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# Agent-based life cycle assessment for switchgrass-based bioenergy systems

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ABSTRACT

Switchgrass is a biomass crop with no established market. Its adoption will involve a wide range of socio-economic factors, making it a particularly difficult system to analyze for environmental impact estimates. Life cycle assessment (LCA) provides a methodology to quantify the environmental impacts of a product or process throughout its entire supply chain. However, traditional LCA approaches fail to account for the local variability in non-homogeneous systems. Because of the time component and other realm dynamics it is essential to visualize as the switchgrass adoption process as a Complex Adaptive System (CAS). Agent-based modeling (ABM) can be used to supplement life cycle information to account for these dynamics variances. Here, we present an Agent-Based Life Cycle Analysis (AB-LCA) model of farmers' potential adoption of switchgrass as a biomass. The chosen modeling approach aims to understand the main factors influencing landowner decision-making and how these adoption patterns can affect the LCA of switchgrass ethanol. To help address these challenges, we developed an Agent-Based Model aimed at: (1) understanding the main factors influencing landowner decision-making and how these adoption patterns can affect the LCA of switchgrass ethanol and (2) improving the LCA modeling methodology by overcoming the issues involved with analyzing emerging technologies with dynamic and evolving supply chains. Particularly, we built an agent-based model using LCA data of switchgrass-based ethanol production that simultaneously captures socioeconomic factors, such as age, level of risk aversion, education level, and level of profit, of farmers that lead to switchgrass adoption and the changes in environmental impact that result from this particular behavior. The results show that the most influential factors affecting farmers' decisions are their current economic situation and crop prices. Age and their level of knowledge of the new crop have some impact but with limited extent.

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## 1. Introduction

The increasing global demand for energy has motivated a search for alternatives solutions to, if not replace, complement the current fossil fuel-based energy production. One of these solutions is renewable energy produced from biomass feedstock. A promising feedstock for bioenergy is switchgrass, a perennial grass native to North America that is well adapted to grow in a large portion of the US with low fertilizer applications and high resistance to naturally occurring pests and diseases (Bransby et al., 2005). In addition to alternative energy production, using switchgrass as bioenergy feedstock has a number of potential benefits, including reducing erosion due to its extensive root system and canopy cover (Ellis, 2006), protecting soil, water, and air quality, sequestering carbon, increasing landscape and biological diversity, returning marginal farmland to production, and increasing farm revenues (McLaughlin and Walsh, 1998; McLaughlin et al., 2002).

As with any modeling effort associated with technology adoption, market forces alone cannot predict user behavior and adoption. Landowner decisions to convert to switchgrass will be based on a variety of factors such as economics, risk tolerance, familiarity with the technology, and ease of implementation. Farmer populations tend to be fairly risk averse and slow to change. The fundamental characteristics of landowner behavior and potential adoption of switchgrass have been explored using a Bayesian statistical approach (Miller et al., 2013).

In general, bioenergy's environmental performance is not always desirable when examining its entire life cycle from feedstock agriculture to final consumption (Hellweg and Canals,

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2014). There are also public policies that require certain life cycle environmental performance standards for bioenergy, such as the U.S. Energy Independence and Security Act. Many life cycle assessment (LCA) studies have been conducted to understand the environmental implications of switchgrass-based bioenergy from the life cycle perspective (e.g., Cherubini and Jungmeier, 2010; Spatari et al., 2005; Mihalek, 2012; Bai et al., 2010; Harden, 2013; Lerkkasemsan and Achenie, 2013). These studies take an attributional LCA perspective, which quantify the environmental flows directly associated with switchgrass bioenergy production irrespective of changes to the initial agricultural system. This paper describes a consequential approach to a switchgrass ethanol LCA, which relies on dynamic modeling of switchgrass adoption to estimate the anticipated environmental changes in the agricultural system relative to the baseline condition.

LCA is most useful for analyzing well-established systems with relatively stable supply chains. Predictive tools are needed to better understand such emerging systems in LCA. Agent-based modeling (ABM) can complement LCA by characterizing the dynamic interactions among components of a product system's supply chain (Davis et al., 2009). This is particularly relevant to the switchgrass-based bioenergy system which is an emerging system under development. Its environmental performance highly depends on how individual farmers adopt switchgrass over other crops, which is not captured in traditional LCA. ABM is potentially useful to capture the dynamics of farmer adoption for switchgrass to complement traditional LCA studies.

In this study, we develop an agent-based LCA (AB-LCA) framework to simulate the dynamics of farmer adoption for switchgrass as a bioenergy feedstock using ABM and evaluate life cycle carbon dioxide ($CO_2$) emissions associated with various adoption mechanisms using LCA. The specific research question is: How different adoption patterns affect LCA results? We also complement our model with a sensitivity analysis in order to determine which of our underlying assumptions have the greatest impact on adoption patterns.

## 2. Agent-based modeling and modeling agricultural sociology

The history of the agent-based model has first been introduced in the 1940s through the Von Neumann machine: a theoretical machine capable of reproduction (Neumann, 1966; Jonathan, 2013). The definition ABM was later coined by Axelrod in his earlier papers (Axelrod, 1997; Axtell et al., 1996), The purpose of ABM is to "understand not only how individuals behave but also how the interaction of many individuals leads to large-scale outcomes" (Axelrod, 2006) It has since became a form of computational simulation that is gaining popularity in various disciplines (Bonabeau, 2002; Macal and North, 2009). In practical terms, ABM allows for the building of models where individual entities and their interactions are directly represented. These agents are adaptive to their environment and can react to the environmental conditions. ABM provides a way to observe the emergence of macro level behavior from micro level (Sapkota, 2010).

There are a large number of studies on agricultural sociology. It is mostly dominated by the paradigm for diffusion research. According to Rogers (2004) it has produced the largest number of diffusion studies. However, the number of ABMs concerned specifically with agricultural diffusion related to crop adoption is still relatively sparse. As of today, diffusion models in the literature (e.g., Kocsis and Kun, 2008; Hohnisch et al., 2008; Cantono and Silverberg, 2009; Faber et al., 2010; Kiesling et al., 2012) typically use simple decision rules based on production costs and prices. On the other hand, social psychology approaches are arguably more sophisticated and are based on psychological theories of behaviour (Kiesling et al., 2012). Rather than representing consumers as instances of "homo economicus", these models incorporate the behavioral richness exhibited by "homo psychologicus" in real life (Jager et al., 2000) Therefore, conceptualizing model of decision-making requires that cognitive strategies of heterogeneous agents are taken into account.

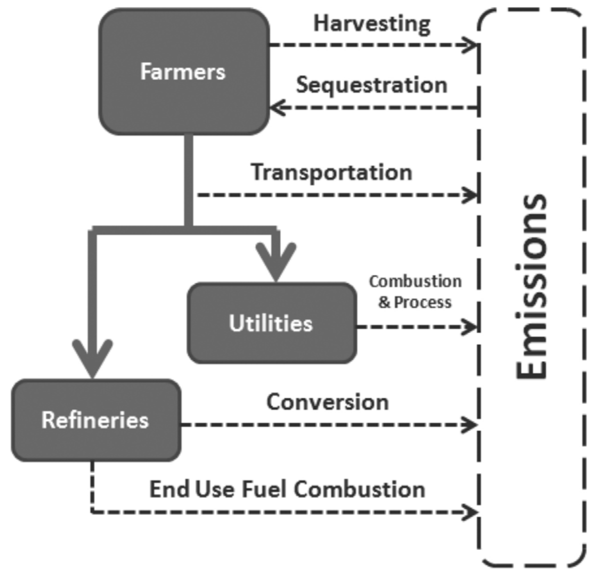


**Fig. 1.** Process flow diagram of switchgrass-based bioenergy system.

## 3. Methods and data

Fig. 1 shows the process flow diagram of the switchgrass-based bioenergy system including two energy production pathways, biofuels and bioelectricity. In this study, the conversion of agricultural land to switchgrass is modeled using ABM, while $CO_2$ emissions from each process are measured using process-based LCA.

The ABM in our AB-LCA framework focuses on the decision-making process of farmers in adopting a new crop. Farmers are assumed to be rational economic agents that aim to maximize utility. Each individual famer's decision whether to adopt switchgrass is made based on both potential economic benefits and the farmer's perspective on market risk and uncertainty. Although the model does include interactions with other agents such as refineries, the study of their interactions has not been studied in this phase of the model because the current focus is on the LCA. A detailed description of the agents including refineries (Fuel Plants and Co-fired generation Plants) can be found in the Supporting Information (SI) appendix. Below, we present the AB-LCA settings using the ODD (Overview, Design concepts, and Details) protocol (Grimm et al., 2006).

### 3.1. Overview

In our ABM, farmers are rational economic agents each of which owns a certain area of land (patches) randomly assigned on a grid. Each round of simulation represents a growing season (year). In each simulation year, farmers make decisions on whether or not to plant a new crop (switchgrass in this case). Any farmers expecting increased profits by converting to switchgrass will consider switchgrass adoption. Once they consider adopting, they will evaluate the market risk based on their own social and economic characteristics including age, income, familiarity with switchgrass, and the ability to learn from neighboring farmers to make the decision whether to adopt or not. The area of planted switchgrass changes in each simulation year, which affects the $CO_2$ emissions from switchgrass agriculture according to differential baseline land types, transportation distances and land uses. Therefore life cycle $CO_2$ emissions of the switchgrass-based bioenergy system can be affected by farmers' adoption decisions.

### 3.2. Design concepts

We design the AB-LCA model in a modular fashion to ensure it can be used in the future, meaning that any components of the model can be replaced without breaking the overall functionality (Nikolic and Dijkema, 2005). In our model, modules are represented by farmer's personal, agricultural, and economic attributes. Each module can be modified or extended in order to explore scenarios from those three aspects. Table S1 provides details of these modules.

### 3.3. Details

Fig. 2 summarizes the decision-making processes of each farmer in our model. In each simulation year, each farmer performs the following tasks in chronological order:

1. At the beginning of each simulation year, each farmer compares their current profit to the expected profit from planting switchgrass. The farmer proceeds to the next step only if the potential profit is higher than the current profit.
2. Each farmer has distinct individual attributes of land size, original crop, age, familiarity with switchgrass, level of risk-aversion, and level of education (Table S1). Farmers determine their willingness to plant by comparing their level of familiarity, risk-aversion and education to the overall average in the system. Farmers with attributes over the average level will adopt switchgrass in their land. The Farmers will plant switchgrass on a portion of their land which is randomly determined based on a normal distribution (see pseudo-code below).
   IF
   age of farmer < average age **and**
   Familiarity with switchgrass > average familiarity with switchgrass **and**
   Risk aversion < average Risk aversion **and**
   Education > average education
   THEN
   [Plant switchgrass]
   **Return** qualified farmers
3. At the end of each simulation year, the amount of harvested switchgrass for each farmer is calculated by multiplying the yield with a post-harvesting loss rate. The yield is randomly determined through a normal distribution (McLaughlin and Kszos, 2005). The post-harvesting loss rate is randomly determined with a normal distribution (Samson, 2007), representing production losses during harvesting activities such as storage, processing and transportation.
   Farmers decide to sell their switchgrass to either a biorefinery to produce bioethanol or a power plant to generate electricity. The decision-making of this part of the model is not studied, therefore no competition between refinery is in place in the current model. Farmers interact with only the closest bio-refinery and closest generator to minimize transportation emissions. Once they harvested their feedstock, they sell automatically the whole quantity of biomass to the plant closest to them whether it is a fuel refinery or a power plant. In a future version of the model this can be changed by setting up allocation of switchgrass that ultimately gets utilized as electricity or ethanol depending on the competition between the closest refinery and generator for each farmer. Coal prices, subsidies, emission penalty costs etc. can then be added and serve as basis for competition.
4. $CO_2$ emissions from each process of the life cycle of the system are calculated using life cycle inventory (LCI) data (Table S3) from the GREET model (Argonne National Laboratory, 2012). The LCI includes $CO_2$ emissions sequestrated by switchgrass cultivation, emissions generated from harvesting, transportation fuel use in logistics, power generation, and biofuel production, and emissions avoided by replacing fossil fuels or fossil fuel-based electricity.
5. Only profitable farmers that grow switchgrass in the previous simulation year will replant in the next year.
6. Farmers who did expect more profits but not plant in this round of simulation have an opportunity to "change their minds" by learning from their neighbor farmers with a certain radius. Only farmers who were close to make a profit but did not (loss $\leq -0.10$) are eligible to "change their mind". If the majority of their neighbors plant switchgrass and are profitable, they will plant switchgrass in the next simulation round.

**Table 1**
AB-LCA global variables.

| | Domain/description | Unit |
|---|---|---|
| Economic | | |
| Price of switchgrass | [200,600] | \$/tonne |
| Price of base crop | [200,600]. Price of crops currently planted that could be replaced by switchgrass | \$/tonne |
| Environmental | | |
| $CO_2$ (growth) | Total $CO_2$ emissions accumulated during the growth phase | Tonnes |
| $CO_2$ (ethanol generation) | Total $CO_2$ emissions accumulated during the ethanol production phase | Tonnes |
| $CO_2$ (electric generation) | Total $CO_2$ emissions accumulated during the electricity production phase | Tonnes |
| $CO_2$ (ethanol distribution) | Total $CO_2$ emissions accumulated during the ethanol distribution phase | Tonnes |
| Social | | |
| Learning ability | True or false. If it is true, farmers who expect increased profits from adopting switchgrass but decided not to adopt will be able to change their perspectives on market uncertainty and risk aversion by "learning" from their neighbors. | Boolean |

In addition to variables characterizing individual farmers, the AB-LCA model also has global variables (Table 1) that affect the interactions of farmers and are not specific to any farmer. Each unique choice of values for these variables represents a socioeconomic scenario for switchgrass-based bioenergy systems.

## 4. Validation

The model is validated to ensure the model simulation reflects the real-world system it intends to describe. Chappin (2012) identifies two methods for model validation in general: static and dynamic. The static method aims at comparing sampled experiments where samples are collected from distinct groups without respect to time. The dynamic method, on the other hand, is a temporal experiment where samples are usually collected over time in order to uncover progressive system behavior. The former does not apply to time-dependent data, while the latter does. In this study, we use both methods by (1) comparing the simulation results with

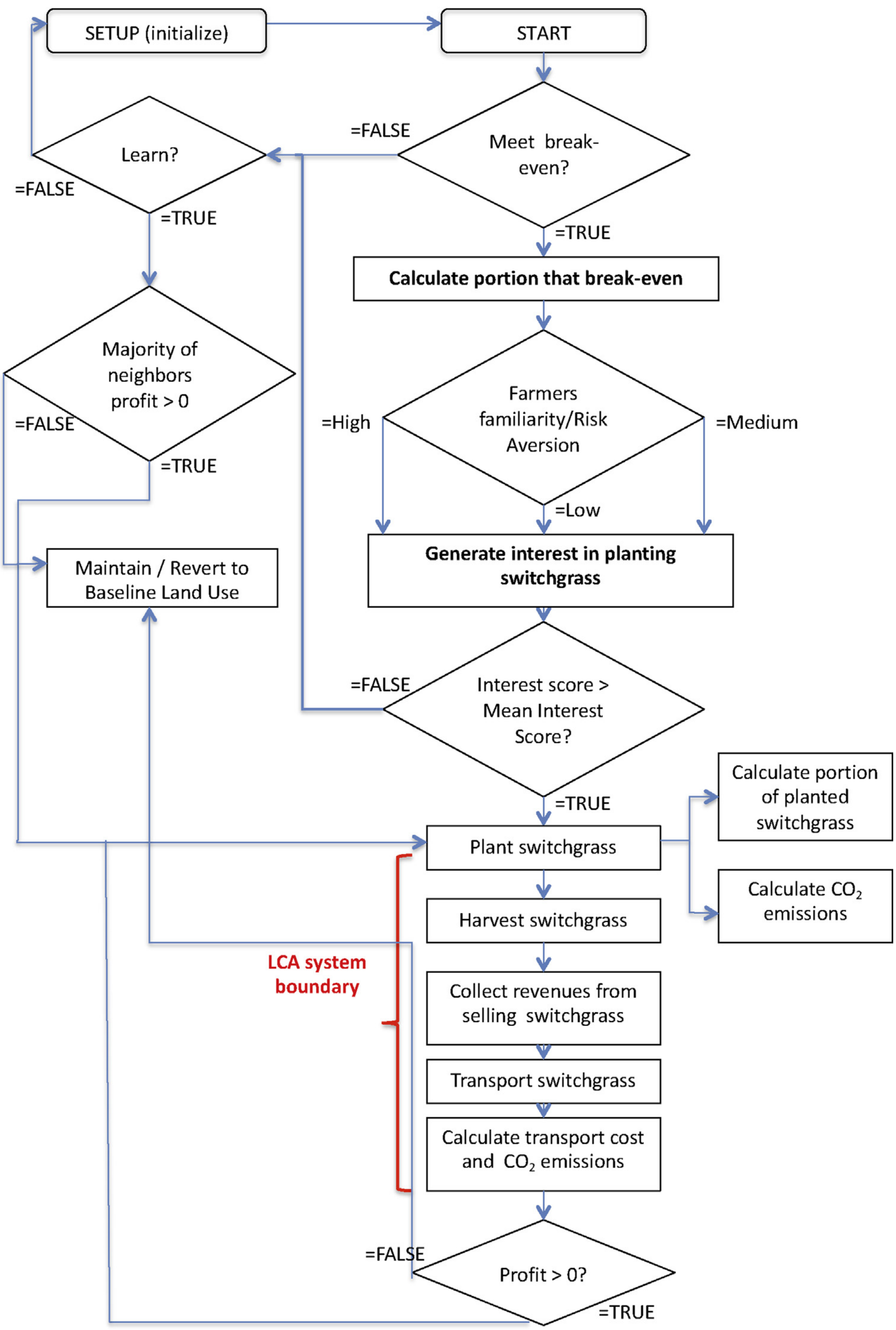


**Fig. 2.** Decision-making processes for each farmer in the ABM.

observed data, and (2) testing the model's fitness through a multiple linear regression analysis.

Just like switchgrass, genetically engineered soybeans (GE soybeans) were new crops being introduced to the market and involved the same actors (farmers). We choose to use historical adoption data of GE soybeans in the U.S (Fernandez-Cornejo and McBride, 2002) for model validation. The rationale is that, if our model can reproduce the adoption pathways of new crops similar to switchgrass, it can generate meaningful estimates of switchgrass adoption. Although there are differences in the implementation of GE soybeans and switchgrass that may have impact adoption, specifically with regard to the perennial nature of switchgrass and different harvesting technologies, there does not appear to be a more suitable proxy for model validation. In addition, our model does not include these elements of switchgrass that may further suppress adoption; therefore, validation with GE soybeans is appropriate, although model estimates may overestimate the rates of switchgrass adoption due to these simplifications.

### 4.1. Validation by comparing to observed data

Fig. 3 shows similar trends of new crop adoption from our model simulation and the historical adoption of GE soybeans. Rapid adoption is observed when new crops are first introduced, with

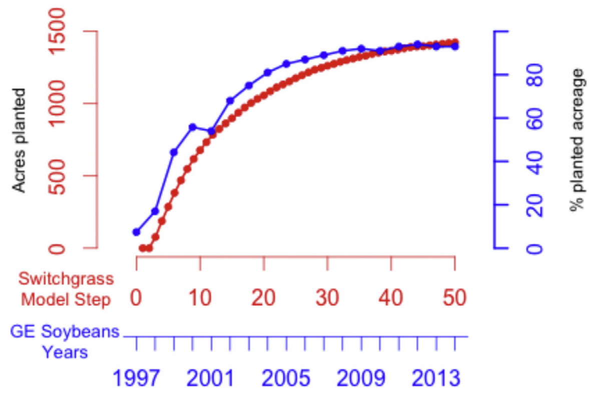


**Fig. 3.** Model simulation results comparing with historical GE soybean adoption.

the rate of adoption slowing until equilibrium is reached. Indeed, U.S. farmers have widely and consistently adopted GE crops since their introduction in the 1990s, despite uncertainties regarding consumer acceptance and economic and environmental impacts (Fernandez-Cornejo and Hendricks, 2003).

### *4.2. Validation by testing the model's fitness through a multiple linear regression analysis*

A multiple linear regression model is applied to explore the relationship between independent variables and a dependent variable by fitting a linear equation to simulated data (Happe, 2005). By evaluating the significance of individual independent variables to the dependent variable, the multiple linear regression analysis can help validate assumptions made in the model. Note that given the intrinsic complex dynamics in ABM where the result of an output variable changes as the simulation runs, this method on its own is not sufficient to claim any proof of validity. Instead, it is considered to be one of the techniques for ABM validation.

For this study, we choose the number of farmers planting switchgrass and the area of land for GE soybean plantation as the dependent variables. Independent variables include farmers' age, education level, learning ability, familiarity with new crops, risk aversion, selling price of the new crop, and profits.

The results (Fig. 4) show the predictive power of each independent variable. The thick line represents the 1st standard deviation range. Variables that are away from the "intercept line" and with longer ranges, such as the selling price of switchgrass, revenue, and selling price of GE soybeans, are statistically significant. If they are left of the intercept line, those variables have positive effects on adopting the new crop. To the contrary, if placed on the right of the intercept line, variables have negative effects on new crop adoption. In our switchgrass ABM, the selling price of switchgrass seems to have a negative effect on adoption, but its effects can vary with a great level of uncertainty. On the other hand, variables on education level, learning ability, and familiarity with new crops show to have positive effects on adoption, but are less significant than variables on price and revenue. This multiple linear regression analysis confirms that the independent variables chosen for our ABM have statistically significant impacts on the adoption of new crops, using either artificially simulated results for switchgrass or historical data on GE soybeans.

## 5. Results and discussion

We divide the simulation results into two different variable categories: endogenous variables and exogenous variables. Endogenous variables are related to individual attributes of farmers described in Table S1, while exogenous variables are the potential

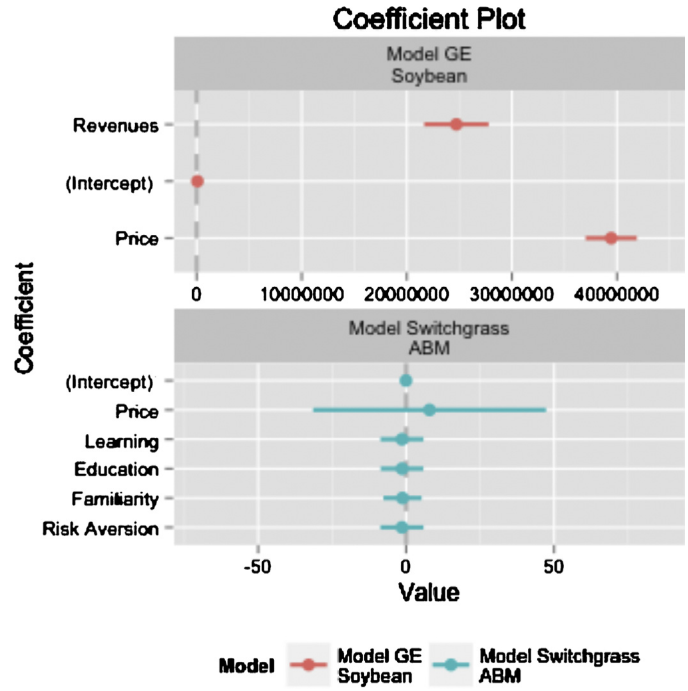


**Fig. 4.** Coefficient plots of multiple linear regression analysis.

profit farmers expect to make from selling switchgrass and the cost of production. We simulate 120 scenarios with 10 repetitions each.

The simulation results on the average number of farmers adopting switchgrass with different levels of familiarity to switchgrass, risk aversion, and education (Fig. S1) show expected patterns. For example, only farmers with the high and medium levels of familiarity with switchgrass are much more likely to adopt than farmers with a low level of familiarity. Meanwhile, it would be expected that high levels of risk aversion hinder farmers' willingness to adopt. However, the results show the opposite. It can be explained by the fact that the most influential factor for adopting a new crop is the expectation of making a profit. The potential of making more profit and being somewhat familiar with switchgrass seem to be enough for farmers to make the adoption decision. We also find that the level of education does have a significant impact on farmers' adoption decisions. In particular, farmers with high and medium levels of education tend to adopt right away, while farmers with lower level of education do not.

As mentioned in #7 of the farmer's scheduling, farmers who did expect more profits but not plant in the previous round of simulation have an opportunity to "change their minds" by learning from neighbor farmers within a certain radius. The concerned farmers, called "on-the-fence", survey their neighbors within a certain radius (radius of influence). If the majority of their neighbors planted switchgrass and made profits, "on-the-fence" farmers will imitate their neighbors by planting switchgrass. Experiment results showed in Fig. S2 aim to check for the combined effects of learning ability and radius of influence by neighbor farmers. On the lower part of the plot, we can clearly see that a significant amount (approximately 40%) of farmers adopting switchgrass are those who were "on-the-fence" and eventually changed their minds by learning from neighbors.

Fig. 5 shows the comparison of $CO_2$ emissions of switchgrass-based bioenergy with fossil fuel-based energy that is replaced by the switchgrass-based bioenergy. We observe that $CO_2$ emissions from the switchgrass-based bioenergy is lower than those for fossil fuel-based alternatives with limited variations. For switchgrass-based bioenergy, its life cycle in our study includes

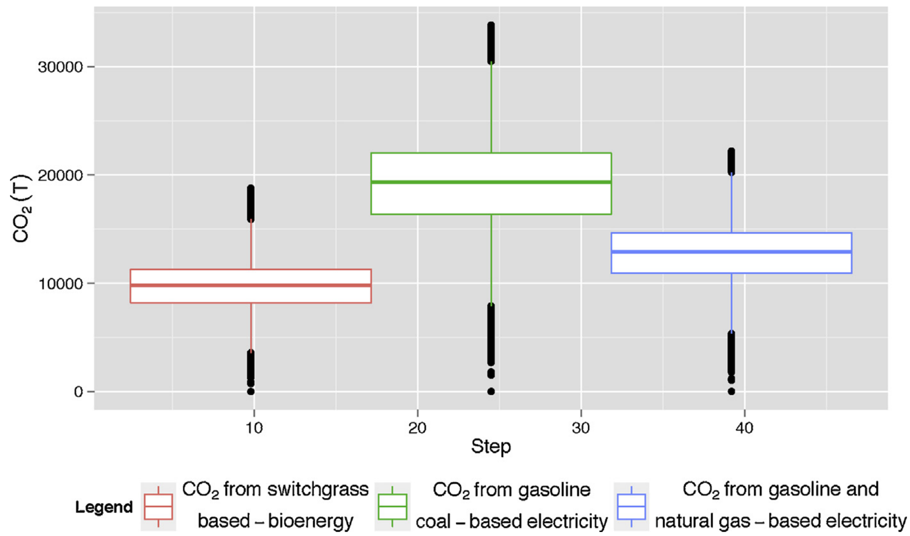


**Fig. 5.** $CO_2$ emissions comparison on an equal energy basis.

crop growth, harvesting, transport, ethanol and electricity production, and the use of ethanol as transportation fuels. Note that emissions from land use change is not considered. Depending on the type of land converted to switchgrass, the amount of $CO_2$ emissions sequestered can be significantly different. Including impacts of land use change is a direction for future model improvement. We compare switchgrass-based bioenergy with its fossil fuel counterparts on an equal energy content basis. In particular, we use 500 MW h electricity generated from either coal or natural gas and 10,000 l of fuel as the reference flow.

In order to identify specific social and economic factors that have particular impacts on the LCA results, we examine the correlation of each factor with the different stages of LCA as shown in Figs. 6 and 7. The plots in the lower left panel of Fig. 7 are the paired plot of individual attribute variables for farmers (age, familiarity with switchgrass, risk aversion, and education) and LCA results by different stages of switchgrass-based ethanol (switchgrass growth, ethanol generation, electricity generation, and ethanol distribution). Values of the column variables are used as *X* coordinates, values of the row variables represent the *Y* coordinates, and the diagonal histograms reflect the marginal distributions of the variables. In the upper right panel, correlation coefficients are reported scaling the font size to reflect the absolute value of the coefficients. Fig. 7 shows the similar results for exogenous variables including the price of the base crop, price of switchgrass, production cost, and potential profit.

In Fig. 6, we notice that plots pairing the different stages of LCA as a function of age (purple boxes) are the only plots that display

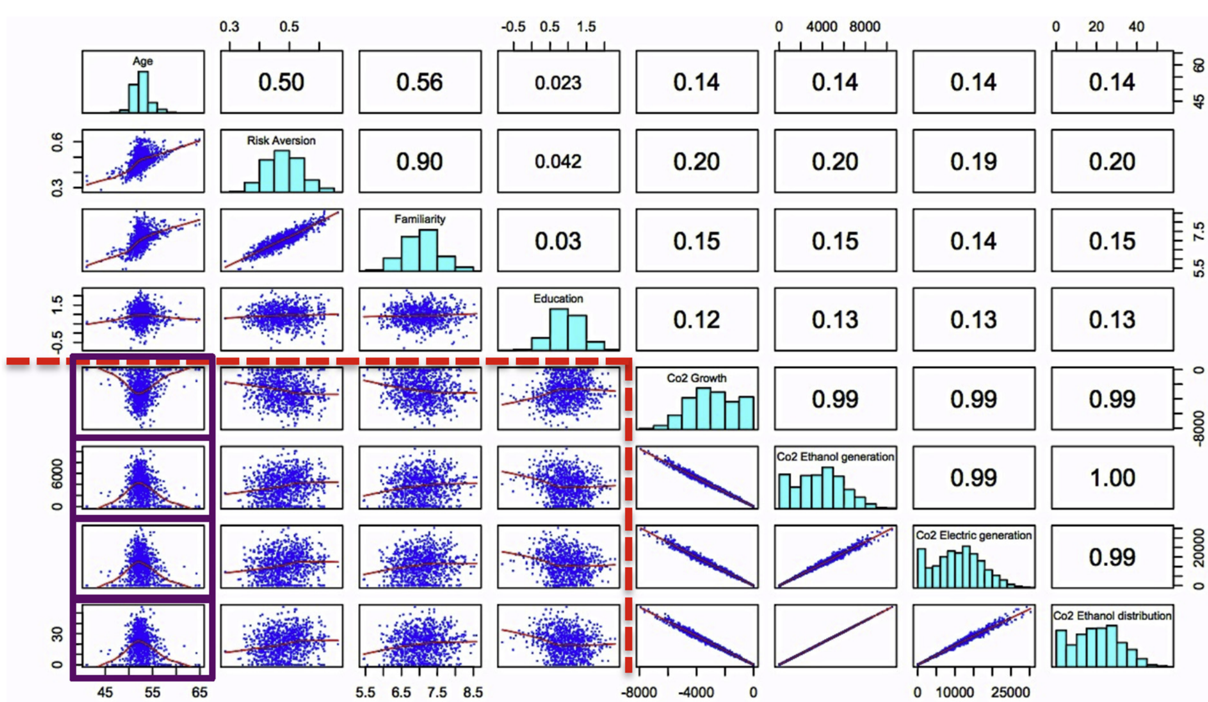


**Fig. 6.** Scatter plot correlation matrix of individual attributes of farmers effecting the LCA results. Values of the column variables are used as *X* coordinates, values of the row variables represent the *Y* coordinates, and the diagonal histograms reflect the marginal distributions of the variables. In the upper right panel, correlation coefficients are reported scaling the font size to reflect the absolute value of the coefficients.

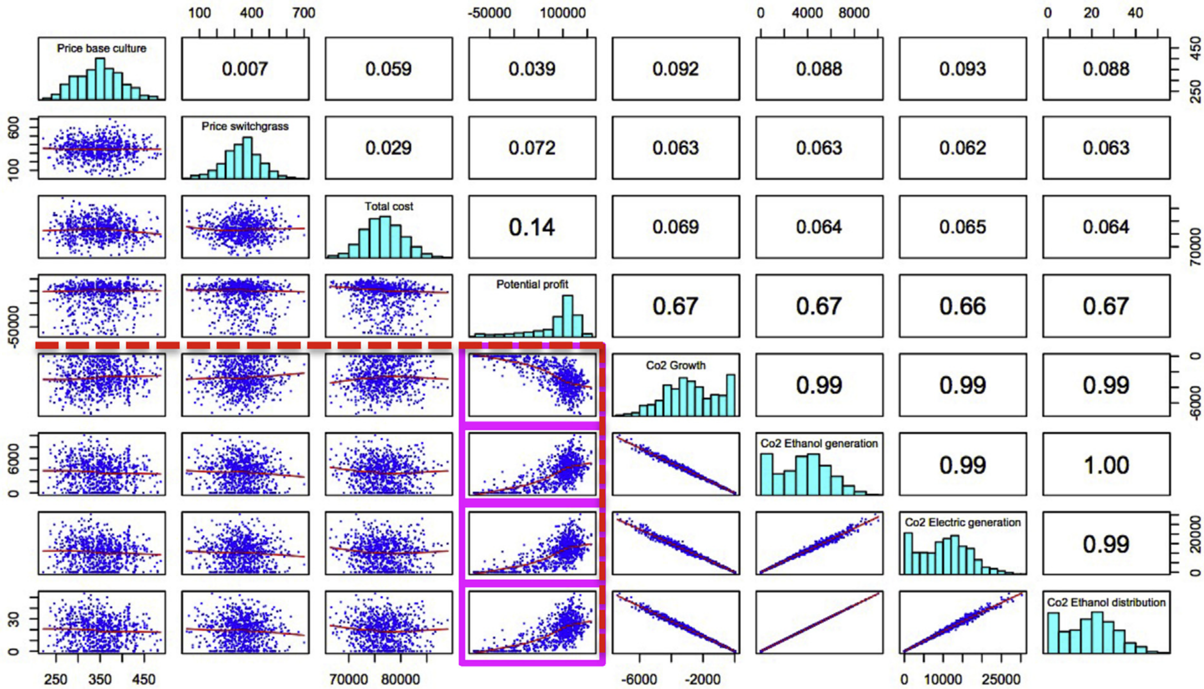


**Fig. 7.** Scatter plot correlation matrix of exogenous variables effecting the LCA results. Values of the column variables are used as *X* coordinates, values of the row variables represent the *Y* coordinates, and the diagonal histograms reflect the marginal distributions of the variables. In the upper right panel, correlation coefficients are reported scaling the font size to reflect the absolute value of the coefficients.

a non-linear relationship. During the growth phase, the U-shaped curve accounts for the sequestration of $CO_2$. Since the vast majority of farmers are grouped around the average age, the amount of $CO_2$ sequestered is at its highest (bottom of the curve). When the "pool" of famers is either too young or too old, we observe an expected pattern of less carbon sequestration. The other plots show consistent results but with inverted U-shape curves. All other individual attributes show linear positive relationships, however weak. This indicates that individual attributes of farmers have limited impacts on switchgrass-based ethanol LCA results, although they are inherent to each farmer and enter at the very beginning of the decision-making process.

In Fig. 7, we find that selling prices either for the base crop or switchgrass has no direct impacts on the LCA results. However, "potential profit" (pink boxes) as a function of switchgrass selling price and switchgrass production shows strong correlations with LCA results at different stages. The higher level of profit is expected by the farmer, the more they adopt and more $CO_2$ is either sequestered or emitted during the life cycle stages. The potential profit that famers expect to make seems to have a major impact on LCA results.

## 6. Conclusion

The primary purpose of this study was to identify the main social and economic factors that contribute to the life cycle environmental performance of switchgrass-based bioenergy through modeling the adoption of switchgrass as a new crop. An ABM was built to identify these variables as well as the main emergent patterns that stems from multi-agent interaction. Overall, the general design of the model in estimating adoption trends seems to fit the real system as it showed similar pattern with GE soybean adoption evolution. The calibration results showed that the AB-LCA model was able to reproduce expected patterns as far as the main variables affecting the decision making for adoption. This combined AB-LCA model shows to be useful in complementing existing LCA model and tackling uncertainties that result from unexpected user behavior. A GIS extension with real-world spatial information, using actual yields and roads for transportation to the refinery can be added. Switchgrass market still being inexistent, expected revenues should be of particular importance to policymakers in developing policies to facilitate the development of this market. ABM has been shown to add fineness to LCA. The results of this theoretical case study may not correlate perfectly with real-world situations because each location will have its own spatially explicit parameters. However, the general methodology employed in this case study remains valid. Future work will apply this methodology to a "real-world" study area with actual farming practices, land covers, and relevant policy scenarios, particularly on specific policy implementation.

## 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.resconrec.2015.08.003.

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