynamics models (similar to a GIS raster format). In the past, this has been useful since each cell (which acts as an individual agent) can gain information and material from neighboring cells, thereby expanding beyond the ability of traditional system dynamics software, such as STELLA® (http://www.iseesystems.com/) or Vensim® (http://www.vensim.com/), to simulate spatial variation through replicated models.[2] However, while the placement of each farmer within the landscape is important because it affects crop yield, the position of farmers

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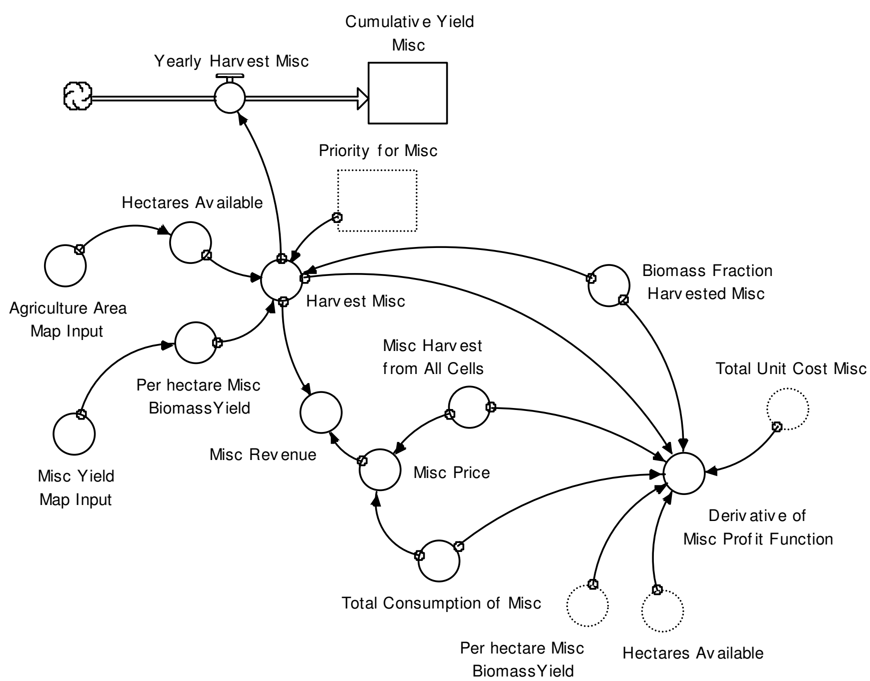
[2] Indices (Vensim) and array functions (STELLA) both allow users to rapidly incorporate multiple, identical structures into a system dynamics model.

within a set of neighboring cells is irrelevant; farmers harvest and sell crops on a market that extends well beyond their neighborhood within the Illinois landscape. As a result, we borrow from SME's structural framework (without actually using it) to create a new system that indexes the position of individual farmers in the landscape as well as their crop yields and costs.

Development of a spatial-dynamic model of biofuel cultivation began with the creation of a dynamic model representing a single agent (or farmer) in the Illinois landscape. In order to do this, we utilized the STELLA iconographic modeling software (for a description of STELLA see Costanza and Voinov 2001). We construct this model to focus on several important factors, including harvesting, prioritization of land devoted to individual crops, investment costs associated with cultivation, and farmer profit based on the mix of crops raised and their market prices. Figure 5 depicts the Miscanthus sector of the model, one of four crop-specific, but structurally identical, sectors. This sector models the ability and willingness of an individual farmer to grow, harvest, and profit from farming a mix of crops that they have chosen.

Figure 5: Miscanthus Sector of the Biofuel Model

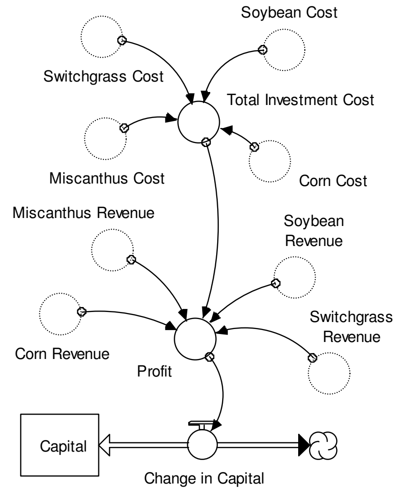


Here, the harvest (h) of each of the four simulated crops (index k) is given as,

$$h^k = AB_y^k f^k r^k \qquad \textbf{Equation 1}$$

Here, A is the available arable land area (hectares), B_y^k is the biomass yield per hectare (map input), f^k is the fraction of biomass growth that is actually harvested (several crops require that stubble be left on the field to aid in the growth of next season's crop), and r^k is the 'priority' given to crop k which is a unit-less fraction that, when multiplied with A, describes the area of a farmer's land that will be planted with a given crop. Given that r^k is the fraction of land in each crop, it follows that $\Sigma\, r^k = 1$ (the sum of all land fractions is the whole). Priority is a key variable, in that it determines the extent to which farmers cultivate multiple crops.

Figure 6: Total Profit Calculation



In order to calculate farmer revenue and profit for each crop, we need to estimate crop market prices and investment costs. We use the equilibrium price function derived in Scheffran (2006) which is the ratio between the funding D^k that all consumers together are ready to spend crop k (demand), and the total harvest $h^k = \Sigma_i h_i^k$ over all farmers i (supply):

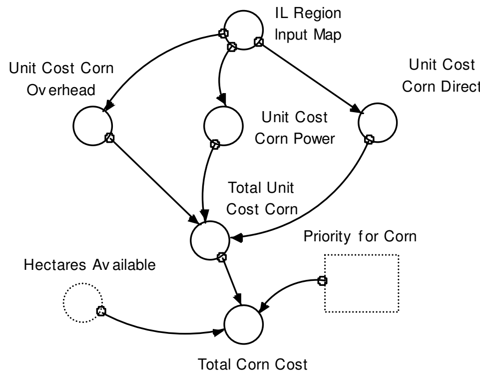
$$p^k = \frac{D^k}{h^k} \qquad \textbf{Equation 2}$$

Since price increases with demand and decreases with supply, this function combines the demand and supply relationships in market equilibrium. Thus, market prices for each crop are dependent on the total harvest supply, thereby requiring information from all agents. The function

$$V_i = \sum_k p^k h_i^k - C_i + S_i = \sum_k \left(\frac{D^k}{h^k} h_i^k - c_i^k r_i^k A_i + s^k h_i^k \right) \qquad \textbf{Equation 3}$$

calculates the net profit for each farmer i from selling the harvest h_i^k of each crop at a market price p^k, yielding revenue $p^k h_i^k$, diminished by the invested cost C_i to cultivate all of the crops, where c_i^k is the per hectare unit cost of harvesting for each crop. $S_i = s^k h_i^k$ is the "political" revenue from biofuels subsidies and carbon credits both of which are assumed to be proportionate to harvest (s^k is a US$ per ton unit subsidy). Capital accumulation occurs when revenue exceeds costs (positive profit) and depletion occurs when costs exceed revenues (negative profit).

Figure 7: Crop Production Cost Calculation



Costs are conceptualized as crop-specific, per-hectare unit costs that are accrued over the entire land area available. Here, we split unit costs into direct (c_m; fertilizer, pesticides, seed, etc.), power (c_p; machine use/lease/depreciation, utilities, fuel, etc.), and overhead costs (c_h; labor, building repair/rent/depreciation, insurance). These costs are then multiplied by the amount of land in the given crop (r^kA) to find the total investment costs for each crop k. These relatively simple formulations for calculating crop harvests, market prices, and farmer profits are duplicated for each of the four crops.

The primary source of dynamics within this model comes from shifting farmer decisions about the type and extent of their crop mix. Here, finding the right mix of crops is based on the profit farmers gain or lose from changing their relative priorities. In order to calculate how profit changes as priority changes, we take the derivative of the profit function V_i for each crop and farmer with respect to crop priority r_i^k:

$$v_i^k = \frac{\partial V_i}{\partial r_i^k} = \frac{D^k}{(h^k)^2} A_i B_{iy}^k f_i^k (h^k - h_i^k) - c_i^k A_i + s B_{iy}^k f_i^k A_i \qquad \textbf{Equation 4}$$

This demonstrates that marginal profit declines with an increasing total harvest. By using the derivative to formulate change in crop choices, farmers are seen to iteratively shift their investment in crops as they find crops that gain them higher profits. This decision model can be thought of as a gradient approach to shifting farmer priorities towards growing profits. In this case, farmers test how quickly small changes in the amount of planted crops can affect their profit on a yearly basis. If one crop yields a high rate of change, it behooves the farmer to increase the priority of that crop, while lowering the priority of other, less profitable crops. ν_i^k represents the change in profit from crop k for each unit increase in priority for that crop which also increases with demand.

Finally, we move on to the calculation of crop priority, shown in Equation 5. In many cases throughout Illinois (and the rest of the Midwestern U.S.), farmers invest their entire land area in one crop, usually either corn or soybeans. However, as biofuels are introduced into the market and government incentives begin to make cultivation of alternate crops viable, this may change.

Since the individual farmer is largely at the whim of market prices, their main tool for enhancing their own profit potential is the mix and extent of crops they produce. Here, change in corn priority is represented by a differential equation, the level of which adapts according to the profitability of that crop as given by:

$$\dot{r}_i^k = \frac{dr_i^k}{dt} = \alpha_i r_i^k \left(\frac{v_i^k - \sum_l r_i^l v_i^l}{\sum_l v_i^l} \right) \qquad \textbf{Equation 5}$$

where α_i is the rate at which farmers i can change their crop mix which is assumed to be the same for each crop k, r_i^k is the priority they are already placing on crop k, and v_i^k is the change in crop profit based on a change of priority for that crop. The term $\sum_l r_i^l v_i^l$ represents the priority weighted average of the marginal profit for each of the crops. Summing all of these gains together represents the average marginal profit from a crop based on the crop's priority relative to other crops. Since the priorities initially sum to one, this function increases priority r_i^k if v_i^k is greater than this average priority. If v_i^k is less than this weighted average, then this function decreases priority r_i^k. This function is then normalized by the sum of the profit derivatives $\sum v_i^l$. This "evolutionary game" (Hofbauer and Sigmund 1998) among competing crops also ensures that the sum of all priorities (crop land fractions) is equal to one, the entire farming area ($\Sigma\ r_i^k$=1).

Although, the farmer adaptation rate α is unknown, empirical tests using other, well established crops could likely be used to estimate how long farmers typically take to retool their operations. We estimate the adaptation rate as 1/10 years for all farmers, although this value can be adjusted on either an individual or regional basis.

Extending the Biofuel Model Spatially

This model, including the crop priority sector, profit and cost calculation sectors, and individual crop harvest and price sectors, simulates the behavior of an individual farmer agent. The lack of direct feedback between crop harvest and crop price in Figure 5 means that an individual farmer can only influence crop prices indirectly through their contribution to the total market supply of a crop. This model is arrayed in a 37 x 65 grid, with 1568 active grid cells representing individual farmer agents (the size of which represents one township) within the State of Illinois (Figure 1). Using a set of Python scripts (http://www.python.org/) developed for this project, every cell within the state was given a unique identification number, while input maps were processed such that each cell's spatial data values were linked to that cell number within a standard, non-spatial database. Equations from the STELLA model were then brought into Berkeley Madonna (http://www.berkeleymadonna.com/), a highly efficient differential equation analysis package with powerful indexing features. Model outputs were then processed through another set of Python scripts to yield a set of GIS maps describing change within each cell over the length of the simulation. By viewing and analyzing the output in this format, we can better understand the spatial dynamics of biofuel crop growth in Illinois.

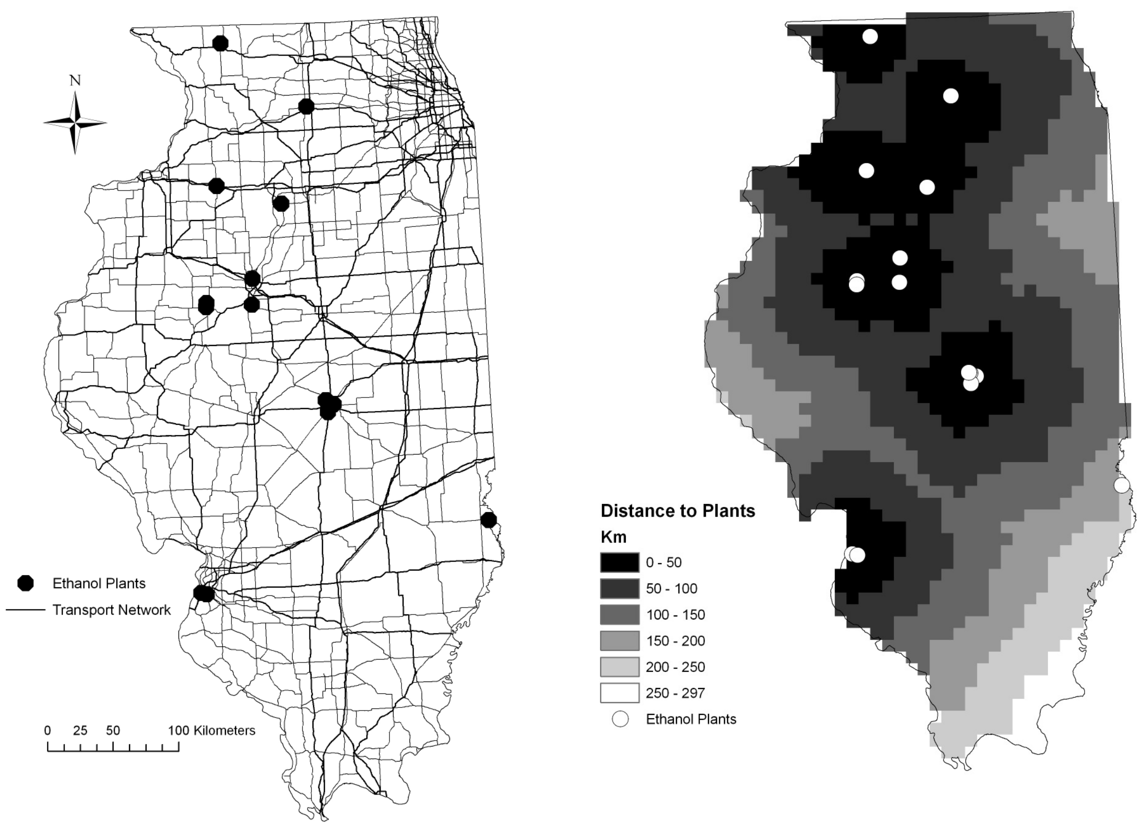
Planned Calibration and Scenario Tests

Future work will calibrate the model based on a corn and soybean mix throughout the State of Illinois. To adjust the model to the initial conditions without switchgrass and miscanthus, we use data on the production, price and distribution of corn and soybeans in Illinois (Sherrick 2005; FARMDOC 2007; NASS 2007). The actual fraction of corn and soybeans determines their initial priority p^k, their amount of production is used to calibrate the production function. After calibration, scenarios will include the integration transportation costs from each cell to nearby ethanol plants, as well as government subsidies for switchgrass and miscanthus.

Transportation Costs

The spatial framework will allow us to include the transportation costs to the next power plant or ethanol refinery which are subtracted from the profit function for each farmer. The transportation costs are calculated as the product of a constant per ton-mile charge and the amount of deliveries, plus the return trip cost. Using the approach developed in Khanna et al. (2006), the cost (originally in 1983 \$ and adjusted to 2007 US\$) of transportation of switchgrass or miscanthus per t-km are: $(1.12+0.07*d*) where *d* is the round trip distance in km between the on-farm storage area and the power plant. Figure 8 shows the location of existing ethanol plants in Illinois and the distance to these plants, which determine the transportation costs and are included in the cost calculation as an additional GIS layer.

Figure 8: Locations of and Distance to Illinois Ethanol Plants



A. Road network and ethanol plant map

B. Current distance to ethanol plants

Subsides and Carbon Credits

To study the impact of government policies, we also include the possibility of taxes, subsidies and carbon credits, both being proportionate to the amount harvested and added to or subtracted from the farmer profit functions. Since switchgrass and miscanthus are perennial grasses that can store carbon in the soil, we will also test the effects of earning additional profits proportionate to the carbon stored through established carbon trading markets. The work of Dhungana (2007) will provide the basis for estimating carbon storage rates and prices.

Potential scenarios may be analyzed within the framework of our model include:

1. Increases in subsidies per biomass unit until switchgrass and miscanthus begin to emerge. This allows us to estimate the relationship between subsidy levels and biomass crop harvest/price.
2. Reduction in costs through farmer 'learning,' meaning that unit costs could decline with the amount produced.
3. Modifications to farmer response rates α or allowing for different α_I among farmers to test for the relevance of adaptation speed.
4. Using fuel price as an exogenous variable, following a continuously growing gasoline price.
5. Testing for the possible impact of climate change by an increasing temperature throughout the century. This would modify yield patterns.
6. Testing different urbanization scenarios, thereby lowering the amount of arable land.
7. Introducing new ethanol plants and bio-refineries, thereby altering the transportation costs for nearby cells.

Conclusions and Implications

The goal of this work is to assess environmentally responsible and economically efficient agricultural land use options for the widespread implementation of renewable bioenergy crops. In order to establish a secure and economically cost-effective infrastructure for the energy supply of Illinois, our research identifies current and future potentials for renewable energy resources and uses in Illinois, while identifying obstacles and opportunities. After scenario testing, this work may provide a framework for examining the availability, feasibility, economic viability and sustainability of bioenergy sources in the Midwest.

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