RESPONSE OF FARMERS' DECISIONS AND STREAM WATER QUALITY TO PRICE INCENTIVES FOR NITROGEN REDUCTION, CARBON ABATEMENT, AND MISCANTHUS CULTIVATION: PREDICTIONS BASED ON AGENT-BASED MODELING COUPLED WITH WATER QUALITY MODELING

BY

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DISSERTATION

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Environmental Engineering in Civil Engineering in the Graduate College of the University of Illinois at Urbana-Champaign, 2010

Urbana, Illinois

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ABSTRACT

The present study develops an agent-based model of farmers' decisions under the influence of nitrogen, carbon and second-generation bioenergy crop prices. This study also estimates the effects in turn of these decisions on water quality, namely stream nitrate load. Given that agriculture is the single largest source of nitrogen in surface waters and is a major contributor to hypoxia in coastal ecosystems and eutrophication in streams and lakes, this study is motivated to explore insights for water quality protection in the context of the environment-energy nexus.

In this study, the price of nitrogen is based on subsidies paid to farmers for reducing their fertilizer inputs, while the price of carbon is based on carbon trading and the price for second-generation bioenergy crops from a market demand for them. Due to climate change concerns, there is a real possibility for carbon emissions reduction trading to be implemented on a large scale in the near future, which will increase the demand for bioenergy crops, including second-generation ones (defined as high-yielding perennial grasses such as switchgrass and miscanthus). Even without carbon trading, it is likely that there will still be an increased demand for second-generation bioenergy crops due to energy independence concerns. Currently, the primary feedstock for biofuel production in the U.S is corn. However, as the technology to produce cellulosic ethanol improves, it can be expected that perennial grasses, which are high in cellulosic content, will take on larger and larger roles.

All this may lead to large-scale changes in agriculture and consequently, stream nitrate load. This study takes a modeling approach to estimate those changes. The conventional approach to modeling water quality policy is to impose upon the system some least cost, or maximum utility, equilibrium. Inherent to this are the assumptions of “rational” behavior, perfect information, zero transaction costs and static conditions. This study explores agent-based modeling (ABM) as an alternative approach, which formulates the system from the perspectives of the individual agents within it. This gives ABM flexibility not found in the least cost equilibrium approach, such that it need not be constrained by the assumptions of the latter.

Thus, an objective of this study is to demonstrate the applicability of ABM for water quality policy modeling. This is done using a semi-hypothetical case study of farmers in the Salt Creek watershed in East-Central Illinois under the influence of the nitrogen fertilizer reduction
subsidy, and carbon and second-generation bioenergy crop (specifically, miscanthus) prices. An agent-based model of the system is developed and linked to an environmental-response model. The former is based on fundamental economic and mathematical programming principles, while the latter is based on the Soil and Water Assessment Tool (SWAT).

The agent-based model is applied to fifty hypothetical farmers. The farmers are heterogeneous in terms of their initial perceptions of prices, costs, yields and the weather, and how they update those perceptions with time. They are heterogeneous in terms of their land areas, fractions of marginal land, economies of scale, yields, time discount rates, foresights, and risk aversions as well. The farmers are also interacting in terms of their knowledge of initially unfamiliar activities. Their uncertainties of the costs and benefits of these activities are reduced as their neighbors or they themselves experiment and gain experience.

The farmers' decisions are dependent on their expectations and uncertainties of future conditions, which are updated with new observations according to a Bayesian algorithm. The Bayesian algorithm weights existing beliefs against new observations. The parameters in the Bayesian algorithm are set differently for different farmers such that each is unique in his processing of new information. In this study, two types of behavior are defined: cautious and bold. For cautious farmers, their Bayesian parameters are set such that they are slow to adjust their expectations in response to new observations but quick to reduce their forecast confidence when new observations fail to match expectations. On the other hand, bold farmers are quick to adjust their expectations with new observations but slow to reduce their forecast confidence when there are unexpected changes. Cautious and bold farmers are also dissimilar in their levels of risk aversion; cautious farmers are more risk averse than bold farmers.

Results show that the different market instruments are not equal in their effectiveness in inducing large-scale land use changes with the ultimate purpose of reducing nitrate load in surface waters. For the scenarios examined, the most effective means of achieving a significant reduction in nitrate load is to have a market demand for miscanthus, followed by the nitrogen fertilizer reduction subsidy. However, carbon trading is unlikely to lead to any major change in nitrate load. The results are meaningful, which demonstrates the suitability of ABM to modeling water quality policy problems. ABM is also able to provide insights not possible using the least cost equilibrium approach. For example, it is able to predict how differences in the way farmers process new information affect their forecasts of future conditions and hence, decisions. It also
appears able to predict patterns of their adoption of new technologies (in this case, conservation tillage and miscanthus cultivation). Its predictions, while empirically untested, appear plausible and consistent with general behavior by farmers.

Further contributions of this dissertation include the parameterization of the crop growth component in SWAT for miscanthus. Even though SWAT comes with a database of default parameters for a number of crops, default values for miscanthus are unavailable as it is a relatively new crop of interest. Others may find the parameters for miscanthus useful for their purposes. Another contribution is the development of an economic model of a single farmer using dynamic programming that may be used to support the farmer’s decision-making regarding the possibility of miscanthus as a crop choice and carbon trading as a potential source of income. The model takes into account the sequential and multi-stage nature of the problem, as well as the initial unfamiliarity and learning process of the farmer.

This work has also brought to the field of bioenergy development a systems perspective which views an aspect of the problem not in isolation but in the context of other aspects; specifically, in this study, the water quality outcomes of bioenergy crop cultivation is studied in the context of market policies targeted at farmers.
To my parents
ACKNOWLEDGMENTS

I thank my advisor and mentor, Prof. J. Wayland Eheart for all his encouragement and guidance. In so many ways, he has been my academic father. Much of my research interests have been influenced by his. I am constantly inspired by his scholarship and academic principles. Under him, I have learned what it means to be critical in thought and accurate in speech.

I also thank my co-advisor, Prof. Ximing Cai, for all the time and work he has put into my dissertation. I thank him for his unlimited ideas. His passion never fails to motivate me; it is my hope to have the same energy and enthusiasm he has for research.

My committee members, Prof. John Braden, Dr. George Czapar and Prof. Jürgen Scheffran have also been wonderful. I truly appreciate their feedback. Their questions and comments, though challenging to address at times, have been vital in refining and improving the current work.

I would also like to express my thanks to past and current members of the Eheart and Cai research groups for their support and comments. I especially thank Jian-Ping Suen, Hua Xie and Xuetao (Thomas) Hu for their advice and the countless hours of discussion we have had.

My Ph.D. studies would not have been possible without funding from the following sources: Energy Biosciences Institute, Engelbrecht Fellowship, Metropolitan Water Reclamation District of Greater Chicago, Water Environment Research Foundation, Institute of Sustainability of Intensively Managed Landscapes and Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign. I am grateful for their generosity and the opportunities they have provided.

My friends here in Urbana-Champaign have been invaluable. My time here would not have been as enjoyable as it has been without their prayers and love. Specifically, I am thankful to Sun-A Kim for her company all those hours of writing. I must also mention Irene Wu, Sooyoung Kim, Heekyong Pyon, Jisook Paik, Jennie Tang and Joy Pang. They have been my pillars of support.

No words can express the depth of my love and gratitude for my parents. Without their encouragement, I would not have even begun the Ph.D. process. Indeed, the people who love you the most are your parents. And lastly, but most importantly, I thank God, my Father in heaven, with whom I can do all things but without whom, I can do nothing.
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1. INTRODUCTION

1.1 Problem Statement

The present study develops an agent-based model of farmers' decisions under the influence of nitrogen, carbon and second-generation bioenergy crop prices. This study also estimates the effects in turn of these decisions on water quality, namely stream nitrate load. Agriculture is the single largest source of nitrogen in surface waters and is a major contributor to hypoxia in coastal ecosystems and eutrophication in streams and lakes. Further, excessive nitrate concentrations in drinking water may have negative health effects, particularly on infants.

In this study, the price of nitrogen is based on subsidies paid to farmers for reducing their fertilizer inputs, while the price of carbon is based on carbon trading and the price for second-generation bioenergy crops from a market demand for them. Currently, in the U.S., the market for carbon credits is very limited and for second-generation bioenergy crops almost non-existent. However, due to climate change concerns, there is a real possibility for carbon emissions reduction trading to be implemented on a larger scale in the near future, which will increase the demand for bioenergy crops, including second-generation ones (defined as high-yielding perennial grasses such as switchgrass and miscanthus). Energy from the combustion of these crops (either directly as solid fuels or indirectly as biomass-derived liquid fuels) can be considered to be carbon-neutral or nearly so, as long as the carbon used in processing is from the same biomass source, as the carbon released during the combustion is offset by the carbon absorbed as the crops are growing.

Even without carbon trading, it is likely that there will still be an increased demand for second-generation bioenergy crops due to energy independence concerns that impel the U.S. to reduce its reliance on foreign oil. In the transportation sector, liquid biofuels from biomass, e.g. ethanol, are a viable alternative to gasoline. Currently, the primary feedstock for biofuel production in the U.S is corn. However, as the technology to produce cellulosic ethanol improves, it can be expected that perennial grasses, which are high in cellulosic content, will take on larger and larger roles.

All this may lead to large-scale changes in agriculture. Nitrogen abatement subsidies may cause farmers to reduce their fertilizer inputs; carbon trading may cause them to adopt certain
best management practices (BMPs); and a market demand for second-generation bioenergy crops may cause them to switch from existing crops to perennial grasses. Consequently, there may also be changes in stream nitrate load. This study takes a modeling approach to estimate those changes. It is hoped that decision-makers will find the results useful in furthering their understanding of the potential of market-based instruments for controlling agricultural pollution.

There are numerous modeling studies in the literature to assess the cost efficiency and environmental effectiveness of water quality policy (e.g. Chowdhury and Lacewell, 1996; Brady, 2003; Ribaudo et al., 2005). The common approach used in these studies is to impose upon the system some least cost, or maximum utility, equilibrium, presuming that an efficient market will achieve such an equilibrium ultimately. Inherent to this are the assumptions of “rational” behavior (often defined as motivated solely by cost considerations), perfect information, zero transaction costs and static conditions.

These assumptions however, often do not apply in reality. A modeling approach that relies on a more realistic set of assumptions is an improvement over such a least cost equilibrium approach. It is proposed that agent-based modeling (ABM) is one such approach. ABM simulates the actions of the individuals, or agents, in a system as functions of their current space-time environment according to predefined decision-making rules. This micro-to-macro property gives ABM flexibility not found in the least cost equilibrium approach such that the former need not be constrained by the aforementioned assumptions that limit the latter.

1.2 Research Objectives and Scope

The primary objectives of the present work are to: (i) demonstrate the applicability of ABM to water quality policy modeling using a semi-hypothetical case study of farmers under the influence of nitrogen subsidies and carbon and second-generation bioenergy crop prices, and (ii) answer, using ABM, questions on the environmental effectiveness and economic efficiency of nitrogen subsidy, carbon trading and bioenergy crop cultivation programs in achieving water quality goals.

Note that the two objectives are mutually supportive. By meeting the second objective, it can be shown that ABM is capable of producing meaningful results; which makes the point of
the first objective, i.e., that ABM is a worthwhile alternative to the least cost equilibrium approach.

To meet these objectives, an agent-based model of farmers' decisions is developed and linked to an environmental-response model. Refer to Figure 1-1 below for a general view of how the two models relate to each other. The latter is used to simulate yield data to feed to the former, which in turn, is used to compute farmers' management decisions to feed to the latter to estimate stream nitrate load. The model of farmers' decisions is based on fundamental economic and mathematical programming (specifically, dynamic programming) principles, while the environmental-response model is based on the Soil and Water Assessment Tool (SWAT) (Arnold and Fohrer, 2005), a watershed-scale semi-distributed hydrologic model that has been widely applied in both government and academia (Gassman et al., 2007).

For this study, the Salt Creek watershed in Illinois (see Figure 1-2 below) is used as a study site. The watershed is typical of most agricultural watersheds in the Midwest (where the dominant crops are corn and soybean) and like many of these systems, faces problems of excessive nitrate levels in its waters. This makes the watershed an ideal setting for the study of nutrient management policies.

The scope of this study is also limited to *Miscanthus x giganteus* as the sole bioenergy crop of interest. Miscanthus is a C4 photosynthesis plant that requires relatively little energy and agrochemical inputs. As summarized by Heaton et al. (2004), it possesses many characteristics desirable in an energy crop, e.g. high water and nutrient use efficiencies, positive soil restoration and carbon sequestration, low nutrient content etc. Further, field trials carried out throughout Illinois (Heaton et al., 2008) showed miscanthus to give yields superior to switchgrass, another perennial grass that has received serious attention for its potential as a model bioenergy crop (McLaughlin et al., 2002).
Figure 1-1: Overview of the coupling of the environmental-response model and the agent-based model of farmers’ decisions

Figure 1-2: Locator map of the Salt Creek watershed in East-Central Illinois
1.3 Dissertation Outline

Chapter 2 gives some background information on water quality policy modeling with an emphasis on agricultural nutrient management programs. Chapter 2 also introduces ABM and explains in greater detail its advantages and disadvantages with respect to the least cost equilibrium approach.

Following that is Chapter 3, which is the first of three chapters outlining the method used in this study. It describes the development of a SWAT model of the Salt Creek watershed that is the environmental-response model in Figure 1-1. Chapter 4 is the second method chapter; it explains the dynamic programming model of the decisions of a single farmer that is then expanded upon in Chapter 5, which is the last of the method chapters, to obtain an agent-based model of the suite of decisions of multiple farmers.

Chapter 6 presents and discusses the simulation results obtained for various scenarios of nitrogen, carbon and miscanthus prices. The results are discussed in terms of their estimated effects on land use and the resulting tradeoffs between crop acreages, farmer income, physical cost and nitrate load reduction. Finally, Chapter 7 concludes this dissertation by summarizing the work done, reiterating major findings, and offering recommendations.
2. BACKGROUND INFORMATION

The traditional approach to modeling water quality policy is to impose upon the system some least cost, or maximum utility, equilibrium. This so-called least cost equilibrium approach, though mathematically convenient, is valid only under the assumptions of rational behavior, perfect information, zero transaction costs and/or static conditions that may not be valid in real systems. One arguably more realistic approach, that does not incorporate these assumptions, is agent-based modeling (ABM).

This chapter gives some background information on water quality policy (with an emphasis on modeling studies on reducing nutrient runoff from agriculture) in Section 2.1 and in Section 2.2, on ABM and how it is potentially a more realistic representation of real water quality systems. Section 2.3 concludes this chapter by reiterating major discussion points and giving a summary on the current state of and research challenges in ABM.

2.1 Modeling Water Quality Policy

Excessive nutrient loads in surface waters are a major cause of hypoxia in coastal ecosystems and eutrophication in streams and lakes. Further, high nitrate concentrations in drinking water may have negative health effects, particularly on infants. Agricultural nonpoint sources are the single largest contributor to the problem. Due to their dispersed nature, agricultural sources, unlike point sources, are largely unregulated. In most places, there is no limit on the amount of fertilizer farmers may apply, nor is there any requirement for them to observe certain land management practices to control runoff.

There are a number of studies in the literature on market-based policies for reducing agricultural nutrient runoff. The use of taxes has been proposed (e.g. Vermersch et al., 1993; Chowdhury and Lacewell, 1996; Kampas and White, 2004), subsidies (e.g. Chowdhury and Lacewell, 1996; Lankoski and Ollikainen, 2003; Brady, 2003) and point/non-point nutrient trading (e.g. Letson, 1992; Crutchfield et al., 1994; Horan et al., 2002; Ribaudo et al., 2005)) to induce farmers to make large-scale land use changes, reduce their fertilizer inputs or adopt appropriate best management practices (BMP).
Many of these studies employ economic modeling, some together with environmental modeling, to estimate the cost and effectiveness of such policies. A common modeling approach is to assume the model outcome as some least cost, or maximum utility, equilibrium (Chowdhury and Lacewell, 1996; Brady, 2003; Ribaudo et al., 2005). A major weakness of this approach is its assumption of profit-maximizing, or "rational", behavior. In real water quality systems, most agents are municipal or agricultural operations who may not be driven by maximizing profit. According to Hoag and Hughes-Popp (1997), non-profit-maximizing behavior was a reason for the outcome of the Tar-Pamlico nutrient trading program in North Carolina. It was found that farmers were unwilling to accept trades due to the perception that by doing so, they were acknowledging themselves as polluters. Point source firms were also hesitant to trade if treatment costs were already low enough for fear of attracting attention to their pollution activities and the possibility of having to communicate sensitive information. Thus, even industrial operations may not be entirely maximum-profit-driven.

Indeed, a survey by Brodt et al. (2006) of farmers in Central Valley, California found the farmers to be quite mixed in their values and goals. Some of the farmers were found to be production (i.e. yield) maximizers, while some others were found to value environmental stewardship over production. There were also those who placed more emphasis on off-farm activities and social networking to acquire and share new information, which helps them to be more aware of new ideas and more willing to risk new technologies. Note that the investigators either did not consider profit maximizers at all or did not distinguish between profit and yield maximizers.

Further, even if traders were driven solely by profit, they are seldom capable of the level of rationality assumed by the least cost equilibrium approach. The rational agent is one that is perfectly logical and deductive in its decision-making process; and who is capable of identifying the most optimal decision even in the most complex of situations. However, real human rationality is “bounded” (Arthur, 1994) such that such that its reasoning is usually inductive and learning is achieved from observing examples and recognizing patterns. In other words, the real agent is rarely able to determine the best decision but typically settles for decisions that are progressively improving.

Another weakness of the least cost equilibrium approach is its assumption of perfect information. In real systems, there is often some degree of uncertainty. This is especially true
for agricultural systems which are vulnerable to environmental (e.g. weather) fluctuations. Further, agricultural pollution sources are usually dispersed and non-point such that only the aggregate effects of multiple polluters are observable i.e. the effects of a single polluter cannot be easily observed. As a result, the relationship between source-level actions and ambient pollution levels is seldom clear. The least cost equilibrium approach incorporates uncertainty by assigning probabilities to possible outcomes, which are then used to predict the equilibrium by minimizing the expected overall cost or where risk is a factor, maximizing expected overall utility (e.g. Shortle and Dunn, 1986; Segerson, 1988; Montero, 1997). However, this assumes that agents are rational and that all possible outcomes and their probabilities of occurrence are known.

In the least cost equilibrium approach, there is also the assumption of **zero transaction costs**. Here, transaction costs are taken to mean costs not directly related to pollution reduction that are often intangible and one-time. They include search, information and negotiation costs, and additional administrative expenses. As shown by Stavins (1995), as transaction costs increase, agents' actions are inhibited in converging to the least cost equilibrium; rather, the equilibrium is now dependent on initial conditions. A statistical analysis of actual data by Gangadharan (2000) also showed transaction costs to reduce the tendency of agents to participate in market-based policy programs.

The least cost equilibrium approach, as it is traditionally applied, also assumes **static conditions**, where neither agents nor their surroundings are changing with time. Static models do not capture the effects of technology innovation, agent entry, exit and adaptation, and varying exogenous variables, all of which are significant factors. Dynamic models on the other hand, allow for the explicit inclusion of time-sensitive variables. In fact, there is a relatively new subclass of equilibrium models, dynamic equilibrium models (Ohanian et al., 2009) that have emerged as a means of incorporating the element of time. In water quality policy modeling, refer to recent works by such as Berntsen et al. (2003), Martinez and Albiac (2006) and Knapp and Schwabe (2008) for examples of dynamic modeling. Note however, the dynamic models in these studies are still static in that they do not endogenously model agent adaptation with time. In a real system, agents' treatment costs, production capacities, forecasts of future conditions or other specifics may change as they make new observations, interact with other agents and/or adopt new technologies.
This study takes a new approach to modeling water quality policy, i.e. ABM. Specifically, its primary objective is to develop an agent-based model of farmers' decisions under various combinations of nitrogen subsidy and carbon and second-generation bioenergy crop (namely, miscanthus) prices. The nitrogen subsidy gives incentive for the farmers to reduce their fertilizer inputs, which as demonstrated by, among others, Hu et al. (2007), should lead to a reduction in riverine nitrate load. The carbon price is from carbon trading, which compensates farmers for practicing conservation tillage or grass planting. Note that even though carbon trading is not a water quality policy per se, it affects farmers' behaviors and consequently, water quality. Conservation tillage leads to significant reductions in soil erosion (Matisoff et al., 2002) and surface runoff (Choudhary et al., 1997). The same goes for cropland conversion to grassland, which is already a central part of the U.S. Department of Agriculture’s (USDA) Conservation Reserve Program (CRP) (www.nrcs.usda.gov/programs/crp/) to retire highly erodible land. In this study, it is envisioned that carbon trading also pays farmers for cultivating second-generation bioenergy crops although in reality, there is yet to be a clear policy on this. Farmers have further reason to cultivate such crops when there is a market demand for them. Studies (Nelson et al., 2006; Christian and Riche, 2006) have shown that they can be expected to have a positive effect on water quality.

The following sub-section introduces ABM. It also explains more in detail its advantages and disadvantages and how it is potentially suitable for modeling water quality policy.

2.2 Agent-Based Modeling (ABM)

ABM is a relatively new modeling paradigm which formulates a system from the perspectives of the individual agents within it. In other words, ABM models the individual agents as discrete autonomous entities, each with its own unique set of goals and actions, and from there, is able to generate macro-level properties of the system. In this manner, the latter can be thought of as naturally emerging from the former. This is in contrast to the least cost equilibrium approach which artificially imposes upon the system the least cost equilibrium, a macro-level property, without explicit consideration for the micro-level properties of the system.
It can therefore be argued that ABM brings more realism into the model, as long as the model itself is accurate and adequate data are available. This is especially true for systems involving biological entities, e.g. humans that more often than not, do not conform to fixed laws.

ABM has been applied to a wide range of disciplines, including ecological modeling (Grimm and Railsback, 2005), urban development (Batty, 2005), business and finance (North and Macal, 2007; Ehrentreich, 2008) and energy policy (Wittmann, 2008). For a more comprehensive introduction to ABM, refer to Epstein and Axtell (1996); Bonabeau (2002) and Gilbert (2008).

A major difference between water quality systems and systems where ABM has most commonly been applied, i.e. economic and social systems, is the strong interdependence and short response time between water quality systems and the environment that does not exist for economic and social systems. In the latter, the system is confined to just the human aspect where only humans agents are relevant. In water quality systems (as contextualized in this study), agents are mostly farmers whose decisions affect and are affected by the environment. Specifically, for the particular case of this study, the link between the environment and the farmers’ decisions is in the formation of the farmers’ perceptions of crop yields. The farmers’ current decisions are affected by their perceptions of future yields, which are based on their observations of past yields, which in turn, are dependent on the weather and their past decisions. Also, the farmers’ decisions affect runoff and consequently, stream water quality. Therefore, a complete model of the system would consist of a physical model of the environment in addition to a socio-economic model of the human agents.

Following this introduction of Section 2.2, Section 2.2.1 describes some seminal works on ABM. Thereafter, Section 2.2.2 discusses some of the advantages and disadvantages of ABM. Section 2.2.3 discusses the issue of model validation in ABM, a critical area of research that requires further attention before ABM can achieve its full potential.

2.2.1 Early works

ABM can be traced back to von Neumann (1966), who created a two-dimensional cellular model of self-replication. The model later provided a basis for the study of artificial life. By having the states of the cells change according to certain transition rules based on the current...
states of their neighboring cells, von Neumann (1966) showed mathematically that a system is able to copy itself simply by following a pre-specified algorithm.

von Neumann’s (1966) model was quickly followed by John Conway’s Game of Life (Gardner, 1970). The game consists of a two-dimensional grid of cells with each cell being either dead or alive. Whether or not the state of a cell changes, i.e. a living cell dying or a dead cell coming alive, depends on the state of its neighbors. To play the game, an initial condition is first defined. The state of each cell is then simulated to generate the second and subsequent generations.

Another early example of ABM is Schelling’s (1971) model of housing segregation between whites and blacks. The author modeled the movements of individuals as they change their locations depending on the racial composition of their neighbors. Results suggested that highly segregated patterns could exist even with low degrees of racial intolerance.

More recently, computer advances have enabled larger scale applications of ABM. One widely cited example is the Sugarscape model by Epstein and Axtell (1996). Sugarscape is an artificial two-dimensional (in space) world composed of agents with the sole purpose of searching for and consuming sugar. Sugarscape is spatially distributed with some regions being richer in sugar than others. By applying simple combat, trade and other rules, the model was able to produce patterns of wealth distribution, migratory behavior, market growth etc. not unlike patterns observable in real societies.

2.2.2 Advantages and disadvantages of ABM

Decision-making rules

The unique micro-to-macro approach in ABM gives it a level of flexibility not found in the least cost equilibrium approach. For instance, ABM does not require the assumption of rational behavior (though it can accommodate it if so desired). There is great flexibility on the part of the modeler to specify agents’ decision-making rules. In the literature, decision-making rules have been defined based on empirical data from surveys or controlled experiments (Dia, 2002; Castella et al., 2005), heuristics (Epstein and Axtell, 1996; Kerridge et al., 2001), neural networks (LeBaron, 2001; Barr and Saraceno, 2005) and mathematical programming (Balmann,
Note that where the rules were based on mathematical programming, rationality was the assumed behavioral rule, and where they were based on empirical data, heuristics and neural networks, rationality was not assumed but, instead, agents were assumed to behave as defined by other types of rules.

In the present study, agents are assumed to be rational and their decision-making based on mathematical programming. This is primarily due to a lack of empirical data that can be used to deduce the cognitive processes of actual farmers in the study area. Indeed, as discussed by Zenobia et al. (2009), a major challenge in ABM lies in the construction of decision-making rules that are sufficiently credible and accurate. Real human behavior is complex; it varies widely from person to person and is not easily condensed into a few lines of mathematics. In short, while ABM does provide the framework for incorporating real behavior, it is not a straightforward task to define what that might be. The data requirements for such a task are significantly greater than for defining rational behavior. It remains an area of research in ABM, and elsewhere, e.g. behavioral economics (Loewenstein, 2007), to develop standard methods of evaluating data needs, acquiring the necessary data, translating them into mathematical terms and characterizing their uncertainties.

Transaction costs

This flexibility of ABM also enables it to incorporate in, without any sacrifice to the ease of solution, transaction costs that are usually intangible and may not be described as simple continuous differentiable functions of cost or other factors. For example, Wilhite (2001) used ABM to investigate the tradeoffs between search and negotiation costs and market efficiency. In that study, the author modeled the actual searching of agents for other agents to conduct bilateral trade with and results were obtained for trade networks of different sizes and interconnectedness. He found that networks with high levels of interconnectedness are not Pareto optimal; such networks have high market efficiencies but also high search and negotiation costs. Rather, networks where the majority of agents are trading locally and just a few are trading globally are more desirable as they are still able to produce high market efficiencies but at much lower search and negotiation costs.
Dynamic conditions and agent adaptation

ABM is also able to accommodate dynamic conditions where the environment and the agents themselves are changing with time. Therefore, unlike the least cost equilibrium approach, ABM need not assume static conditions or even equilibrium (should there be an equilibrium, it will naturally emerge from the micro-level and not be pre-imposed upon the model).

This allows ABM to include in the effects of agent learning as agents make new observations or gain new experience. A common method for simulating agent learning is genetic algorithms (Holland, 1975). For instance, Palmer et al. (1994) used a genetic algorithm to evolve agents' behavior rules (in the study, each agent was modeled as a set of condition-action rules) with time such that weaker rules were eventually dropped and stronger rules increased in selection probability. Note that the evolution occurred only within an agent’s own population of rules, meaning that the learning depended only on the agent’s own past experiences. On the other hand, Lettau (1997) modeled agent learning as group learning where agents learned by interacting with each other. In that study, each agent was modeled as a binary string (as opposed to a set of strings) and crossovers between strings were analogous to interactions between agents.

Agent learning has also been modeled as neural network learning. In a study by Barr and Saraceno (2005), neural networks were used to model the output decisions of firms in a duopoly. At the beginning of each time period, the firms would make their decisions according to the weights in their neural networks; at the end of the time period after certain stochastic factors became known, the firms would compare their actual outputs to the ideal. With this, the firms’ neural network weights would then be adjusted, or improved, using backward propagation.

Note however, that even though genetic algorithms and neural networks have been widely applied to modeling human learning, they are nonetheless still gross simplifications of the actual process. As articulated by Castelfranchi (2001), current models are overly simple and do not capture the complex relationships between individual intention, beliefs, goals, association and conditioning. In other words, the ability to accurately model human learning and adaptation remains a challenge that to overcome, will require a multi-disciplinary approach involving expertise from the fields of artificial intelligence, cognitive psychology and social science.

In the present study, neither neural networks nor genetic algorithms are used; agents are assumed to be rational and therefore, in terms of their decision-making, there is no learning per
Their decision-making is limited only by the quality of their information, not their ability to process that information. As they are rational, they are already making the best decisions possible given their individual properties and perceptions of their surroundings. In terms of those perceptions however, there is learning as the agents adapt their forecasts of future prices, costs, yields, weather variables and other factors with time and experience. Here, this adaptation of perceptions is modeled using Bayesian inference (Gelman, 1995), which provides a mathematically tractable way of weighting new data against existing beliefs.

Agent interactions

The dynamic nature of ABM also makes it suitable for modeling interactions between agents. For example, ABM has been widely applied to modeling markets where their outcomes very much depend on how agents interact with each other. Many of the agent-based market models in the literature are of the stock market, of which the most well-known is perhaps, the Santa Fe Institute Artificial Stock Market (SFI-ASM), which was first described by Palmer et al. (1994) and subsequently by LeBaron et al. (1999), Palmer et al. (1999) and Ehrentreich (2008).

The SFI-ASM consists of a number of heterogeneous agents who have to decide, at the beginning of each time period, whether to invest in a stock or leave their money in an interest-earning savings account. Each agent has a set of condition-action rules that dictate his decisions based on his expectations of future stock prices and dividends. The rules progressively improve with time as the agent makes adjustments according to his observations of their successes and failures. The SFI-ASM has been shown to produce patterns of bubbles, crashes and high trading volumes common in real stock markets.

Apart from financial markets, ABM has also been applied to power markets. Sueyoshi and Tadiparthi (2008) presented an agent-based model of a decentralized electricity market comprising a market administrator, generators, wholesalers, a network operator and a utility policy administrator. Applying data from the California electricity market, the authors simulated the prices of electricity for a 20-month period and found them to closely approximate actual prices.

In the present study, farmers are interacting with each other in terms of their likelihoods of taking unfamiliar actions. A risk-averse farmer is less likely to actions that are new to him.
However, as his neighbors who may be more risk tolerant or may have more optimistic views of circumstances decide to experiment with the relatively unknown, the farmer's uncertainty is reduced. Thus, with time, the farmer becomes more and more willing to experiment himself and in turn, influence his neighbors. In this particular case, there are three items that are considered new to the farmers: carbon trading, conservation tillage and bioenergy crop cultivation. The farmers are modeled as having relatively large initial uncertainties of their costs and benefits that with experience, are adjusted downwards. This approach to modeling the farmers' taking up of the three new items is in line with Marra et al. (2003), who listed farmers' risk attitudes, perceptions of current and future economic returns and learning of relevant information as key factors in their willingness to adopt new technology.

2.2.3 Model validation

Despite its wide-ranging application in the literature and growing popularity, there remains some skepticism towards ABM. As discussed by Leombruni and Richiardi (2005) and Midgley et al. (2007), a major reason for this is the issue of model validation, which is the process of affirming that the model adequately represents real life within the scope of its intended use. Earlier works focused on defining ABM and demonstrating its capabilities but overlooked questions of model credibility. Also, as discussed by Axelrod (1997), many of these works were deliberately simple in their definitions of agent behavior as their ultimate objective was not to represent any real system but to investigate fundamental processes. Thus, it was desirable that the models remained as simple as possible (though not their outcomes) to allow more straightforward interpretations of results.

Some recent works are starting to address this subject of model validation by empirical testing. Gilli and Winker (2003) developed an optimization method for calibrating agent-based models. The method is a combination of the Nelder-Mead simplex algorithm and threshold accepting, a local search heuristic based on simulated annealing. Such an approach is necessary as agent-based models are seldom globally convex and differentiable. In the study, the authors used the method to determine the combination of parameters that gave the minimum distance between simulated Monte Carlo and historical means and variances of the DM/USD foreign exchange rate.
Bianchi (2007) provides another example of empirically validating an agent-based model. The author validated an agent-based model of firms’ entry and exit behavior by comparing simulated and actual data on firm productivity, capital distribution, growth rate and other measures for a five year period. The model included over 6400 small and large firms. For the most part, the results showed a good fit between simulated and actual data.

Another approach to validating agent-based models is to observe if simulation results match qualitative expectations. Compared to empirical validation however, this approach is only second-best, but it may be all that is practicable where empirical data are unavailable as is often the case for social systems. Such an approach was used by Dosi et al. (2006) to substantiate their model of industry dynamics. From the model, the authors were able to produce results conforming to key stylized facts pertaining to employment, investment, consumption, firm size and growth and other variables and thus claim some confidence that the model is indeed realistic.

2.3 Summary of State of the Art

The conventional method to model water quality policy is to impose some least cost, or maximum utility, equilibrium upon the entire system, composed of multiple independent agents. This method assumes agents are motivated identically and have perfect information and zero transactions costs. ABM is an alternative method. It is a micro-to-macro approach that models the system from the perspectives of individual agents. This makes it arguably more realistic as it gives the modeler greater flexibility not to make the assumptions of the conventional least cost equilibrium approach.

Many current and past models in the literature are abstract, conceptual and/or hypothetical in that they do not claim to represent real systems. These models have based their definitions of agents on heuristics, neural networks, evolutionary algorithms and/or mathematical programming (e.g. Epstein and Axtell, 1996; Kerridge et al., 2001; LeBaron, 2001; Barr and Saraceno, 2005; Balmann, 1997; Berger, 2001), thus avoiding the problem of data scarcity and the burden of empirical validation. These models have been helpful in gaining valuable insights into fundamental processes and providing new ways of viewing old problems. However, their applicability is limited to just that. As these models do not represent reality, it is difficult, without stretching their boundaries, to rely on them for prediction or decision-making purposes.
Nonetheless, a small number of studies are starting to base their agent-based models on empirical data, whether by using the data for model calibration and validation (e.g. Gilli and Winker, 2003; Bianchi, 2007) or for defining agents (Dia, 2002; Castella et al., 2005). These models have stronger claims to realism, which enhance their usefulness. Perhaps, it can be expected for their number to increase as more and more empirical data become available. Further, with improvements in the cognitive sciences to give new insights into human behavior and in the computational sciences to give new methods of converting subjective knowledge to precise algorithms, it can also be expected for agent-based models to improve as well in their ability to represent reality. At the same time, it must be acknowledged that that portion of human behavior associated with market psychology is stubbornly difficult to predict, and is likely to remain so.

In this study, ABM is used to develop a model of farmers’ crop and BMP decisions under various scenarios of a nitrogen fertilizer reduction subsidy and market prices for carbon emission reduction and a second-generation bioenergy crop (namely, miscanthus). The model takes into consideration the farmers’ adaptation of their forecasts of future conditions with experience. The model also accounts for the interactions among farmers as they learn from each other the costs and benefits of new activities. Included as well in the model are time and decision-dependent factors and constraints. It is challenging, if not impossible, to incorporate all these into the model using the conventional least cost equilibrium approach.
The Salt Creek in East-Central Illinois is about 217 km southwest of Chicago. It drains into the Illinois River and eventually to the Gulf of Mexico. Its watershed (U.S. Geological Survey (USGS) hydrologic unit code 07130009) has one major urban area, the City of Bloomington, and is predominantly agricultural; its primary crops are corn and soybean planted in rotation with each other. The watershed has been selected as the example study site for the present work as typical of many agricultural watersheds in the Midwest where excessive nutrient runoff to surface waters is a problem. The watershed is selected also because of the ready availability of observed data required for calibrating and validating the Soil and Water Assessment Tool (SWAT) (Arnold and Fohrer, 2005) model of the watershed used in this study.

To achieve the objectives of this study, the SWAT model of the Salt Creek watershed is first calibrated and validated using historical data for daily stream flow, annual corn and soybean yields and monthly nitrate load at the watershed outlet. Work is then carried out to parameterize the crop growth component in SWAT for miscanthus. Even though SWAT comes with a database of default parameters for a number of crops, including corn, soybean, sugarcane, wheat etc., default values for miscanthus are unavailable as it is a relatively new crop of interest.

Once calibrated and validated, the Salt Creek watershed model is linked to the agent-based model of farmers' decisions (as described in Chapters 4 and 5). Specifically, it is used to generate corn, soybean and miscanthus yield data to be fed to the agent-based model. It is also used to simulate stream nitrate load as a function of the farmers' crop management decisions as computed by the agent-based model.

SWAT has been selected for use here as it is widely accepted and has been applied in numerous studies (Gassman et al., 2007) including water quality studies similar to the present work. For instance, Nelson et al. (2006) used SWAT to predict potential reductions in sediment yield, surface runoff, nitrate load and edge-of-field erosion from planting switchgrass for a watershed in Kansas. Refer also to Hu et al. (2007) who used SWAT simulate the nitrogen export from a watershed in Illinois for various levels of nitrogen fertilization. Other examples of using SWAT to model water quality as a function of land use management decisions are Vache et al. (2002), Saleh et al. (2000) and Varanou et al. (2002).
3.1 Model Calibration and Validation

3.1.1 Method

The Salt Creek watershed SWAT model is developed using input data on elevation, land use, soil type, temperature, precipitation etc. from the USDA, USGS and National Oceanic and Atmospheric Administration (NOAA). To model farmers’ activities in SWAT, the crop management schedule reported by Hu (2003) is adapted for use here. A nitrogen fertilizer application rate for corn of about 190 kg-N/ha per year is used based on historical fertilizer sales as estimated by Hu (2003). As for soybean, which is a legume, the nitrogen fertilizer application rate is assumed as zero. The watershed has been estimated by Sugg (2007) to be about 60% tile drained by area.

The SWAT model is calibrated and validated for daily stream flow at four USGS gages: Greenview (site number 05582000), Cornland (05579500), Waynesville (05580000) and Rowell (05578500). The model is also calibrated and validated for annual corn and soybean yields with data obtained from the USDA National Agricultural Statistics Service (NASS), and for monthly riverine nitrate load at the watershed outlet at Greenview with data from the Illinois Environmental Protection Agency (IEPA) and M. B. David (personal communication, 2006). The calibration period is eight years from 1996 to 2003. The validation period is also eight years from 1988 to 1995.

To calibrate the SWAT model, the Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven and Binley, 1992) method is used to estimate the probability distributions of twenty-two adjustable parameters controlling surface runoff, nutrient transformation, evapotranspiration, groundwater flow and crop growth. Refer to Table 3-1 for a list of the parameters and their descriptions.

GLUE is a stochastic calibration method that accounts for the problem of equifinality (Beven, 1993) often encountered in large complex models (such as SWAT). It is a sampling-based method which works by first randomly generating a large number of possible sets of the adjustable parameters. The parameter sets are then tested by running the model repeatedly to assess their likelihoods of being “true” based on their abilities to reproduce observed data. In this study, 65,000 parameter sets are generated using Latin Hypercube sampling assuming the
adjustable parameters are uniformly distributed with the upper and lower bounds given in Table 3-1. The SWAT model is then run for each of the 65,000 realizations and the resulting Nash-Sutcliffe Efficiencies (NSE) (Nash and Sutcliffe, 1970) for stream flow, corn and soybean yields and nitrate load are recorded.

Based on their NSE values, a likelihood score is calculated for each realization. Realizations that fail to meet the minimum criteria described as follows are assigned likelihoods of zero: the NSEs for the stream flow at Greenview, Cornland, Waynesville and Rowell must be at least 0.5, 0.3, 0.3 and 0.5 respectively; the NSEs for corn yield must be at least -2.5 and for soybean yield -5; and the NSE for nitrate load at Greenview must be at least 0.5. Admittedly, there is some subjectivity in deciding these minimum criteria, which are fixed using best judgment based on the results of a previously conducted deterministic calibration of the model using a genetic algorithm (Ng et al., 2010). For the remaining realizations that are considered to be acceptable, their likelihood scores are calculated as functions of the normalized NSEs of the various outputs as described below:

\[
LS = \frac{1}{4} \left( \frac{N_{f,1} - 0.5}{1 - 0.5} + \frac{N_{f,2} - 0.3}{1 - 0.3} + \frac{N_{f,3} - 0.3}{1 - 0.3} + \frac{N_{f,4} - 0.5}{1 - 0.5} \right)
+ \frac{N_{\text{corn}} + 2.5}{1 + 2.5} + \frac{N_{\text{soyb}} + 5}{1 + 5} + \frac{N_{\text{NO3}} - 0.5}{1 - 0.5}
\]  

(3-1)

\(N_{f,1}\) is the NSE for stream flow at Greenview, \(N_{f,2}\) at Cornland, \(N_{f,3}\) at Waynesville and \(N_{f,4}\) at Rowell. \(N_{\text{corn}}\) and \(N_{\text{soyb}}\) are respectively, the NSEs for corn and soybean yields; and \(N_{\text{NO3}}\) is the NSE for nitrate load at Greenview.

Once the likelihood scores for all 65,000 realizations are computed, the non-zero likelihood scores are then normalized by dividing each by the sum of all scores, such that the sum of the normalized likelihoods is unity. The probabilities of the realizations being “true” can thus be found. The SWAT model is now run again for only the realizations with non-zero probabilities to find the weighted means, standard deviations as well as the minimum and maximum limits of the relevant outputs.
Table 3-1: List of SWAT parameters adjusted in the calibration process and the lower (LB) and upper bounds (UB) used in the GLUE calibration

| Parameter (Units) | Description | GLUE Range
|------------------|-------------|-------------
|                 |             | LB   | UB   |
| $cn_2$ (-)      | SCS runoff curve number (for untiled subbasins) | -20% | +10% |
| $cn_2_{-tile}$ (-) | SCS runoff curve number (for tiled subbasins) | -60% | -20% |
| $surlag$ (-)    | Surface runoff lag coefficient | 0.5  | 10   |
| $canmx$ (mm)    | Maximum canopy storage | 0    | 100  |
| $sol_{awc}$ (mm/mm) | Available water capacity of the soil layer | -20% | +20% |
| $sol_{k}$ (mm/hr) | Saturated hydraulic conductivity | -20% | +20% |
| $drain$ (mm)    | Depth to subsurface drain | 800  | 1400 |
| $t_{drain}$ (hr) | Time to drain soil to field capacity | 12   | 60   |
| $esco$ (-)      | Soil evaporation compensation factor | 0.01 | 1    |
| $epco$ (-)      | Plant uptake compensation factor | 0.01 | 1    |
| $cncoef$ (-)    | Plant evapotranspiration curve number coefficient | 0.5  | 2    |
| $smfmx$ (mm/°C-day) | Melt factor for snow on June 21 | 1.4  | 6.9  |
| $smfmm$ (mm/°C-day) | Melt factor for snow on December 21 | 1.4  | 6.9  |
| $t_{opt}$ (corn) (°C) | Optimal temperature for plant growth for corn | -20% | +20% |
| $t_{base}$ (corn) (°C) | Base temperature for plant growth for corn | -20% | +20% |
| $alpha_{bf}$ (day) | Baseflow alpha days | 0.01 | 1    |
| $gw_{delay}$ (day) | Groundwater delay time | 1    | 200  |
| $gwqmn$ (mm)    | Depth of water in the shallow aquifer for return flow to occur | 100  | 1200 |
| $gw_{revap}$ (-) | Groundwater revap coefficient | 0.02 | 0.2  |
| $cmn$ (-)       | Rate factor for humus mineralization of active organic nutrients | 0.0001 | 0.02 |
| $cdn$ (-)       | Denitrification exponential rate coefficient | 0    | 0.15 |
| $sol_{orgn}$ (ppm) | Initial organic nitrogen concentration in the soil | 500  | 6000 |

1. Where the bounds are + or - a percentage, it is in reference to the default value, e.g. -20% means 0.8 of the default.
2. Soil Conservation Service (SCS)
3.1.2 Results

Out of the 65,000 random parameter sets tested to calibrate the SWAT model of the Salt Creek watershed using GLUE, 106 sets are found to be acceptable, i.e. to have positive likelihoods of being true. Refer to Table 3-2 for the parameter set that has the greatest likelihood of being true that is best able to reproduce observed stream flow, crop yield and nitrate load data for the calibration period 1996 to 2003. Their SWAT default values are also provided for comparison. Refer also to Figure 3-1 which shows dotty plots of the probabilities of the acceptable parameter sets against the values of the individual parameters.

Table 3-3 gives the goodness-of-fit between simulated and observed data obtained when the most likely parameter set is applied. The goodness-of-fit is expressed in terms of the coefficient of determination, $R^2$ and NSE for daily stream flow at four locations within the watershed (Greenview, Cornland, Waynesville and Rowell), annual corn and soybean yields and monthly nitrate load at the watershed outlet at Greenview.

Of particular interest in this study is nitrate load. Figure 3-2 gives a graphical comparison between simulated and observed nitrate load. The figure gives the historical values of nitrate load for the calibration and validation periods 1996-2003 and 1988-1995 respectively plotted against their corresponding simulated values. Note that the simulated values in Figure 3-2 are not deterministic but are stochastic and are expressed in terms of their means and mean plus/minus one standard deviation ranges.

As can be seen in the figure, as well as in Table 3-3, the SWAT model is able to reproduce observed data reasonably well for nitrate load and the other output variables. The $R^2$ and NSE values are comparable to those of Hu (2003), who obtained $R^2$ and NSE values for daily stream flow of 0.57 and 0.55, for annual corn yield of 0.31 and -0.49, for annual soybean yield of 0.007 and -1.36 and for monthly nitrate load of 0.72 and 0.20, respectively for the calibration period 1994-2002 for a SWAT model of the upper Embarras River watershed (also in East-Central Illinois).

For more details on the results of the calibration and validation of the Salt Creek watershed model, refer to Ng et al. (2010).
Table 3-2: The SWAT default values of the adjustable parameters and their most likely values as estimated using GLUE

<table>
<thead>
<tr>
<th>Parameter (Units)</th>
<th>SWAT Default Value</th>
<th>Most Likely Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$cn2$ (-)</td>
<td>78</td>
<td>+3.5%</td>
</tr>
<tr>
<td>$cn2_{tile}$ (-)</td>
<td>78</td>
<td>-52.1%</td>
</tr>
<tr>
<td>$surlag$ (-)</td>
<td>4</td>
<td>1.204</td>
</tr>
<tr>
<td>$canmx$ (mm)</td>
<td>0</td>
<td>5.782</td>
</tr>
<tr>
<td>$sol_awc$ (mm/mm)</td>
<td>0.07–0.23</td>
<td>+7.3%</td>
</tr>
<tr>
<td>$sol_k$ (mm/hr)</td>
<td>0.29–300</td>
<td>-10.5%</td>
</tr>
<tr>
<td>$ddrain$ (mm)</td>
<td>0</td>
<td>820</td>
</tr>
<tr>
<td>$tdrain$ (hr)</td>
<td>0</td>
<td>44</td>
</tr>
<tr>
<td>$esco$ (-)</td>
<td>0.95</td>
<td>0.247</td>
</tr>
<tr>
<td>$epco$ (-)</td>
<td>1</td>
<td>0.757</td>
</tr>
<tr>
<td>$cncoef$ (-)</td>
<td>1</td>
<td>1.994</td>
</tr>
<tr>
<td>$smfmx$ (mm/°C-day)</td>
<td>4.5</td>
<td>6.554</td>
</tr>
<tr>
<td>$smfmm$ (mm/°C-day)</td>
<td>4.5</td>
<td>6.481</td>
</tr>
<tr>
<td>$t_opt$ (corn) (°C)</td>
<td>25</td>
<td>+5.6%</td>
</tr>
<tr>
<td>$t_base$ (corn) (°C)</td>
<td>8</td>
<td>+18.1%</td>
</tr>
<tr>
<td>$alpha_bf$ (day)</td>
<td>0.048</td>
<td>0.932</td>
</tr>
<tr>
<td>$gw_delay$ (day)</td>
<td>31</td>
<td>15</td>
</tr>
<tr>
<td>$gw_qmn$ (mm)</td>
<td>0</td>
<td>677</td>
</tr>
<tr>
<td>$gw_revap$ (-)</td>
<td>0.02</td>
<td>0.156</td>
</tr>
<tr>
<td>$cnn$ (-)</td>
<td>0.0003</td>
<td>0.006</td>
</tr>
<tr>
<td>$cdn$ (-)</td>
<td>1.4</td>
<td>0.051</td>
</tr>
<tr>
<td>$sol_orgn$ (ppm)</td>
<td>42.86–2493</td>
<td>2055</td>
</tr>
</tbody>
</table>
Figure 3-1: Dotty plots (o) of the probabilities of possible parameter sets against their individual parameter values as determined from the GLUE calibration of the SWAT model of the Salt Creek watershed; the right and left borders of the plots correspond to the parameter upper and lower bounds as given in Table 3-1.
Table 3-3: The $R^2$ and NSE values corresponding to the most likely parameter set as found using GLUE for the calibration period 1996-2003 and validation period 1988-1995

<table>
<thead>
<tr>
<th>Output Variable</th>
<th>Calibration $R^2$ / NSE</th>
<th>Validation $R^2$ / NSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily stream flow, Greenview</td>
<td>0.61 / 0.59</td>
<td>0.66 / 0.64</td>
</tr>
<tr>
<td>Daily stream flow, Cornland</td>
<td>0.52 / 0.49</td>
<td>0.57 / 0.48</td>
</tr>
<tr>
<td>Daily stream flow, Waynesville</td>
<td>0.52 / 0.51</td>
<td>0.42 / 0.40</td>
</tr>
<tr>
<td>Daily stream flow, Rowell</td>
<td>0.57 / 0.55</td>
<td>0.63 / 0.61</td>
</tr>
<tr>
<td>Monthly nitrate load, Greenview</td>
<td>0.74 / 0.74</td>
<td>0.73 / 0.73</td>
</tr>
<tr>
<td>Annual corn yield</td>
<td>0.34 / 0.24</td>
<td>0.72 / 0.64</td>
</tr>
<tr>
<td>Annual soybean yield</td>
<td>0.38 / -2.07</td>
<td>0.46 / 0.41</td>
</tr>
</tbody>
</table>

Figure 3-2: Historical values (—) of monthly nitrate load at the watershed outlet and their corresponding simulated means (---) and mean plus/minus one standard deviation ranges (■)
3.2 Modeling Miscanthus in SWAT

3.2.1 Method

Additional work is carried out in this study to parameterize the crop growth model in SWAT for miscanthus. Even though SWAT comes with a database of default parameters for a number of crops, including corn, soybean, wheat, etc., default values for miscanthus are unavailable as it is relatively new as a potentially commercial crop. To estimate them, the crop growth parameters are divided into three subsets: those describing optimal biomass growth under zero stress conditions, parameters characterizing nitrogen and phosphorus limitations, and miscellaneous parameters not included in the first two subsets. Refer to Table 3-4 for a list of the parameters and their definitions.

3.2.1(a) Optimal Biomass Growth Parameters

There are ten parameters in SWAT describing optimal crop growth, i.e. the theoretical maximum growth achievable when there are no nutrient and water limitations and when ambient temperature is in the optimal range. These parameters for miscanthus are unknown and their values are identified here by fitting SWAT’s optimal crop growth equations (as given by Neitsch et al. (2005)) to simulated biomass and leaf area index (LAI) data from a second model.

That second model is an improved version of the miscanthus model by Miguez et al. (2009) which, due to its mechanistic nature, is more robust and performs better in locations where no data are available for site-specific calibration. The model has been previously parameterized and tested using empirical data from European studies (which are as listed in Miguez et al. (2009)). The implementation used in this study is based on Windows Intuitive Model of Vegetation Response to Atmospheric and Climate Change (WIMOVAC), which is described in detail by Miguez et al. (2009) and Humphries and Long (1995). The current implementation is called BioCro and will be available in the near future as an R (The R Development Core Team, 2009) package (F. Miguez, personal communication, 2009) with its main algorithms coded in the C programming language.
Table 3-4: SWAT crop growth parameters and their estimated values for miscanthus

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Value</th>
<th>Method / source / assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Optimal growth parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>bio_e</td>
<td>RUE(^1)</td>
<td>3.9 g/(MJ/m(^2))</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>ext_coef</td>
<td>Light extinction coefficient</td>
<td>0.65</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>blai</td>
<td>Maximum LAI(^1)</td>
<td>11.5</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>frgrw1</td>
<td>Fraction of the growing season corresponding to point 1 on the crop’s LAI-time curve</td>
<td>0.1</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>laimx1</td>
<td>Fraction of the maximum LAI corresponding to point 1 on the crop’s LAI-time curve</td>
<td>0.2</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>frgrw2</td>
<td>Fraction of the growing season corresponding to point 2 on the crop’s LAI-time curve</td>
<td>0.5</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>laimx2</td>
<td>Fraction of the maximum LAI corresponding to point 2 on the crop’s LAI-time curve</td>
<td>0.95</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>heat units</td>
<td>Total accumulated heat units required for the plant to reach maturity</td>
<td>2100 °C-day</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>t_base</td>
<td>Base temperature, minimum temperature for crop growth</td>
<td>10 °C</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td>dlai</td>
<td>Fraction of the growing season when leaf senescence exceeds leaf growth</td>
<td>0.85</td>
<td>By data fitting (refer to Section 3.2.1(a))</td>
</tr>
<tr>
<td><strong>Nutrient parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>cnyld</td>
<td>Optimal fraction of nitrogen in yield</td>
<td>0.00500</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>pltnfr(1)</td>
<td>Optimal fraction of nitrogen in the plant at emergence</td>
<td>0.03040</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>pltnfr(2)</td>
<td>Optimal fraction of nitrogen in the plant at 50% maturity</td>
<td>0.00740</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>pltnfr(3)</td>
<td>Optimal fraction of nitrogen in the plant at maturity</td>
<td>0.00570</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>cpyld</td>
<td>Optimal fraction of phosphorus in yield</td>
<td>0.00063</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>pltpfr(1)</td>
<td>Optimal fraction of phosphorus in the plant at emergence</td>
<td>0.00337</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>pltpfr(2)</td>
<td>Optimal fraction of phosphorus in the plant at 50% maturity</td>
<td>0.00104</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td>pltpfr(3)</td>
<td>Optimal fraction of phosphorus in the plant at maturity</td>
<td>0.00082</td>
<td>Beale and Long (1997)</td>
</tr>
<tr>
<td><strong>Miscellaneous parameters</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>hvsti</td>
<td>Fraction of above ground biomass removed in harvest</td>
<td>1.0</td>
<td>Assume all above-ground biomass is harvestable</td>
</tr>
<tr>
<td>wsysf</td>
<td>Lower harvest index under water stress</td>
<td>1.0</td>
<td>Assume all above-ground biomass is harvestable</td>
</tr>
<tr>
<td>chtmx</td>
<td>Maximum canopy height</td>
<td>4 m</td>
<td>Scurlock (1999)</td>
</tr>
<tr>
<td>rdmx</td>
<td>Maximum root depth</td>
<td>4 m</td>
<td>F. Dohleman and C. Bernacchi (2009)(^2)</td>
</tr>
<tr>
<td>t_opt</td>
<td>Optimal temperature for plant growth</td>
<td>30 °C</td>
<td>F. Dohleman and C. Bernacchi (2009)(^2)</td>
</tr>
<tr>
<td>rsdco_pl</td>
<td>Plant residue decomposition coefficient</td>
<td>0.05</td>
<td>SWAT crop database(^3)</td>
</tr>
<tr>
<td>alai_min</td>
<td>Minimum LAI during dormancy</td>
<td>0</td>
<td>SWAT crop database(^3)</td>
</tr>
<tr>
<td>usle_c</td>
<td>Minimum value of the USLE(^1) C factor for water erosion</td>
<td>0.003</td>
<td>SWAT crop database(^3)</td>
</tr>
<tr>
<td>wavp</td>
<td>Rate of decline in RUE per unit increase in vapor pressure deficit</td>
<td>0.72 g-kPa/(MJ/m(^2))</td>
<td>SWAT crop database(^3)</td>
</tr>
</tbody>
</table>

\(^1\) Radiation use efficiency (RUE), leaf area index (LAI), Universal Soil Loss Equation (USLE)

\(^2\) Personal communication.

\(^3\) The parameter value is estimated based on the default values for other crops of the same class (perennial grasses) in the SWAT crop database.
Using this model, optimal above-ground and below-ground biomass and LAI data for fourteen years are generated. The data are generated with input solar radiation and temperature data from the Illinois State Water Survey’s (ISWS) Water and Atmospheric Resources Monitoring (WARM) database for the weather station at Kilbourne, Illinois.

While a few empirical data for Miscanthus cultivation are available, the length of run is inadequate to calibrate a growth model. This alternative approach of using simulated data is appropriate, since simulated data are not subject to the uncontrollable factors to which field data are vulnerable. If using field data, it would not be possible to isolate the effects of water, nutrient and temperature stress on biomass growth to identify the optimal biomass and LAI curves. Nevertheless, for verification, the few empirical observations that have been made are compared to the results of the model as calibrated.

3.2.1(b) Nutrient and Miscellaneous Parameters

SWAT calculates nutrient stress in a crop by comparing actual nitrogen and phosphorus levels in the crop against ideal optimal levels. The crop’s actual nitrogen and phosphorus contents are endogenous variables within SWAT that are computed based on the availability of the nutrients in the soil. The optimal nitrogen and phosphorus contents of the crop are computed based on six parameters provided by the user; three for nitrogen and three for phosphorus. The six parameters refer to the optimal fractions of the nutrients in the plant at emergence, 50% maturity, and full maturity, and are used to interpolate for the optimal fractions of the nutrients throughout the growing season. Further, there are two other user-provided parameters related to the nitrogen and phosphorus content of the plant. These parameters refer to the fractions of the nutrients in the above-ground biomass at harvest. SWAT uses these parameters to calculate the amounts of nutrients removed from the system at harvest, which affect the content of nutrients in the soil.

To estimate these eight parameters for miscanthus, data reported in the literature are used. Literature data, together with expert opinion and the default values for other crops of the same class (perennial grasses) in the SWAT crop database, are also used to estimate the miscellaneous parameters not included in the first two subsets of parameters. For the specific source, assumption or method used to estimate each individual parameter, refer to Table 3-4.
3.2.2 Results

Refer again to Table 3-4 for the optimal crop growth parameter values for miscanthus determined by following the steps outlined above. Refer also to Figure 3-3 for the LAI, above-ground biomass and total new biomass curves obtained when applying those values to the optimal biomass growth equations in SWAT. As can be seen from the figure, the parameter values determined are able to reproduce satisfactorily the “ideal” optimal curves produced using the Miguez et al. (2009) miscanthus model described above. For the calibration period 1995-2001, for LAI, above-ground biomass and total new biomass, the $R^2$ values are 0.92, 0.96 and 0.98 respectively and NSE values 0.88, 0.80 and 0.98 respectively. As for the validation period 1995-2001, their $R^2$ values are 0.77, 0.90 and 0.94 respectively and NSE values 0.62, 0.79 and 0.94 respectively.

Note however that the SWAT optimal growth equations tend to overestimate total new biomass. This is because the procedure in SWAT to predict partitioning between above- and below-ground biomass is insufficiently detailed that it is able accurately to predict both total new and above-ground biomass at the same time. In this study, above-ground biomass is deemed to be of greater interest than total new biomass and hence, when adjusting the optimal growth parameters, greater emphasis is given to the former than the latter.

Note that the bio_e for miscanthus is set to be the same as the SWAT default bio_e for corn. Theoretically, crops of the same photosynthesis type should have about the same optimal radiation use efficiency (RUE) values (Monteith, 1978). Like miscanthus, corn is a C4 photosynthesis plant. Miscanthus RUE values reported in the literature range from 1.91 to 4.2 g per MJ/m$^2$ (Clifton-Brown et al., 2000; Clifton-Brown et al., 2004; Beale and Long, 1995; Tayot et al., 1995; Price et al., 2004). These are however, empirical values projected from field data (that are subject to water, temperature and/or nutrient limitations) and not theoretical optimal values which are the interest in this study.

Similarly, the blai values reported in the literature are observed field values ranging from 5 to 8 (Price et al., 2004; Scurlock, 1999) and are generally smaller (as they should be) than the optimal blai determined in this study, 11.5 m/m.

As for the other parameters, their values here are agreeable with literature values. For t_base the 10 °C estimated here is well within the 6 to 15 °C range found in the literature.
(Clifton-Brown et al., 2000, 2004; Price et al., 2004); while for heat units the 2100 °C-day obtained here is comparable to the 1800 °C-day value used by Clifton-Brown et al. (2004). For \textit{ext coef}, its value is set at the SWAT default for all crops, regardless of type, at 0.65 which is very close to the values (0.67-0.68) applied in Clifton-Brown et al. (2000) and Price et al. (2004).

![Graph showing LAI, above-ground biomass and total new biomass optimal curves](image_url)

Figure 3-3: LAI, above-ground biomass and total new biomass optimal curves as obtained using the SWAT optimal crop growth equations (---) and the Miguez et al. (2009) miscanthus model (▬)
Table 3-4 also gives the estimated values of the miscanthus nutrient and miscellaneous parameters determined in this study. The nitrogen parameters $pltnfr(1)$, $pltnfr(2)$, $pltnfr(3)$ and the phosphorus parameters $pltpfr(1)$, $pltpfr(2)$, $pltpfr(3)$ refer to the optimal fractions of the nutrients in the plant at various stages of growth and are used by SWAT to compute nutrient stress. Note that their values for miscanthus are less than their SWAT default values for corn, for which $pltnfr(1)$ is 0.0470, $pltnfr(2)$ 0.0177 and $pltnfr(3)$ 0.0138, and $pltpfr(1)$ is 0.0048, $pltpfr(2)$ 0.0018 and $pltpfr(3)$ 0.0014. This means that when compared to corn, on a per unit biomass basis, miscanthus has a smaller nutrient demand. Similarly, $cnyld$ and $cpyld$ for miscanthus are less than for corn, which has a $cnyld$ of 0.014 and $cpyld$ of 0.0016. Therefore, in terms of per unit biomass harvested, fewer nutrients are removed from the system when harvesting miscanthus than when harvesting corn. All this translates to a lower fertilizer requirement for the former over the latter.

$usle_c$ is a factor affecting erosion and sediment runoff. The higher is $usle_c$, the greater the erosion and sediment runoff. Here, a miscanthus $usle_c$ factor of 0.003 is assumed. This value corresponds to the SWAT default $usle_c$ for most of the perennial grasses in its crop database and is significantly lower than the default for corn and soybean (which is 0.2 for both crops). The higher $usle_c$ value for corn and soybean reflects the fact that they are annuals requiring tillage and replanting every year. Perennials (like miscanthus), on the other hand, do not require yearly replanting but can continue yielding for many years once established. This allows them to provide year round ground cover, thus protecting the ground from wind and water erosion.

$t_{opt}$ and $rdmx$ for miscanthus are estimated from expert opinion (F. Dohleman and C. Bernacchi, personal communication, 2009); $chtmx$ from the literature (Scurlock, 1999); and $rsdco_pl$, $alai_min$ and $wavp$ from their default values for other crops in the SWAT crop database. $hvsti$ and $wsyf$ are both fixed at one, assuming that the entire above-ground biomass is harvestable under normal as well as highly stressed conditions.

To validate the parameterization of the crop growth model in SWAT for miscanthus, the parameter values in Table 3-4 are substituted into the Salt Creek watershed SWAT model. The model is then run numerous times to simulate “actual” biomass growth (which is, as opposed to optimal growth, growth under real conditions where nutrient, water and temperature stress are present) for 2007 and 2008 when there is zero nitrogen fertilization. Comparison between the
simulated results and field data (refer to Figure 3-4) show that the model is able to produce reasonable results. The field data are from Dohleman and Long (2009), who conducted miscanthus field trials at a nearby site in Champaign, Illinois about 130 km east of the Salt Creek watershed. Figure 3-4 also gives SWAT’s predictions of actual biomass growth when the nitrogen fertilizer application rate is set at 40 kg-N/ha, then 80 kg-N/ha. The optimal growth curves for the two years are presented in the figure as well. Note that the data in Figure 3-4, with the exception of the field data, are not deterministic but are stochastic; they represent the most likely biomass growth that will occur, given the uncertainties in the Salt Creek watershed SWAT model as characterized in the GLUE calibration of the model.

Refer also to Figure 3-5 for a 14-year average of the yield-fertilizer relationship based on yield estimates for different fertilizer rates for different years (from 1995 to 2008) as predicted using SWAT and the miscanthus growth parameters presented above. The results are for a mid-December harvest date. From the average relationship, it can be inferred that farmers cultivating miscanthus in the Midwest are likely to apply somewhere between 80 and 100 kg-N/ha of nitrogen fertilizer (or less if the fertilizer price is high). This is significantly less than the typical rate for corn, which is about 190 kg-N/ha (Hu, 2003).

The range of 80 to 100 kg-N/ha of nitrogen fertilizer application rate inferred from Figure 3-5 (i.e., where yield reaches an asymptote) is within the range of rates recommended for miscanthus in the literature. Himken et al. (1997) recommended a nitrogen fertilizer application rate of 50 to 70 kg-N/ha to replenish the nitrogen removed from the field during harvest, even though they found the yield to be unaffected by fertilization. Lewandowski et al. (2000) also recommended a rate between 50 to 70 kg-N/ha, while Bullard (2001) recommended a rate of 80 kg-N/ha and Huisman et al. (1997) a rate of 75 kg-N/ha.
Figure 3-4: Optimal miscanthus biomass growth (---) and actual biomass growth when nitrogen fertilizer application rate in kg-N/ha is 0 (—), 40 (---) and 80 (-----) as predicted by SWAT; and actual biomass growth (Δ) when nitrogen fertilization is zero as measured in field trials.

Figure 3-5: Points estimated by SWAT (Δ) representing most likely miscanthus yield for each of the years 1995-2008, and the corresponding best-fit line (—) for various nitrogen fertilization rates assuming a mid-December harvest date.
The results here somewhat contradict those of Danalatos et al. (2007), Christian et al. (2008) and Himken et al. (1997), who found fertilization of miscanthus to have no effect on yield. On the other hand, others have found miscanthus to demonstrate a positive response to fertilization; Ercoli et al. (1999) observed an average nitrogen response rate of about 37 to 50 kg biomass per kg-N applied. Also, Miguez et al. (2008), by applying a statistical analysis on a database of published data from thirty-one studies on miscanthus cultivation and growth, found nitrogen fertilization to affect biomass growth after the first three years of establishment, though not before. Thus, as it can be seen, there is a wide range in the results reported in the literature, which may be attributed to the possibility that the response of miscanthus to nitrogen is a strong function of local soil and weather conditions. Further, it is possible that miscanthus has the ability to obtain nitrogen from atmospheric fixation (e.g. Eckert et al., 2001; Davis et al., 2010), greatly reducing its need for synthetic fertilizer.
4. ECONOMIC MODEL OF DECISIONS OF A SINGLE FARMER

This chapter describes an economic model to predict the decisions of a single farmer subject to crop, fertilizer, carbon and nitrogen prices, and crop production costs and yields. The model is linked to the calibrated and validated SWAT model of the Salt Creek watershed in Chapter 3, which is used to generate the necessary corn, soybean and miscanthus yield data. Together with the Salt Creek watershed model, the model forms the basis for the development of the agent-based model in Chapter 5.

Given his\(^1\) perceptions of prices, costs and yields, the farmer has to decide on the best combination of crops and whether or not to adopt certain best management practices (BMPs). In this study, two BMPs (conservation tillage and grass planting) and three crops (corn, soybean and miscanthus) are considered. To maximize utility, the farmer has to find the right balance between potential gains from crop sales, carbon trading and nitrogen subsidies and potential losses from fertilizer and other production costs.

Unlike corn and soybean, which are conventional crops, miscanthus is a second generation bioenergy crop that is only recently gaining attention. It is a perennial grass with a relatively long lifetime of up to twenty years. This means that once established, it can continue yielding for many years before replanting is required. Its yield and production costs are age-dependent. Typically, there is insufficient biomass for a harvest in the first year of establishment, about 50% of the maximum yield in the second year and maximum yields in the third year and onwards (Heaton et al., 2004). Miscanthus yield and production costs are however, assumed in this study to be relatively insensitive to flood and frost damage.

The same however, may not be assumed for corn and soybean. Flooding decreases their yields, while frost increases their production costs. Here, it is assumed that should frost occur, it happens early enough in the growing season that there is no decline in yields but there is an additional cost of replanting. Note that the likelihood of frost damage is higher for conservation tillage than conventional tillage (Carter, 1995).

Corn and soybean yields and production costs are also affected by crop choice for the previous year. Generally, there is a greater cost of pest and disease control when an annual crop

\(^1\) In this dissertation, the use of male personal pronouns is meant in the most generic sense, with the intention of referring to both male and female.
is planted after itself than when it is rotated. Further, due to the nitrogen carryover effect of soybean, it is usually more productive to plant corn after soybean than after itself or miscanthus.

Note that the current work does not consider the effects of pests and diseases on crop yields, which increase farmers’ uncertainty. Currently, miscanthus has no known pest or disease (Heaton et al., 2004); however, it is possible that once it is cultivated on a larger scale, pests and diseases to which it is vulnerable will start to become known. Further, changes in temperature and precipitation patterns due to global warming will likely alter the geographic distributions of pests and diseases (Patterson et al., 1999), possibly introducing new ones to the region that may be harmful to miscanthus, as well as corn and soybean. This means that in the future, as the climate changes, current pest and disease management strategies may become obsolete, further increasing farmers’ uncertainty of crop yields.

Here, carbon trading is modeled after the Illinois Conservation and Climate Initiative (ICCI) (http://illinoisclimate.org/) which provides a platform for farmers to earn carbon credits that they can then sell on the Chicago Climate Exchange (CCX) (chicagoclimatexchange.com). A high enough carbon price should prompt the farmer to adopt conservation tillage, convert existing cropland to uncultivated grassland and/or cultivate miscanthus. (In this study, even though miscanthus is botanically a grass, its cultivation is differentiated from what is called “uncultivated grass.” In the former, there is fertilization, harvesting and other activities to maximize yield and profit; in the latter, there are no such cultivation activities beyond initial planting, except for occasional mowing for weed control.) As per CCX rules, should the farmer decide to perform any of these activities for the purpose of claiming carbon credits, he is required to commit to doing so for five years continuously.

As for the nitrogen subsidies, they are modeled as payments to the farmer for reducing his use of nitrogen fertilizer to below a certain baseline amount whereby the payments are proportional to a pre-defined price. A high enough nitrogen price provides incentive for the farmer to switch from corn (a high-fertilizer crop) to miscanthus (which requires less fertilizer), soybean (which has zero nitrogen fertilizer requirements) or even uncultivated grass (which requires no fertilizer at all).

Refer to Figure 4-1 below for a flow diagram giving an overview of the different factors affecting the farmer's decisions and how they are interlinked. Refer also to Section 4.1 below, which gives the specific equations of the model in deterministic form. Although the actual model
is stochastic, the equations are first described in deterministic terms as a convenient means of introducing them. Following that, in Section 4.2, the equations are redefined in stochastic terms to take into consideration the farmer's lack of certainty in yields, the weather, prices and costs. Section 4.3 describes the optimization method used to solve the model.

### 4.1 Deterministic Model

If rational behavior and perfect information are assumed, the farmer’s objective function is as follows:

$$\text{MAX } TP = \sum_{n=1}^{N} \gamma^{n-1} R_n = \sum_{n=1}^{N} \gamma^{n-1} \left( CS_n - FC_n - OC_n + CC_n + NC_n \right)$$

(4-1)

that is to maximize total profit, $TP$, which is his sum of discounted returns over $N$ years. $R_n$ are his yearly net returns and $\gamma$ is a discount factor between zero and one to represent the farmer’s time valuation of money. In this study, $\gamma$ is assumed to fall between 0.92 and 0.98 and is different from one farmer to the next. $CS_n$ is the farmer’s gain from crop sales in year $n$ and is a function of crop prices and yields as given in equation (4-2a) below. $FC_n$ is his cost of nitrogen fertilizer in year $n$ and is a function of fertilizer price and usage as given in equation (4-2b). $OC_n$ is his total cost of crop production (excluding his nitrogen fertilizer cost) in year $n$ and is a function of crop choice and tillage type as given in equation (4-2c). $CC_n$ is his income from carbon trading in year $n$ and is a function of carbon price, crop choice and tillage type as given in equation (4-2d). $NC_n$ is his income from nitrogen subsidies in year $n$ and is a function of nitrogen price and fertilizer usage as given in equation (4-2e). Thus, for $n = 1, 2, \ldots, N$:

$$CS_n = \sum_{i=1}^{3} A_i \left\{ X_{\text{corn},n,i} Y_{\text{corn},n,i} P_{\text{corn},n} + X_{\text{soyb},n,i} Y_{\text{soyb},n,i} P_{\text{soyb},n} ight. \\
+ \left. \left( X_{\text{misc},n,i} + X_{\text{min},n,i} \right) Y_{\text{misc},n,i} P_{\text{misc},n} \right\}$$

(4-2a)

$$FC_n = \sum_{i=1}^{3} A_i F_{n,i} P_{\text{fert},n}$$

(4-2b)
Figure 4-1: Flow diagram showing the different factors affecting the farmer's crop and BMP decisions and how they are interlinked
\[ OC_n = \sum_{i=1}^{3} A_i \left\{ X_{\text{corn}, n, i} D_{\text{corn}, n, i} + X_{\text{soyb}, n, i} D_{\text{soyb}, n, i} + \left( X_{\text{misc}, n, i} + X_{\text{misn}, n, i} \right) D_{\text{misc}, n, i} \right\} \\
+ \left\{ 1 - \prod_{i=1}^{3} \left( 1 - X_{\text{ctill}, n, i} \right) \left( 1 - X_{\text{ctnc}, n, i} \right) \right\} D_{\text{cteq}, n} \] (4-2c)

\[ CC_n = \sum_{i=1}^{3} A_i \left\{ X_{\text{grass}, n, i} V_{\text{grass}} + X_{\text{ctill}, n, i} V_{\text{ctill}} + X_{\text{misc}, n, i} V_{\text{misc}} \right\} P_{\text{cc}, n} \] (4-2d)

\[ NC_n = N_n P_{\text{nit}, n} \] (4-2e)

\( A_i \) are constants representing the areas of the plots of land under the farmer’s care. There are altogether three plots of land \((i = 1, 2, 3)\), one of which is marginal land and the other two, normal cropland of equal sizes. The fraction of marginal land over total cropland is assumed to range from 0.02 to 0.2 and differs from farmer to farmer.

\( X_{\text{corn}, n, i}, X_{\text{soyb}, n, i}, X_{\text{misn}, n, i}, X_{\text{misc}, n, i} \) and \( X_{\text{grass}, n, i} \) are binary decision variables representing crop choice for year \( n \) and plot \( i \). When \( X_{\text{corn}, n, i} \) are unity, the crop of choice is corn. Similarly, the crop of choice is soybean when \( X_{\text{soyb}, n, i} \) are unity and miscanthus when \( X_{\text{misn}, n, i} \) or \( X_{\text{misc}, n, i} \) are unity. \( X_{\text{misn}, n, i} \) that are unity mean the establishment of new miscanthus crops while \( X_{\text{misc}, n, i} \) that are unity mean the continuation of existing miscanthus crops. When \( X_{\text{grass}, n, i} \) are unity, the land is converted to grassland and left uncultivated for the purpose of generating carbon offsets. Only one crop of choice (assuming uncultivated grass as a crop) is possible at any one time. Therefore, for all \( n \), for all \( i \):

\[ X_{\text{corn}, n, i}, X_{\text{soyb}, n, i}, X_{\text{misn}, n, i}, X_{\text{misc}, n, i}, X_{\text{grass}, n, i} = \{0, 1\} \] (4-3a)

\[ X_{\text{corn}, n, i} + X_{\text{soyb}, n, i} + X_{\text{misn}, n, i} + X_{\text{misc}, n, i} + X_{\text{grass}, n, i} = 1 \] (4-3b)

\( X_{\text{ctill}, n, i} \) and \( X_{\text{ctnc}, n, i} \) are also binary decision variables. When \( X_{\text{ctill}, n, i} \) are unity, conservation tillage (as opposed to conventional tillage) is practiced for the primary purpose of generating carbon offsets. The farmer may also choose to practice conservation tillage without the intention
of carbon trading. This is the case when \( X_{\text{ctnc},n,i} \) are unity. Note that the option to practice conservation tillage over conventional tillage is applicable only when corn or soybean is cultivated. When miscanthus is cultivated or the land is converted to uncultivated grass, \( X_{\text{ctill},n,i} \) and \( X_{\text{ctnc},n,i} \) go to zero. Therefore, for all \( n \), all \( i \):

\[
X_{\text{ctill},n,i}, X_{\text{ctnc},n,i} = \{0, 1\} \tag{4-3c}
\]

\[
X_{\text{ctill},n,i} \left(1 - X_{\text{corn},n,i}\right) \left(1 - X_{\text{soyb},n,i}\right) = 0 \tag{4-3d}
\]

\[
X_{\text{ctnc},n,i} \left(1 - X_{\text{corn},n,i}\right) \left(1 - X_{\text{soyb},n,i}\right) = 0 \tag{4-3e}
\]

\( F_{n,i} \) represent the farmer’s rates of nitrogen fertilizer application as functions of crop choice. For all \( n \), all \( i \):

\[
F_{n,i} = \begin{cases} 
0, & X_{\text{grass},n,i} = 1 \\
0, & X_{\text{soyb},n,i} = 1 \\
0.190, & X_{\text{corn},n,i} = 1 \\
0.108, & X_{\text{misc},n,i} = 1, \alpha_{\text{misc},n,i} = 1 \\
0.099, & X_{\text{misc},n,i} = 1, \alpha_{\text{misc},n,i} = 2 \\
0.090, & X_{\text{misc},n,i} = 1, \alpha_{\text{misc},n,i} \geq 3 
\end{cases} \tag{4-3f}
\]

The figures in equation (4-3f) are in the units ton-N/ha. For soybean, the nitrogen fertilizer rate is zero as soybean is a legume and is able to naturally fix nitrogen from the atmosphere. The nitrogen fertilizer rate for corn is assumed as 0.19 ton-N/ha, which is the average historical rate as estimated from past records of fertilizer sale (Hu, 2003). As for miscanthus, its nitrogen fertilizer rate is dependent on the age of the crop, \( \alpha_{\text{misc},n,i} \) and is based on the results of the miscanthus modeling exercise in Chapter 3, which found the optimal rate to be about 0.09 ton-N/ha when the crop is fully matured (which is assumed to be the case when \( \alpha_{\text{misc},n,i} \geq 3 \)). And when the miscanthus crop is in its first (\( \alpha_{\text{misc},n,i} = 1 \)) or second (\( \alpha_{\text{misc},n,i} = 2 \)) year of
establishment, the nitrogen fertilizer rate is assumed to be, respectively, 20% and 10% more (Lewandowski et al., 2003).

\( \alpha_{\text{misc},n,i} \) are subject to the farmer’s decisions for the current year (i.e. whether or not to begin or continue planting miscanthus), as well as the state of the system in the previous year. For all \( n \), all \( i \):

\[
\alpha_{\text{misc},n,i} = \begin{cases} 
\alpha_{\text{misc},n-1,i} + 1, & X_{\text{misc},n,i} = 1 \\
1, & X_{\text{misc},n,i} = 1 \\
0, & \text{otherwise}
\end{cases} \quad (4-3g)
\]

Equation (4-3g) sets the age of the current crop of miscanthus to one if it is a new establishment or increases it by one if it is a continuation of an existing establishment. Note that \( X_{\text{misc},n,i} \) can only be unity when there is already an existing miscanthus crop in the previous year. Thus, for all \( n \), all \( i \):

\[
X_{\text{misc},n,i} \left( 1 - \alpha_{\text{misc},n-1,i} \right) \leq 0 \quad (4-3h)
\]

4.1.1 Yields and yield coefficients

\( CS_n \) are functions of \( Y_{\text{corn},n,i} \), \( Y_{\text{soyb},n,i} \) and \( Y_{\text{misc},n,i} \) which are respectively, the per unit area corn, soybean and miscanthus yields for a given year \( n \). \( Y_{\text{corn},n,i} \) for a particular year \( n \) and plot \( i \) depends on the crop planted the year before. It is usually more productive to plant corn after soybean than corn after corn, due to the nitrogen carryover effect of soybean. Corn yield is also vulnerable to weather effects, specifically, to flooding which may cause reductions in yield. Thus, for all \( n \), all \( i \), \( Y_{\text{corn},n,i} \) may be estimated as follows:

\[
Y_{\text{corn},n,i} = \left( \left( 1 - X_{\text{soyb},n-1,i} \right) a_{\text{corn},n} + X_{\text{soyb},n-1,i} b_{\text{corn},n} \right) \left( 1 - T_{\text{flood},n,i} X_{\text{flood},n,i} \right) \quad (4-4a)
\]

where \( a_{\text{corn},n} \) are coefficients representing the typical year-to-year yields of corn that can be expected when the nitrogen carryover effect is absent and \( b_{\text{corn},n} \) when the nitrogen carryover
effect is present and for both cases, when the nitrogen fertilizer application rate is as specified in equation (4-3f).

$X_{\text{flood},n,i}$ are binary variables to indicate when there is flooding and are estimated from historical USGS stream flow records. $X_{\text{flood},n,i}$ differentiate marginal from normal cropland. In the present context, marginal land is defined as low-lying riparian land that is flood prone and therefore, has a higher frequency of flooding. On the other hand, it is assumed that there is zero risk of flooding on normal cropland. $T_{\text{flood},n,i}$ represent the extent of damage caused by flooding and are zero when $X_{\text{flood},n,i}$ are zero and are varying between 0.1 to 0.4 when $X_{\text{flood},n,i}$ are unity.

Like corn, soybean yield is also vulnerable to flooding. And therefore, if defining $a_{\text{soy},n}$ as the soybean yields that can be expected when there is no flooding, $Y_{\text{soy},n,i}$ can be characterized, for all $n$, all $i$, as follows:

$$Y_{\text{soy},n,i} = a_{\text{soy},n} \left(1 - T_{\text{flood},n,i} \cdot X_{\text{flood},n,i}\right)$$

(4-4b)

Miscanthus yield, however, is assumed to be more insensitive to occasional flooding (though not continuous flooding) than corn and soybean. (Currently, there is no firm evidence in the literature on the flood tolerance of Miscanthus $x$ giganteus, the particular species of miscanthus that is the focus of this study. However, one of its parents, Miscanthus sacchariflorus is known to grow naturally in riparian areas and has been shown to be fairly resistant to flood damage (Cho and Cho, 2005). Without further data, it is probably safer to assume Miscanthus $x$ giganteus to be at least more flood resistant than corn and soybean than to assume otherwise.) Its yield is however, affected by the age of the crop:

$$Y_{\text{misc},n,i} = \beta_{\text{misc},n,i} \cdot a_{\text{misc},n}$$

(4-4c)

$a_{\text{misc},n}$ are the typical miscanthus yields can be expected if ignoring the effect of age, i.e. the yields when the crop is fully matured. Note that due to their strong dependence on precipitation and temperature which change with time, $a_{\text{misc},n}$, as well as $a_{\text{corn},n}$, $b_{\text{corn},n}$ and $a_{\text{soy},n}$, are also changing with time and are different from one year to the next. In this study, their values are extracted from the SWAT hydrologic model of the Salt Creek watershed described in Chapter 3, which is used to simulate the required yield data.
\(\beta^{1}_{\text{misc},n,i}\) in equation (4-4c) are zero-to-one correction factors to account for the effect of age on miscanthus yield. Typically, there is insufficient biomass for a harvest in the first year of establishment, about 50% of the maximum yield in the second year and maximum yields in the third year and onwards (Heaton et al., 2004). A miscanthus crop can continue yielding up to ten to twenty years before replanting is required (Lewandowski et al., 2003; Vleeshouwers, 2002). Here, yields are assumed to start declining at a linear rate at year fifteen to reach zero at year twenty:

\[
\beta^{1}_{\text{misc},n,i} = \begin{cases} 
0, & \alpha_{\text{misc},n,i} = 0 \\
0.5(\alpha_{\text{misc},n,i} - 1), & 1 \leq \alpha_{\text{misc},n,i} \leq 3 \\
1, & 3 < \alpha_{\text{misc},n,i} < 15 \\
1 - 0.2(\alpha_{\text{misc},n,i} - 15), & 15 \leq \alpha_{\text{misc},n,i} \leq 20 \\
0, & 20 < \alpha_{\text{misc},n,i} 
\end{cases}
\]  

(4-4d)

4.1.2 Prices and costs

In equations (4-2a) and (4-2b), \(P_{\text{corn},n}\) for year \(n\) is the annual average price of corn for that year, \(P_{\text{soyb},n}\) of soybean, \(P_{\text{misc},n}\) of miscanthus and \(P_{\text{fert},n}\) of nitrogen fertilizer (specifically, anhydrous ammonia). \(P_{\text{corn},n}\), \(P_{\text{soyb},n}\) and \(P_{\text{fert},n}\) are set such that they are equal to historical values, which for corn and soybean are obtained from University of Illinois records (www.farmdoc.uiuc.edu) and for nitrogen fertilizer, are obtained from the USDA Economic Research Service (ERS) (www.ers.usda.gov).

However, there are no data on actual miscanthus price that can be used here as miscanthus is relatively new as a crop of interest. Thus, it is assumed \(P_{\text{misc},n}\) to be peg at some constant ratio to the average of the prices of corn and soybean and simulations are carried out for several values of this ratio to estimate the effect of \(P_{\text{misc},n}\) on the farmer’s behavior. This assumption is plausible if the miscanthus market is by long-term contracts between farmers and a nearby power plant or biofuel refinery, which is currently the case of a number of local bioenergy crop markets in the U.S. and Europe. Accordingly, it is also assumed that should the farmer decide to plant miscanthus, he is committed to doing so for at least ten years. Therefore, for all \(n\), all \(i\):
\[ 0 < \alpha_{\text{misc},n-1,i} \leq 10 \Rightarrow X_{\text{misc},n,i} = 1 \quad (4-5a) \]

In equation (4-2c), \( D_{\text{corn},n,i} \) and \( D_{\text{soyb},n,i} \) are the per unit area non-fertilizer production costs associated with corn and soybean cultivation, respectively, and include the costs of energy, labor, chemicals, equipment etc. and are estimated as below. For all \( n \), all \( i, \):

\[
D_{\text{corn},n,i} = \varepsilon d_{\text{corn},n} \left( 1 + T_{\text{crop}} X_{\text{corn},n-1,i} \right) \left\{ 1 - T_{\text{ctill,}n} \left( X_{\text{ctill,}n,i} + X_{\text{ctnc,}n,i} \right) \right\} \\
\left\{ 1 + T_{\text{frost,}n} \left( X_{\text{frost,}n,i} + X_{\text{ctnc,}n,i} \right) X_{\text{frost,}n} \right\} 
\]

\[
D_{\text{soyb},n,i} = \varepsilon d_{\text{soyb},n} \left( 1 + T_{\text{crop}} X_{\text{soyb},n-1,i} \right) \left\{ 1 - T_{\text{ctill,}n} \left( X_{\text{ctill,}n,i} + X_{\text{ctnc,}n,i} \right) \right\} \\
\left\{ 1 + T_{\text{frost,}n} \left( X_{\text{frost,}n,i} + X_{\text{ctnc,}n,i} \right) X_{\text{frost,}n} \right\} 
\]

(4-5b)

(4-5c)

where \( d_{\text{corn},n} \) and \( d_{\text{soyb},n} \) are the normal costs of corn and soybean production under typical conditions, defined here as conventional tillage and a 1:1 corn-soybean rotation schedule. \( d_{\text{corn},n} \) and \( d_{\text{soyb},n} \) are estimated from Schnitkey and Gupta (2007) and Schnitkey and Lattz (2007). \( \varepsilon \) is a factor between 0.75 and 1.25 to adjust \( d_{\text{corn},n} \) and \( d_{\text{soyb},n} \) (which are average values) for the farmer’s economy of scale. \( \varepsilon \) here is assumed to be inversely proportional to land area such that the larger the farmer’s total land area, the more favorable his economy of scale and thus, the smaller is \( \varepsilon \).

In this study, \( D_{\text{corn},n,i} \) (\( D_{\text{soyb},n,i} \)) is assumed to be a certain fraction, \( T_{\text{crop}} \) greater when corn (soybean) is planted continuously than when it is planted after soybean (corn) or another crop. This is to account for the greater level of pest and disease management required when a crop is planted after itself (Turco et al., 1990; Katsvairo and Cox, 2000). Here, \( T_{\text{crop}} \) is assumed to vary between 3\% and 7\% and is different from farmer to farmer.

To account for the savings in fuel and labor when switching from conventional to conservation tillage (Schnitkey and Lattz, 2006), it is assumed \( d_{\text{corn},n,i} \) and \( d_{\text{soyb},n,i} \) to be slightly less when conservation tillage is practiced as denoted by the presence of \( T_{\text{ctill,}n} \) in equations (4-5b) and (4-5c) which are assumed to fluctuate between 0.03 and 0.04 from one year to the next.

\( D_{\text{corn},n,i} \) and \( D_{\text{soyb},n,i} \) are also assumed to be respectively, \( T_{\text{frost,}n,i} \) greater when conservation tillage is practiced and when spring temperatures for a particular year \( n \) are
sufficiently low to cause frost damage. $X_{\text{frost,corn},n}$ and $X_{\text{frost,soy},n}$ in equations (4-5b) and (4-5c) are binary variables estimated from NOAA temperature records to indicate when there is such an event. Generally, there is a greater risk of frost damage to young plants under conservation tillage than conventional, tillage (Carter, 1995). Conservation tillage leaves behind a layer of residue on the ground, which intercepts radiant heat from the soil, resulting in cooler leaf temperatures at night (Bland, 1993). Conservation tillage has also been found to result in lower temperatures in the upper layers of the soil due to changes in its thermal admittance and heat flux (Johnson and Lowery, 1985).

Note that corn tends to be more susceptible to frost than soybean as it is usually planted earlier in the spring. Here, it is assumed that the risk of frost damage to soybean is negligible, while for corn, there is a positive risk. $T_{\text{frost,corn},n}$ are zero when $X_{\text{frost,corn},n}$ are zero and are assumed to be between 0.1 and 0.4 (depending on the severity of the frost damage) when $X_{\text{frost,corn},n}$ are unity.

For all $n$, all $i$, to estimate $D_{\text{misc},n,i}$, the per unit area cost associated with miscanthus production, the following equation applies:

$$D_{\text{misc},n,i} = \varepsilon \left( \beta_{1\text{misc},n,i} d_{\text{misc},n}^{1} + \beta_{2\text{misc},n,i} d_{\text{misc},n}^{2} \right)$$ (4-5d)

The production cost of miscanthus can be split into two parts: the costs of harvesting and transportation, $d_{\text{misc},n}^{1}$ and the costs of planting and chemicals, $d_{\text{misc},n}^{2}$. Note that the cost of chemicals here does not include the cost of nitrogen fertilizer which is accounted for in equation (4-2b). These costs are linked to the age of the crop. Generally, the costs of planting and chemicals are significant in the first year of establishment but there are no costs of harvesting and transportation then. In the second year, there is no cost of planting and a reduced cost of chemicals. However, the costs of harvesting and transportation are greater in the second year. In the third and onwards, when yields have leveled off, there is no cost of planting, a reduced cost of chemicals and even greater costs of harvesting and transportation.

$\beta_{1\text{misc},n,i}$ and $\beta_{2\text{misc},n,i}$ are coefficients to adjust $D_{\text{misc},n,i}$ for the age of the crop. $\beta_{1\text{misc},n,i}$ are as defined in equation (4-4d) and $\beta_{2\text{misc},n,i}$ are as defined below. For all $n$, all $i$: 
\[
\beta^2_{\text{misc},n,i} = \begin{cases} 
0, & \alpha_{\text{misc},n,i} = 0 \\
1, & \alpha_{\text{misc},n,i} = 1 \\
0.06, & \alpha_{\text{misc},n,i} > 1 
\end{cases} \tag{4-5e}
\]

\(d^1_{\text{misc},n}\) and \(d^2_{\text{misc},n}\) are estimated from data given by Khanna et al. (2008). Note that the figures there are for the year 2003. To obtain estimates for other years, those figures are extrapolated such that they increase and decrease to match the increases and decreases in the production costs for corn and soybean, \(d_{\text{corn},n}\) and \(d_{\text{soyb},n}\) (which are known).

\(D_{\text{cteq},n}\) is the cost of converting existing tillage equipment to be capable of conservation tillage in year \(n\) and depends on whether or not the farmer already owns the necessary equipment. Thus, for all \(n\):

\[
D_{\text{cteq},n} = (1 - E_{\text{cteq},n})d_{\text{cteq},n} \tag{4-5f}
\]

where \(E_{\text{cteq},n}\) are binary variables indicating if the farmer already owns the necessary equipment, which is the case when \(E_{\text{cteq},n}\) are unity. For all \(n\), \(E_{\text{cteq},n}\) may be computed as follows:

\[
E_{\text{cteq},n} = \begin{cases} 
1, & E_{\text{cteq},n-1} = 1 \\
1 - \prod_{i=1}^{3} (1 - X_{\text{ctill},n,i})(1 - X_{\text{cteq},n,i}), & E_{\text{cteq},n-1} = 0 
\end{cases} \tag{4-5f}
\]

which is to say that \(E_{\text{cteq},n}\) for year \(n\) is unity if the farmer already owns the equipment the previous year and if not, it becomes unity should the farmer decide to practice conservation tillage on one or more of his plots. \(d_{\text{cteq},n}\) are estimated from Al-Kaisi et al. (2002), which gives the cost of converting existing equipment per planter row as $400/planter row, and Schnitkey (2004), which estimates the number of planter rows in a farm, given its size. The per-planter-row cost in Al-Kaisi et al. (2002) is for the year 2002 and is used to extrapolate the per-planter-row cost for other years using the Producer Price Index for farm machinery and equipment manufacturing.
4.1.3 Carbon trading

In equation (4-2d), $P_{cc,n}$ for year $n$ is the effective price of carbon in that year, i.e. the actual price of carbon minus any trading fee imposed. Here, the fee to buy or sell carbon credits is assumed to be $0.20 per ton CO$_2$e, which is the standard rate used by the CCX. Historical carbon prices are available from the CCX as well as from the European Climate Exchange (ECX). However, they are available only for the end of 2003 and onwards for the former and 2005 and onwards for the latter. These prices are insufficient for use here and therefore, artificial prices based on possible future scenarios are assumed.

$V_{grass}$ and $V_{ctill}$ are the rates of carbon offset from grass planting and conservation tillage. $V_{grass}$ is assumed as 1.0 ton CO$_2$e per year per acre of cropland converted to uncultivated grassland and $V_{ctill}$ is assumed as 0.6 ton CO$_2$e per year per acre of land practicing conservation tillage. These numbers are in accordance with CCX regulations.

$V_{bioe}$ is the rate of carbon offset from cultivating bioenergy crops (in this case, miscanthus). Current CCX regulations are not clear as to whether or not cellulosic bioenergy crops qualify for carbon offsets. This is probably because they are relatively new, not widespread and without an established precedent. Nonetheless, research has shown bioenergy crops to have the ability to sequester soil organic carbon (Liebig et al., 2005; Clifton-Brown et al., 2007). Therefore, $V_{bioe}$ is assumed to have a positive value of 0.8 ton CO$_2$e per year per acre. It is also assumed that the farmer may claim offsets only in the second year of establishment and onwards when the level of disturbance to the soil is minimal.

A $V_{bioe}$ value of 0.8 ton CO$_2$e per year per acre is assumed for miscanthus as it is the average of $V_{grass}$ and $V_{ctill}$. This value is selected as bioenergy crops can be thought of as somewhat between grass planting and conservation tillage in terms of the intensity of crop cultivation. When cultivating bioenergy crops, there is usually nitrogen fertilization; in this study, for miscanthus, a nitrogen fertilization rate of 0.09-0.108 ton-N/ha is assumed depending on the age of the crop. Bioenergy crops are also regularly harvested. On the other hand, when land is converted to uncultivated grassland, there is no fertilization and no harvesting, increasing its effective carbon sequestration level. Nitrogen fertilization increases soil nitrous oxide (a greenhouse gas) emissions (Bouwman, 1996); while harvesting removes biomass that would otherwise remain in the system and be converted to soil carbon (Cowie et al., 2006). It is
therefore not unreasonable to assume cellulosic bioenergy crop cultivation to have a smaller carbon sequestration potential than grass planting.

According to CCX regulations, farmers who decide to adopt grass planting or conservation tillage for the purpose of carbon trading are required to commit to doing so for five years continuously. The same is assumed in this study and therefore, for all \( n \), all \( i \):

\[
Z_{\text{grass},n,i} > 0 \Rightarrow X_{\text{grass},n,i} = 1
\]  
\[4-6a\]

\[
Z_{\text{ctill},n,i} > 0 \Rightarrow X_{\text{ctill},n,i} = 1
\]  
\[4-6b\]

where \( Z_{\text{grass},n,i} \) and \( Z_{\text{ctill},n,i} \) are the number of remaining years of commitment left at year \( n \) of grass planting and conservation tillage respectively and may be computed as follows:

\[
Z_{\text{grass},n,i} = \begin{cases} 
\frac{(Z_{\text{grass},n-1,i} - 1)X_{\text{grass},n-1,i}}{4}, & \frac{(Z_{\text{grass},n-1,i} - 1)X_{\text{grass},n-1,i}}{4} \geq 0 \\
\text{otherwise} & 
\end{cases}
\]  
\[4-6c\]

\[
Z_{\text{ctill},n,i} = \begin{cases} 
\frac{(Z_{\text{ctill},n-1,i} - 1)X_{\text{ctill},n-1,i}}{4}, & \frac{(Z_{\text{ctill},n-1,i} - 1)X_{\text{ctill},n-1,i}}{4} \geq 0 \\
\text{otherwise} & 
\end{cases}
\]  
\[4-6d\]

Note further that even though it is reasonable to assume the same long-term commitment for bioenergy crop cultivation if it is used to claim carbon offsets, it is unnecessary to have additional constraints to impose this requirement, as equation (4-5a) is sufficient to ensure that should the farmer decide to start a miscanthus crop, he will maintain it for at least ten years.

4.1.4 Nitrogen subsidy

\( P_{\text{nit},n} \) is the nitrogen subsidy in year \( n \) and is the payment offered to the farmer for each unit of reduction in nitrogen fertilizer application below some pre-defined baseline, \( F_{\text{base}} \). \( N_n \) are the nitrogen fertilizer reductions made by the farmer and for all \( n \), are calculated as follows:
\[ N_n = \begin{cases} \sum_{i=1}^{3} A_i (F_{\text{base}} - F_{n,i}), & \sum_{i=1}^{3} A_i F_{n,i} < \sum_{i=1}^{3} A_i F_{\text{base}} \\ 0, & \text{otherwise} \end{cases} \] (4-7a)

\( N_n \) are positive when the nitrogen fertilizer applied is less than the baseline amount and zero when it is more. \( F_{\text{base}} \) is assumed to be 0.075 ton-N/ha per year which is slightly less than the amount of nitrogen the farmer would apply if half his land is corn and the other half is soybean (the average historical pattern in the Midwest).

### 4.2 Stochastic Model

When the system is deterministic, all price, cost, yield and weather variables are expressed as time-varying but known variables. However, in reality, the system is stochastic, such that these variables are unknown to the farmer, who instead forms personal perceptions of their values, which can be expressed in terms of probability distributions. The farmer’s objective now becomes one of maximizing his total utility as a function of those perceptions. Thus, if assuming a time-separable form of utility, the farmer’s objective function is now:

\[
\text{MAX Total Utility} = U(R_1) + \gamma U(R_2) + \gamma^2 U(R_3) + \ldots = \sum_{n=1}^{N} \gamma^{n-1} U(R_n) \] (4-8a)

where \( U(\ ) \) is the farmer’s utility function of return, \( R_n \). Here a mean-variance type of utility function is assumed, where utility is proportional to expected return and inversely proportional to variance of return. This form of utility weights uncertainty quadratically; when uncertainty is large, its marginal effect on utility is greater than when it is small. For all \( n \):

\[
U(R_n) = E(R_n) - r\text{Var}(R_n) \] (4-8b)

\( E(\ ) \) is expectation and \( \text{Var}(\ ) \) is variance. \( E(R_n) \) and \( \text{Var}(R_n) \) can be readily computed from basic statistical relationships if the expectations, variances and covariances of the independent random variables defining \( R_n \) are known (refer to Section 4.2.1 below). \( r \) is a coefficient representing the
farmer’s risk aversion. The greater is $r$, the higher his level of risk aversion i.e. the lower his tolerance for uncertainty. When $r$ is zero, the farmer is risk-neutral and his objective simplifies to one of maximizing sum of discounted expected returns. In this study, $r$ is varied from farmer to farmer and is assumed to fall between 0 and 0.001 (see Chapter 5 for more explanation). This range of $r$ has been selected to induce a variety of decisions but to exclude those that are deemed implausible.

Unlike the deterministic case, in which the decision variables for all years may be determined simultaneously, for the stochastic case, the problem is a multi-stage one where the farmer makes his decisions one year at a time as new information becomes available with each new year. At the beginning of each year, the problem is solved to identify the best decisions for the current year and all subsequent years based on the farmer’s perceptions at that time. However, only the decisions for the current year are kept. This means that to obtain a complete solution for all years in the simulation period, the problem has to be solved multiple times, once for each year of the simulation period.

Note that in any given year, the decisions or states of the previous years are no longer relevant except to define the state of the current year. Therefore the subscript $n = 1, 2, 3, \ldots, N$ in the deterministic model used to denote specific years in the simulation period now refers to the years following the current year, i.e. $R_1$ refers to the return for the current year, $R_2$ for the year ahead, $R_3$ for the year after that and so on. Also, the parameter $N$, which in the deterministic model is used to represent the total number of years in the simulation period, now represents the number of years that the farmer sees into the future.

The system in the current year is also defined by new information that previously, was not available, but now is. For instance, the prices of corn and soybean futures for later in the year when the farmer is ready to sell crops are now known. This affects perceptions of future prices which, in turn, affect decisions. The farmer’s perceptions also change with each passing year with new observations of prices, costs, yields and the weather. Section 4.2.2 below explains more in detail the Bayesian algorithm used to update the farmer’s perceptions with time.
4.2.1 Independent random variables

The independent random variables defining $R_n$ are as listed in Table 4-1 below. Except for $X_{\text{flood},n,i=1}$ and $X_{\text{frost},\text{corn},n}$, the variables are assumed to be normally distributed. $X_{\text{flood},n,i=1}$ and $X_{\text{frost},\text{corn},n}$, which are binary variables, are assumed to be binomially distributed.

The $i = 1$ in $X_{\text{flood},n,i=1}$ and $T_{\text{flood},n,i=1}$ refers to the farmer’s first of three plots of land which by definition, is the plot with the marginal land. For the other two plots of land with normal cropland, it is assumed that there is zero risk of flooding and hence, it is not necessary to define their $X_{\text{flood},n,i}$ and $T_{\text{flood},n,i}$ probability distributions here. Similarly, as it is assumed that there is no risk of frost damage to soybean (as opposed to corn), the probability distributions for $X_{\text{frost},\text{soyb},n}$ and $T_{\text{frost},\text{soyb},n}$ are not defined here.

Table 4-1: Random variables unknown to the farmer

<table>
<thead>
<tr>
<th>Yield variables</th>
<th>Price variables</th>
<th>Cost variables</th>
<th>Weather variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{\text{corn},n}$</td>
<td>$P_{\text{corn},n}$</td>
<td>$d_{\text{corn},n}$</td>
<td>$X_{\text{flood},n,i=1}$</td>
</tr>
<tr>
<td>$b_{\text{corn},n}$</td>
<td>$P_{\text{soyb},n}$</td>
<td>$d_{\text{soyb},n}$</td>
<td>$T_{\text{flood},n,i=1}$</td>
</tr>
<tr>
<td>$a_{\text{soyb},n}$</td>
<td>$P_{\text{misc},n}$</td>
<td>$d_{\text{misc},n}$</td>
<td>$X_{\text{frost},\text{corn},n}$</td>
</tr>
<tr>
<td>$a_{\text{misc},n}$</td>
<td>$P_{\text{cc},n}$</td>
<td>$d_{\text{misc},n}$</td>
<td>$T_{\text{misc},n}$</td>
</tr>
</tbody>
</table>

Note that $a_{\text{corn},n}$ and $b_{\text{corn},n}$ are correlated as they both refer to the same item, corn yield, and are differentiated only by the nitrogen carry-over effect of planting soybean in the previous year. $P_{\text{corn},n}$ and $P_{\text{soyb},n}$ are also correlated as the two crops substitute for each other to an extent and thus, the price of one affects that of the other. $d_{\text{corn},n}$, $d_{\text{soyb},n}$, $d_{\text{misc},n}^1$ and $d_{\text{misc},n}^2$ are correlated too as they break down into more or less the same cost components, primarily energy, machinery and labor. For simplicity, the correlation coefficients between these variables are assumed to be unchanging with time and known to the farmer. Their assumed values, based on real yield, price and cost data, are as follows:
Correl($a_{\text{corn,n}}, b_{\text{corn,n}}$) = 0.90 \hspace{1cm} (4-9a)

Correl($P_{\text{corn,n}}, P_{\text{soyb,n}}$) = 0.55 \hspace{1cm} (4-9b)

Correl($P_{\text{corn,n}}, P_{\text{misc,n}}$) = 0.90 \hspace{1cm} (4-9c)

Correl($P_{\text{soyb,n}}, P_{\text{misc,n}}$) = 0.90 \hspace{1cm} (4-9d)

Correl($d_{\text{corn,n}}, d_{\text{soyb,n}}$) = 0.95 \hspace{1cm} (4-9e)

Correl($d_{\text{corn,n}}, d_{\text{misc,n}}$) = 0.95 \hspace{1cm} (4-9f)

Correl($d_{\text{corn,n}}, d_{\text{misc,n}}^2$) = 0.95 \hspace{1cm} (4-9g)

Correl($d_{\text{soyb,n}}, d_{\text{misc,n}}^2$) = 0.95 \hspace{1cm} (4-9h)

Correl($d_{\text{soyb,n}}, d_{\text{misc,n}}^2$) = 0.95 \hspace{1cm} (4-9i)

Correl($d_{\text{misc,n}}^1, d_{\text{misc,n}}^2$) = 0.95 \hspace{1cm} (4-9j)

where Correl( ) is correlation coefficient. This assumption of constant correlation coefficients is fairly common and has been used by, among others, Elton et al. (1977) and Patel and Subrahmanyam (1982). It is necessary to simplify the calculation of the variance-covariance matrix of dependent variables that would otherwise be mathematically challenging.

4.2.2 Bayesian inference of unknown parameters

Bayesian inference is a statistical method of updating existing knowledge, in the form of a probability distribution, with new observations. It is rooted in Bayes’ Theorem that constitutes the theoretical underpinning to update a so-called “prior” distribution, on the basis of observation of new data, to produce a so-called “posterior” distribution. The Bayesian approach is useful for capturing the effect of one’s current view on his future view. In the present case, the effect of the prior can be significant as observation sizes are generally small.

In this study, Bayesian inference is used to model the learning process of the farmer with experience. As described above, the farmer is required to make decisions subject to a number of random variables, namely the yield, price, cost and weather variables described above. Using this approach, at the beginning of a given year, the farmer possesses a set of probability distributions...
of these random variables. These prior distributions represent the farmer’s current view of the world and are updated to their corresponding posteriors as new observations of yields, prices, costs and the weather become available as the year progresses. The farmer’s observations are drawn from publicly available information, his own experiences, as well as his interactions with his neighbors (see Chapter 5 for more details). The resulting posteriors are then applied as the priors for the next time period (which in this case, is the next year). By this mechanism, with time and experience, the farmer is assumed to refine and adapt his view of the world and predictive capabilities.

Note that Bayesian inference, as it is applied here, does not account for the influence of information outside of the time-series data used in the model, which in reality, is probably not insignificant (Brown and Rozell, 1979). The inclusion of such information is beyond the scope of this study, particularly because such information is often difficult to characterize and its effects are not easily defined in a mathematical sense.

This Bayesian approach is consistent with the adaptive expectations model (Schmalensee, 1976; Figlewski and Wachtel, 1981; Williams, 1987), which has been shown to explain adequately expectation formation by real agents. In the adaptive expectations model, as in Bayesian inference, an agent's forecast of a future event is a function of his past forecasts and forecast errors. The adaptive expectations model, however, unlike Bayesian inference, does not contain any mechanism to compute the agent's forecast confidence, which, as shown by Schmalensee (1976), is affected by the accuracy of his past predictions. The application of Bayesian inference to model the beliefs of individual farmers is not unique to this study; for example, Feder and O'Mara (1982) and Foltz (2004) used it to model farmers' learning of new technology and assessments of prices, respectively.

For the specifics of the Bayesian model used in this study, refer to the following subsections; for the details on how the parameters defining the model are set, refer to Chapter 5.

4.2.2(a) Bayesian point estimation of binomial variables

For the case of the binomially distributed parameters in Table 4-1, the following method applies. Let $G$ be a set of those parameters.
\[ G = \{ X_{\text{flood}, i=1}, X_{\text{frost, corn}} \} \] (4-10a)

For a variable \( g \in G \), assume its prior distribution to be binomially distributed with an uncertain probability of success \( \theta_g \). Assume further that \( \theta_g \) follows a beta distribution with the shape parameters \( \alpha_{g0} \) and \( \beta_{g0} \):

\[ g \mid \theta_g \sim \text{bin}(n_g, \theta_g) \] (4-10b)

\[ \theta_g \sim \text{beta}(\alpha_{g0}, \beta_{g0}) \] (4-10c)

where \( n_g \) is the number of trials of \( g \). This is known as the binomial-beta distribution. It is the conjugate prior for the binomial distribution. The binomial-beta distribution results in a posterior distribution of the same form (Press, 2003):

\[ g \mid \theta_g \sim \text{bin}(n_g, \theta_g) \] (4-10d)

\[ \theta_g \sim \text{beta}(\alpha_{g*}, \beta_{g*}) \] (4-10e)

\( \alpha_{g*} \) and \( \beta_{g*} \) are the updated shape parameters \( \alpha_{g0} \) and \( \beta_{g0} \) upon new observations of \( g \):

\[ \alpha_{g*} = \alpha_{g0} + s_g \] (4-10f)

\[ \beta_{g*} = \beta_{g0} + t_g - s_g \] (4-10g)

\( t_g \) is the total number of observed trials of \( g \), out of which \( s_g \) is the observed number of successful trials. Thus, from the posterior, the updated expectation and variance of \( \theta_g \) can be obtained as:

\[ E(\theta_g) = \frac{\alpha_{g*}}{\alpha_{g*} + \beta_{g*}} \] (4-10h)
\[ \text{Var}(\theta_g) = \frac{\alpha_g^* \beta_g^*}{(\alpha_g^* + \beta_g^*)^2 (\alpha_g^* + \beta_g^* + 1)} \]  

which gives the predictive mean and variance of the outcome of \( n_g \) new trials as (Bi, 2006):

\[ E(x_g) = \frac{n_g \alpha_g^*}{\alpha_g^* + \beta_g^*} \]  

\[ \text{Var}(x_g) = \frac{n_g \alpha_g^* \beta_g^* (\alpha_g^* + \beta_g^* + n_g)}{(\alpha_g^* + \beta_g^*)^2 (\alpha_g^* + \beta_g^* + 1)} \]

where \( x_g \) is the number of successful trials out of \( n_g \) trials.

4.2.2(b) Bayesian point estimation of normal variables

For the case of the normally distributed parameters in Table 4-1, the following method applies. Let \( H \) be a set of those variables:

\[ H = \{ a_{\text{ycom,}n}, b_{\text{ycom,}n}, a_{\text{ysoy,}n}, a_{\text{yarm,}n}, P_{\text{corn,}n}, P_{\text{soy,}n}, P_{\text{misc,}n}, P_{\text{cc,}n}, P_{\text{nit,}n}, \]
\[ P_{\text{fert,}n}, T_{\text{ctil,}n}, d_{\text{cteq,}n}, d_{\text{corn,}n}, d_{\text{soy,}n}, d_{\text{misc,}n}, d_{\text{flood,}n,i=1}, T_{\text{frost,}corn, n} \} \]

For a variable \( h \in H \), assume it is normally distributed with a standard deviation \( \sigma_h \) that follows a scaled inverse chi-square distribution and a conditional mean \( \mu_h \) given \( \sigma_h \) that follows a normal distribution:

\[ h|\mu_h, \sigma_h^2 \sim N(\mu_h, \sigma_h^2) \]  

\[ \mu_h|\sigma_h^2 \sim N(\mu_{h0}, \sigma_h^2/\kappa_{h0}) \]
This is known as the $N$-Inv-$\chi^2$ distribution and is the conjugate prior for the normal distribution. It is defined by four parameters: $\mu_{h0}$, $\kappa_{h0}$, $v_{h0}$ and $\sigma^2_{h0}$. The first two denote the location and scale of $\mu_h$, while the last two denote the degrees of freedom and scale of $\sigma^2_h$. The $N$-Inv-$\chi^2$ distribution results in a posterior of the same form (Gelman et al., 1995; Press, 2003):

\[
\sigma^2_h \sim \text{Inv-}\chi^2(v_{h0}, \sigma^2_{h0}) \tag{4-11d}
\]

\[
h|\mu_h, \sigma^2_h \sim N(\mu_h, \sigma^2_h) \tag{4-11e}
\]

\[
\mu_h|\sigma^2_h \sim N(\mu_{h*}, \sigma^2_h/\kappa_{h*}) \tag{4-11f}
\]

\[
\sigma^2_h \sim \text{Inv-}\chi^2(v_{h*}, \sigma^2_{h*}) \tag{4-11g}
\]

where:

\[
\mu_{h*} = \frac{\kappa_{h0}}{\kappa_{h0} + n_h} \mu_{h0} + \frac{n_h}{\kappa_{h0} + n_h} m_h \tag{4-11h}
\]

\[
\kappa_{h*} = \kappa_{h0} + n_h \tag{4-11i}
\]

\[
v_{h*} = v_{h0} + n_h \tag{4-11j}
\]

\[
v_{h*}\sigma^2_{h*} = v_{h0}\sigma^2_{h0} + (n_h - 1)\kappa^2_{h0} + \frac{\kappa_{h0}n_h}{\kappa_{h0} + n_h} (m_h - \mu_{h0})^2 \tag{4-11k}
\]

$n_h$ is the number of data points in the current observation, $s_h$ is the observed standard deviation and $m_h$ is the observed mean. As given in equation (4-11h), the posterior mean is simply the weighted average of the prior mean and observed mean; and in equation (4-11k), the posterior sum of squares is the total of the prior sum of squares, the observed sum of squares and an
additional uncertainty term to account for the difference between the observed and prior means. The above equations are also such that the influence of the observed data on the posterior dominates when \( n_h \) is large, and when it is small, it is the prior that dominates.

Once the posterior is quantitatively determined, it becomes a prior the next time there are new observations of \( h \) and can be used to obtain a new posterior distribution. The following expressions may be used to find the predictive distribution of \( h \), which can then be used to forecast the expectation and variance of future observations of \( h \):

\[
\text{Prob}(h) = \int \int \text{Prob}(h \mid \mu_h, \sigma_h^2) \text{Prob}(\mu_h, \sigma_h^2) d\mu_h d\sigma_h^2
\]  
\text{(4-11l)}

\[
\text{Prob}(\mu_h, \sigma_h^2) = \text{Prob}(\mu_h \mid \sigma_h^2) \text{Prob}(\sigma_h^2)
\]  
\text{(4-11m)}

where the probability distributions \( \text{Prob}(h \mid \mu_h, \sigma_h^2) \), \( \text{Prob}(\mu_h \mid \sigma_h^2) \) and \( \text{Prob}(\sigma_h^2) \) are as defined in equations (4-11e) to (4-11g). As derived in Gelman et al. (1995), integrating equation (4-11l) yields:

\[
h \sim t_{v_{h^*}} \left( \mu_{h^*}, (1 + 1/\kappa_{h^*})\sigma_{h^*}^2 \right)
\]  
\text{(4-11n)}

which states that \( h \) is a Student-\( t \) distribution with \( v_{h^*} \) degrees of freedom and the following expectation and variance:

\[
E(h) = \mu_{h^*}
\]  
\text{(4-11o)}

\[
\text{Var}(h) = (v_{h^*}/(v_{h^*} - 2))(1 + 1/\kappa_{h^*})\sigma_{h^*}^2
\]  
\text{(4-11p)}

4.3 Method of Solution

The current economic model of crop decisions of a single farmer fits into a multistage Markovian framework where the state of the system in a given time period is dependent on its
state and the decisions of the farmer in the previous time period. In other words, the farmer's decision-making process is sequential in nature such that the decisions made in one time period affect the next time period's optimum and subsequently, the optima of all following time periods.

Problems of this kind are commonly solved using dynamic programming, as is the case in this study. More specifically, backward induction is used to solve the Bellman equation (Bellman, 1957) repeatedly in a systematic manner to identify the optimal sequence of decisions. Backward induction functions by first identifying the optimal decisions for all possible states for the last time period, then based on that, the optimal decisions for all possible states for the second last time period and so on. This process proceeds backwards until the optimal decisions for all states for all time periods are known.

In this particular model, there are a number of parameters defining the state of the system. They are: (i) the previous year's (one time period is one year) crops, (ii) the miscanthus ages of the previous year's crops (the miscanthus age of a crop is zero when the crop is not miscanthus), (iii) the numbers of years left of mandatory conservation tillage and grass planting for each of the farmer's three plots of land and (iv) whether or not the farmer is equipped for conservation tillage (if not, existing equipment must be modified at some cost).

The farmer's perceptions of prices, costs, yields and the weather all change from year to year with new observations (as explained in Section 4.2). Hence, to obtain the complete sequence of optimal actions by the farmer for the entire simulation period, the economic model has to be solved numerous times, once for each year of the simulation period. At the beginning of a given year, the model is solved to identify the best decisions for the current year and all subsequent years within the farmer's time horizon. However, only the decisions for the current year are kept. The process is repeated for the next year until the optima for all years are obtained.

The single-farmer model described in this chapter can be used to support decision-making at the individual farm level. In next chapter, the model is extended to support the decisions of multiple farmers at the watershed scale.
5. AGENT-BASED MODEL OF DECISIONS OF MULTIPLE FARMERS

An agent-based model of the crop and best management practice (BMP) decisions of multiple agents is developed based on the economic model of a single farmer presented in Chapter 4. Section 5.1 gives an outline of the model showing how its components link together; Section 5.2 provides details of the individual agents in the model; and Section 5.3 explains the approach used to solve it.

5.1 Overview of the Model

The primary objective of the agent-based model is to simulate the individual decisions of farmers and the attendant effects on stream nitrate load. This is accomplished by linking the single-framer economic model presented in Chapter 4, the SWAT model of the Salt Creek watershed presented in Chapter 3, and the representation of multiple agents (i.e., farmers) in the watershed context described in this chapter. The farmers make their decisions subject to expectations of crop (namely, corn, soybean and miscanthus), nitrogen fertilizer (specifically, anhydrous ammonia) and carbon prices, crop production costs and a nitrogen fertilizer reduction subsidy. The farmers’ decisions are also influenced by their expectations of yields. Figure 5-1 below gives a schematic of the overall flow of the agent-based model.

The model simulates the decisions of fifty farmers, the largest feasible number within computational limitations. At the beginning of the simulation, before the start of the first year in the simulation period, the farmers’ initial perceptions, expressed as probability distributions, of prices, costs and yields, are set. Simulations are then carried out iteratively, year by year, for the entire simulation period. At the beginning and end of each year, the farmers’ perceptions are updated, as they make new observations, according to the Bayesian algorithm described in Section 4.2.2. The algorithm provides a mathematically tractable means of adjusting the farmers’ future expectations and forecast confidence with new information considering their existing expectations and confidence. Depending on how the parameters in the Bayesian equations are set, a farmer can be defined to react to new data in one way or another. For example, he can be quick or slow to adapt his perceptions with time, or, he can be averse or relatively neutral to
unexpected changes. In this study, two types of behavior are defined: cautious and bold. Refer to Section 5.2.1 below for a more thorough definition of the two behavior types.

At the start of each new year, the nitrogen fertilizer reduction subsidy for the year is made known to the farmers, which compensates the farmers for any reduction in their fertilizer use beyond 0.075 ton-N/ha ($F_{\text{base}}$ in equation (4-7a)). This baseline amount is a little less than what a typical farmer would need if he were to commit half of his land to corn and the other half to soybean (which is roughly the average historical pattern in the Midwest). Though the model does allow for the subsidy to vary with time, in this study, it is assumed constant from year to year.

Also at the start of each new year, the farmers will update their perceptions of the prices of corn, soybean and miscanthus as their futures prices become known. Note however, the farmers' perceptions for other prices, costs, yields and the weather however, are assumed unchanged at this point, presumably due to a lack of reliable forecast information for those items. The crop and BMP decisions of the farmers for that particular year are then determined by solving the economic model presented in Chapter 4 multiple times; once for each farmer for his unique set of perceptions and other properties (e.g. risk aversion, foresight etc.).

After the farmers’ decisions are computed, it is considered to be the end of the year. At this point, the farmers' perceptions of all prices (including those of corn, soybean and miscanthus) and also of the weather are updated as their actual values for the year become known. This updating of the farmers’ perceptions of prices and the weather is done by all farmers for all prices and all weather variables based on publicly available information that are accessible to all.

The farmers' perceptions of costs and yields are also updated. Note, however, the updating of cost and yield perceptions is carried out by only certain farmers, and not necessarily for all costs and all yields. For a given farmer, his updating of cost and yield perceptions depends on his decisions for the year and interactions with neighbors, which determine the kinds of information he has access to. Here, it is assumed that cost and yield information are not readily available and are available only when certain related activities are performed. For example, the cost of and savings from conservation tillage are not obvious and can only be known to a particular farmer if the farmer or one of his neighbors practices it. Similarly, the production cost and yield of a crop are observable to the farmer only if he or his neighbor is cultivating the crop.
To assign neighbors, the SWAT model of the Salt Creek watershed is referred to. There are fifty agricultural subbasins in the model, each of which is assumed to correspond to one of the fifty farmers. Each subbasin is further divided into three Hydrologic Response Units (HRUs); the first to represent the farmer’s plot of marginal land and the second and third to represent his plots of normal cropland. Each farmer (except Farmers 1 and 50) is assigned two neighbors, i.e., the farmers associated with subbasins n+1 and n-1. Farmers 1 and 50 are assigned only one neighbor each; Farmer 1’s neighbor is Farmer 2, while Farmer 50’s neighbor is Farmer 49. The Salt Creek watershed SWAT model is also used to simulate yields, for use in updating the
farmers’ yield perceptions, and nitrate load at the watershed outlet as a function of the farmers’ decisions.

Note that the current model neglects the general equilibrium effects of the nitrogen subsidy, and carbon and miscanthus prices. The subsidy and prices will cause large-scale land use changes (as discussed in Chapter 6). Conceivably, this will affect crop supplies and as a result, crop prices. The current model does not consider this secondary effect but instead assumes crop prices as exogenous variables that are independent of land use changes.

The current model also neglects long-term effects of the nitrogen subsidy. In the long term, the subsidy may attract farmers to cultivate previously uncultivated land, leading to an overall increase in nitrogen runoff (Baumol and Oates, 1975) (although such activity could easily be specifically declared ineligible for the subsidy). The modeling of these effects is not within the scope of this study, but may be meaningful to include in future work (refer to Section 7.3).

5.2 Farmer Specifications

5.2.1 Specifications of Agent Perceptions

Each farmer in the agent-based model is unique in terms of initial perceptions of prices, costs and yields; each possesses a set of twenty probability distributions representing those perceptions: four distributions to represent his perceptions of yields (one each for corn-after-corn, corn-after-soybean, soybean and miscanthus), five of prices (one each for corn, soybean, miscanthus, fertilizer and carbon), one of the nitrogen subsidy, another six of costs (one each for the production costs of corn and soybean, the establishment and harvesting costs of miscanthus, and the cost of and percent savings from conservation tillage) and four of the weather (one each for the probability and extent of damage of flooding on the marginal plot of land, and for the probability and extent of frost damage on all three plots of land).

The farmers’ initial perceptions are set somewhat randomly based on historical data. Historical data are unavailable or unobvious in the cases of the establishment and harvesting costs of miscanthus, the price of carbon, and the cost of and percent savings from switching to conservation tillage. In these cases, the initial perceptions are set to have large variances to represent the farmers’ initial unfamiliarity with miscanthus cultivation, carbon trading and
conservation tillage (which are assumed in this study to be activities with which the farmers, at the start of the simulation period, have no prior experience). The large variances have the effect of decreasing the farmers' initial confidence in predicting future profits. Thus, those farmers that are highly risk averse will be less inclined to pursue these activities initially; instead they tend to wait for their neighbors to adopt these practices and learn from them before making a commitment themselves.

The farmers also differ in updating their perceptions with new observations. As outlined in Section 4.2.2(a), the updating of those perceptions of variables assumed as binomially distributed (i.e. certain weather variables) by a particular farmer follows a Bayesian algorithm and depends on the parameters \( \alpha_{g0} \) and \( \beta_{g0} \) in equations (4-10f) and (4-10g). For a given binomial variable \( g \), the sum of \( \alpha_{g0} \) and \( \beta_{g0} \) can be thought of as the sum of the farmer’s experiences with \( g \), out of which \( \alpha_{g0} \) is the number of "successful" experiences and \( \beta_{g0} \) the number of "unsuccessful" ones. In this study, \( \alpha_{g0} \) and \( \beta_{g0} \) are rescaled after each new update so their sum is constant. This is to fix the influence of the farmer's existing perception of \( g \) on his updated perception of it (or in Bayesian terminology, the influence of the prior on the posterior). The larger the sum of the two parameters, the greater the influence of the existing perception versus new information. A larger sum of the two parameters can also be thought of as the farmer having a longer memory. In this study, the sum of \( \alpha_{g0} \) and \( \beta_{g0} \) is different for different farmers, though is assumed to be the same for all \( g \) for the same farmer.

The process of updating the farmer's perceptions of variables that are assumed as normally distributed (i.e. prices, costs, yields and other weather variables) is also based on Bayesian inference (as explained in Section 4.2.2(b)) and depends on the parameters \( \kappa_{h0} \) and \( \nu_{h0} \) in equations (4-11h) through (4-11k). For a given normal variable \( h \), the two parameters define the weight that is given to the farmer's existing perception of \( h \) against new information (or in Bayesian terminology, the weight of the prior against new observations), as well as his reaction toward unexpected changes. A greater weight is given to the farmer's existing expectation of \( h \) when \( \kappa_{h0} \) is large, and vice versa. Further, a large \( \kappa_{h0} \) together with a small \( \nu_{h0} \) means a relatively large increase in his level of uncertainty when an actual outcome is vastly different from expectation. In this study, \( \kappa_{h0} \) and \( \nu_{h0} \) are constantly readjusted to keep them constant so that, as for the case of the binomial variables, the influence of the farmer's existing perception of \( h \) on his
updated perception of it is unchanging with time. Different farmers have different values of $\kappa_{h0}$ and $\nu_{h0}$. Note however, that they are assumed to be the same for all $h$ for a given farmer.

Without empirical data on the belief formation of real farmers, it is not possible to know the values for $\kappa_{h0}$, $\nu_{h0}$ and the sum of $\alpha_{g0}$ and $\beta_{g0}$ that adequately represent reality. Therefore, for the purposes of this study, two extremes of behavior are defined: **cautious** and **bold**. Cautious farmers have relatively high $\kappa_{h0}$ (assumed here as 15-25) and low $\nu_{h0}$ (10-25) values and large sums of $\alpha_{g0}$ and $\beta_{g0}$ (15-20). This translates to mean that they are slow to adjust their expectations in response to new observations but quick to reduce their forecast confidence when new observations do not match expectations. On the other hand, bold farmers have low $\kappa_{h0}$ (0.5-5) and high $\nu_{h0}$ (50-100) values and small sums of $\alpha_{g0}$ and $\beta_{g0}$ (5-10), meaning that they are quick to adjust their expectations with new observations but slow to reduce their forecast confidence when there are unexpected changes in the system. To illustrate the difference between cautious and bold farmers, Figure 5-2 below shows how new observations of corn price affect a cautious farmer and a bold farmer's perceptions of it. In this particular example, the former has a $\kappa_{h0}$ of 24.86 and $\nu_{h0}$ of 15.45, while the latter has a $\kappa_{h0}$ of 2.71 and $\nu_{h0}$ of 66.79.

![Figure 5-2: Cautious and bold farmers' expectations (---) and forecast confidence (mean plus/minus one standard deviation) (●) of corn price in relation to real prices (---).](image-url)
5.2.2 Other Specifications

Each farmer is also unique in terms of land area. The total size of the Salt Creek watershed is about 4750 km\(^2\) and the average size of a farm 95 km\(^2\). The smallest and largest farms are 12 and 200 km\(^2\), respectively. The farm sizes are taken from the Salt Creek watershed SWAT model (each agricultural subbasin in the SWAT model is assumed to correspond to a farmer). (Note that the farm sizes are entirely hypothetical and based solely on SWAT’s delineation of the watershed.) The farmers’ fractions of marginal land are also different and are set arbitrarily between 0.02 and 0.2.

Farmers with larger land areas also enjoy economies of scale. In this study, the economy of scale of a farmer is represented by the parameter \(\varepsilon\) in equations (4-5b) and (4-5c) in Chapter 4. \(\varepsilon\) is inversely proportional to the farmer’s total land area; the farmer with the largest land area has an \(\varepsilon\) of 0.75 and the farmer with the smallest land area, an \(\varepsilon\) of 1.25. The greater is \(\varepsilon\), the greater the farmer’s per-unit-area costs of crop production. This means that, everything else being equal, farmers with larger land areas are better poised to cultivate crops that have higher sale values but also higher production costs.

The corn, soybean and miscanthus yields are also different from farmer to farmer due to differences in soil type, and from year to year as well due to differences in the weather. Other factors differentiating one farmer from another are: time discount rate, foresight and risk aversion. The time discount rate of a farmer is represented by \(\gamma\) in equation (4-1) and is assigned randomly between 0.92 and 0.98. The foresight of a farmer in this case is defined as the number of years the farmer sees into the future. It is represented by \(N\) in equations (4-1) and (4-8a) and is assigned randomly between 2 and 5 years. Lastly, the risk aversion of a farmer is represented by \(r\) in equation (4-8b) and for cautious farmers (as defined above), is assigned randomly between 0.0005-0.0010 and for bold farmers, 0-0.0005. Generally, a farmer with a greater \(r\) value is less tolerant of uncertainty and is risk neutral when \(r\) is zero.

5.3 Method of Solution

As can be seen in Figure 5-1, the agent-based model consists of two loops, an outer loop that is time (year)-incremented and an inner loop that is farmer-incremented. The outer loop
contains Bayesian procedures to update the farmers' perceptions of prices, costs, yields and the weather, as well as procedures to call the SWAT model of the Salt Creek watershed to calculate yields and stream nitrate load. Also contained within the outer loop is the inner loop, which encompasses computations to predict the crop and BMP decisions of a single farmer. For each iteration of the outer loop, the inner loop is repeated fifty times to estimate the decisions of all fifty of the farmers for the year.

As described in Section 4.3, to estimate the decisions of a farmer, the economic model in Chapter 4 is solved by backward induction using dynamic programming (Bellman, 1957). Since the decision-making of a farmer is independent of all others', to speed up the overall run time of the agent-based model, parallel programming is applied at this point. Instead of solving the economic model sequentially for one farmer at a time (which would be the case were it not for parallel programming), multiple executions of the economic model for different farmers are solved concurrently. The parallel programming is implemented using the OpenMP Application Program Interface (API) (http://openmp.org/wp/).

To accomplish the objectives of this study, the agent-based model is solved numerous times for various scenarios of the nitrogen fertilizer reduction subsidy, and carbon and miscanthus prices. For each scenario of subsidy and prices, two sets of simulations are carried out, one for a population of fifty cautious farmers and another for a population of fifty bold farmers. Refer to Chapter 6 for more discussion on the scenarios and simulation results.
6. RESULTS AND DISCUSSION

6.1 Management Scenarios

The agent-based model described in Chapter 5 is run numerous times to estimate how a nitrogen fertilizer reduction subsidy, carbon trading and a positive market price for miscanthus might affect farmers' decisions and consequently, stream water quality (namely, nitrate load at the watershed outlet). Except for the nitrogen subsidy and prices of carbon and miscanthus, the same time series of corn, soybean and fertilizer prices, production costs, crop yields, and weather and other variables are applied across all simulations. The time series are based on historical data, which are obtained as explained in Chapter 4. The nitrogen subsidy and carbon and miscanthus prices are specified differently for different simulations depending on the management scenario that is being portrayed. As presented in Table 6-1, there are altogether six scenarios of interest in this study. For each scenario, two sets of simulations are carried out; one for a population of 50 cautious farmers and the other for a population of 50 bold farmers (where the definitions of cautious and bold are as given in Chapter 5). The simulation period for all scenarios is from 1985 to 2008.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>No nitrogen subsidy, no carbon trading, no miscanthus price</td>
</tr>
<tr>
<td>B</td>
<td>Nitrogen subsidy only</td>
</tr>
<tr>
<td>C</td>
<td>Carbon trading only</td>
</tr>
<tr>
<td>D</td>
<td>Miscanthus price only</td>
</tr>
<tr>
<td>E</td>
<td>Carbon trading and miscanthus price</td>
</tr>
<tr>
<td>F</td>
<td>Nitrogen subsidy, carbon trading and miscanthus price</td>
</tr>
</tbody>
</table>
6.2 Impact on Farmers' Decisions

6.2.1 Scenario A: No nitrogen subsidy, no carbon trading, no miscanthus price

This scenario represents the status quo, where there is no nitrogen subsidy, no carbon trading and the miscanthus market price is zero. Under this scenario, rational farmers would consider only corn or soybean cultivation even though the model does allow for other crop choices. Refer to Figure 6-1 below for a watershed level summary of the aggregate of the individual decisions of the farmers in both the cautious and bold populations.

As can be seen from the figure, the decisions of the cautious farmers do not change much with time. Probably due to the relatively smaller weights they give to new observations, they do not change their existing perceptions of prices, costs etc. easily and therefore, are less inclined to react to market changes. Their consistency can also be attributed to their relatively higher levels of risk aversion. Risk averse farmers tend to cultivate mixed crops (as opposed to single crops) so to reduce the uncertainties in their expectations of net profit. Thus, it is not unexpected to find that for the majority of the time, the cautious farmers have allocated roughly the same amount of the land to corn as to soybean. This observation is consistent with other studies in the literature such as Scott and Baker (1972), Bhende and Venkataram (1994) and Falco and Perrings (2005), which have found risk aversion to be a major driver of farmers diversifying their activities.

Note also that when there are large price uncertainties (such as in 2008 when the prices of corn and soybean are abnormally high), the cautious farmers are prone to favor soybean over corn, as soybean yield is generally more stable and thus, predictable than corn yield. Further, soybean has a smaller cost of production than corn. This tendency can be observed in the simulation results for 2008, which show a slight increase in soybean acreage despite a higher rate of increase in corn price than soybean price in that year.
In contrast to the cautious farmers, the bold farmers are quick to adapt their decisions to market changes. Their decisions seem most sensitive to their estimates of the ratio of the prices of corn to soybean. These estimates are based on their past perceptions, as well as their current observations of the corn and soybean futures prices for the year. As can be seen in Figure 6-1, changes in the percent watershed allocated to corn are closely tied to the ratio of the futures prices of corn to soybean. The greater this ratio, the greater the bold farmers' expected profits of planting corn over soybean. Two instances stand out, the years 1996 and 2007-2008; in those
years, the corn to soybean futures price ratio is unusually high and as a result, the corn acreage for those years is unusually high as well.

As for the farmers’ conservation tillage decisions, for the case of the cautious farmers, none is choosing to practice conservation tillage. This is due to their initial lack of familiarity with it as represented by the large variances in their initial prior distributions of the cost of and percent savings from switching to conservation tillage (refer to Section 5.2.1). Due to their relatively higher levels of risk aversion, the cautious farmers are unable to overcome that initial unfamiliarity. On the other hand, some of the bold farmers do choose to switch to conservation tillage. These farmers, with their higher levels of risk tolerance, are able to overcome their initial unfamiliarity to take advantage of the savings in fuel and labor that comes with conservation tillage. As these farmers practice conservation tillage, their neighbors are influenced by them until the stage when they too are comfortable enough to make the switch from conventional to conservation tillage. And in this way, provided that all other factors are favorable, the amount of land with conservation tillage should show a steady increase with time as is indeed the case here as shown in Figure 6-1(c).

Also, if looking at the individual decisions of these farmers, it can be found that without additional incentive, they tend to practice conservation tillage only when they are cultivating soybean and to avoid it when cultivating corn. The reason for this is, as explained in Section 4.1.2, is that there is a greater risk of frost damage to young plants when conservation tillage is practiced than when it is not, and that risk is greater for corn (due to its earlier planting date) than for soybean. This explains the drop in conservation tillage acreage in 1996, 1997 and 2008 for the case of the bold farmers (refer to Figure 6-1(c)). In those years, the corn to soybean price ratio is higher than average, propelling the bold farmers to choose corn over soybean for nearly the entire watershed.

6.2.2 Scenario B: Nitrogen subsidy only

To explore the effects of the nitrogen subsidy on the farmers, four cases of the subsidy ($P_{nit,n}$ in equation (4-2e)) are examined; for the first case, for all $n$, $P_{nit,n}$ are set to 500 and for the second, third and fourth cases respectively, to 1000, 1500 and 2000 $/ton-N$. Note that when
$P_{\text{nit},n}$ are zero, there is no subsidy; when this is the case, the resulting scenario is Scenario A as described above. Refer to Figure 6-2, Figure 6-3 and Table 6-2 below for the results.

Figure 6-2 gives a watershed level summary of the aggregate of the farmers' decisions averaged over time. As can be seen in the figure, the presence of a nitrogen fertilizer reduction subsidy, for both the bold and cautious populations, does lead to the desired effect of decreasing the farmers' overall fertilizer use as they switch from corn (which is more fertilizer-intensive) to soybean (which is less so). This switch from corn to soybean may also lead to higher levels of conservation tillage acreage as, as discussed in the previous section (Section 6.2.1), there is less risk of frost damage to the crops when conservation tillage is practiced on land cultivating soybean than on land cultivating corn.

Note however, that even though the nitrogen subsidy has been shown to be beneficial, its benefits are not as great as might be expected given its overall cost (see Table 6-2). It can be observed in the table that on average, when the nitrogen subsidy is low, actual reductions in fertilizer use (as computed by comparing the fertilizer use for a given $P_{\text{nit},n}$ with that when $P_{\text{nit},n} = 0$) are far less than the reductions claimed by the farmers for subsidy payments. This is because there is no cap on the amount of fertilizer a farmer may use, thus, there is no mechanism in place to prevent the farmer from reducing his fertilizer use to below $F_{\text{base}}$ (as defined in equation (4-7a)) one year and increasing it to above $F_{\text{base}}$ the next year. Figure 6-3 confirms that, indeed, this is the cause of the observed difference between actual and claimed reductions in fertilizer use. As revealed in the figure, with increasing nitrogen subsidy, the time-series for corn acreage will start to show a sawtooth pattern. This reflects the changing of the farmers' cropping behavior from devoting roughly half of their land to corn and the other half to soybean in the same year, to devoting all of their land to corn in one year and all to soybean the next year and then back to corn in the third. By changing their behavior from the former to the latter, the farmers are able to claim subsidy payments every other year without actually having to reduce the average amount of land allocated to corn.
Table 6-2: Fertilizer use and nitrogen credit data for the different cases of the nitrogen subsidy examined

<table>
<thead>
<tr>
<th>Item</th>
<th>Cautious farmers</th>
<th>Nitrogen subsidy, P_{nit,n} ($/ton-N)</th>
<th>0</th>
<th>500</th>
<th>1000</th>
<th>1500</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>N fertilizer use (ton-N/ha/yr)</td>
<td>0.103</td>
<td>0.096</td>
<td>0.086</td>
<td>0.066</td>
<td>0.047</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual reduction in N fertilizer use (ton-N/yr)</td>
<td>0</td>
<td>3558</td>
<td>8151</td>
<td>17781</td>
<td>26807</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claimed reduction in N fertilizer use for subsidy payments (ton-N/yr)</td>
<td>0</td>
<td>14939</td>
<td>19428</td>
<td>23309</td>
<td>26880</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N subsidy ($/ton-N)</td>
<td>0</td>
<td>500</td>
<td>1000</td>
<td>1500</td>
<td>2000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total N subsidy payments (million $/yr)</td>
<td>0</td>
<td>7.47</td>
<td>19.43</td>
<td>34.96</td>
<td>53.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal cost of fertilizer reduction ($/ton-N)</td>
<td>--</td>
<td>2099</td>
<td>2384</td>
<td>1966</td>
<td>2005</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Item</th>
<th>Bold farmers</th>
<th>Nitrogen subsidy, P_{nit,n} ($/ton-N)</th>
<th>0</th>
<th>500</th>
<th>1000</th>
<th>1500</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>N fertilizer use (ton-N/ha/yr)</td>
<td>0.115</td>
<td>0.104</td>
<td>0.087</td>
<td>0.069</td>
<td>0.055</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual reduction in N fertilizer use (ton-N/yr)</td>
<td>0</td>
<td>5440</td>
<td>13633</td>
<td>22125</td>
<td>28457</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Claimed reduction in N fertilizer use for subsidy payments (ton-N/yr)</td>
<td>3096</td>
<td>15976</td>
<td>19370</td>
<td>22745</td>
<td>25250</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N subsidy ($/ton-N)</td>
<td>0</td>
<td>500</td>
<td>1000</td>
<td>1500</td>
<td>2000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total N subsidy payments (million $/yr)</td>
<td>0</td>
<td>7.99</td>
<td>19.37</td>
<td>34.12</td>
<td>50.50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marginal cost of fertilizer reduction ($/ton-N)</td>
<td>--</td>
<td>1468</td>
<td>1421</td>
<td>1542</td>
<td>1775</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1All items in terms of their time-averages
The implication of the result discussed above is that a simple nitrogen subsidy scheme such as the one modeled here may not be effective in achieving its environmental goals; probably additional constraints (incentives) will have to be imposed on (offered to) the farmers to ensure their continuous cultivation of soybean (or other low fertilizer crops). Nonetheless, despite the above problem, the marginal cost of reducing farmers' nitrogen fertilization, and consequently, nitrogen runoff to surface waters, under a subsidy scheme such as the present one is still less than the cost of point source treatment. Refer again to Table 6-2. Based on the data
there, the marginal cost of fertilizer reduction is $1421-2384/ton-N depending on the nitrogen subsidy offered and the farmers' behavior type. This translates to a marginal cost of nitrate load reduction of about $4,737-7,947/ton-N, assuming 30% (Hu et al., 2007) of every unit of fertilizer applied to land will eventually run off into receiving waters. In comparison, the cost to upgrade existing facilities at the Bloomington-Normal WWTP to remove up to 300 ton-N/yr from its effluent flow can be estimated from data published by Reardon (1994) and Zenz (2003) to be about $14 million/yr, or $47,000/ton-N.

6.2.3 Scenario C: Carbon trading only

There is not a long history of carbon trading in the U.S. nor elsewhere. Carbon trading commenced on the CCX only in the end of 2003 and on the European Climate Exchange (ECX) in 2005. There is therefore insufficient historical carbon price data that can be used in this study. Thus, as a second-best alternative, forecasts of future carbon prices provided by the Pew Center on Global Climate Change (2008) are used to construct four scenarios of carbon prices for use here. Refer to Figure 6-4 below for the four scenarios. They shall henceforth be identified by their starting prices in 1985, the first year of the simulation period. In the first sub-scenario, the 1985 carbon price is $13/ton-CO2e and in the second, third and fourth, 17, 28 and 33 $/ton-CO2e, respectively. As shown in the figure, the scenarios differ from one another in terms of their starting and ending prices but are similar in that they all show a steady rise in the price with time.

Figure 6-5 and Figure 6-6 give the simulation results. As shown in the figures, carbon trading (without a market value for miscanthus) can be expected to result in significant increases in conservation tillage acreage but not in uncultivated grass or miscanthus acreage. For conservation tillage, Figure 6-5(c) and (d) and the right-column graphs in Figure 6-6, show that a relatively low carbon price is sufficient to cause the bold farmers to increase their adoption of it and the cautious farmers to start practicing it. Note however, by comparing Figure 6-5(c) and Figure 6-5(d), it is observed that when the price of carbon is low, some conservation tillage is practiced not for carbon credits but simply for its inherent benefits. This allows the farmers more flexibility to switch out of conservation tillage back to conventional tillage depending on their crop choices (recall that farmers are generally disinclined to practice conservation tillage when
cultivating corn due to the higher risk of frost damage). As a result, especially for the bold farmers, there may be times when the conservation tillage acreage may dip as a disproportionate number of the farmers choose corn over soybean.

On the other hand, when the price of carbon is sufficiently high, most, if not all, of the conservation tillage practiced is for the purpose of carbon trading, which requires the farmers to maintain the conservation tillage for five years continuously. When this is the case, the conservation tillage acreage is more stable and does not change as much with time. Higher carbon prices also lead to the farmers more quickly overcoming their initial misgivings for conservation tillage.

As for the effect of carbon trading on the farmers' decisions to convert to uncultivated grass, according to Figure 6-5(e), the cautious farmers will never choose to do so under all the sub-scenarios of carbon prices. This is due to their higher levels of risk aversion, which make them more sensitive to their initial lack of familiarity with carbon trading. They are also more sensitive to unexpected changes in the carbon price. This is especially so post 2000 when increases in the price are happening too fast (refer to Figure 6-4), which intensify the cautious farmers' uncertainties of future prices, causing them to be unwilling to convert to uncultivated grass despite the higher prices.

On the other hand, the bold farmers will start converting to uncultivated grass even under the first sub-scenario of relatively low carbon prices. However, the amount of land converted to uncultivated grass under that sub-scenario, as under the other sub-scenarios, constitutes less than 1% of the watershed. Further, an examination of the individual decisions of the farmers (not shown here) shows that most of the land converted to uncultivated grass is marginal, and that it is only under the third and fourth sub-scenarios of carbon prices that prices are sufficiently high that the bold farmers will start to convert their normal cropland.
Figure 6-4: Four scenarios of carbon prices

Figure 6-5: Time-averages of the aggregate of the bold (o) and cautious (▲) farmers' decisions under Scenario C for the different sub-scenarios of carbon prices as given in Figure 6-4
Figure 6-6: Year-to-year acreages of uncultivated grass and conservation tillage for the bold (o) and cautious (▲) populations of farmers under Scenario C for the different sub-scenarios of carbon prices as given in Figure 6-4
6.2.4 Scenario D: Miscanthus price only

Under this scenario, it is assumed that there exists a miscanthus price and that that price is pegged at some fixed multiple of the average of the prices of corn and soybean. As mentioned in Section 4.1.2, such a scenario is plausible if the miscanthus market is by long-term contracts between the farmers and a nearby power plant or biofuel refinery. In this study, four sub-scenarios are examined: in the first, the miscanthus price multiple (i.e. the ratio of the price of miscanthus to the average of the prices of corn and soybean) is pegged at 0.3; in the second, 0.4; in the third, 0.5 and in the fourth, 0.6. Refer to Figure 6-7 and Figure 6-8 for the simulation results.

![Figure 6-7: Time-averages of the aggregate of the bold (o) and cautious (▲) farmers’ decisions under Scenario D as functions of the miscanthus price multiple](image-url)
According to Figure 6-7(e), the farmers will start to cultivate miscanthus on a large-scale when the miscanthus price multiple is set at about 0.4 or above. And when it is 0.8 or greater, about 0.75 of the watershed will be converted to miscanthus. When the miscanthus price multiple is 0.4, the average price of miscanthus over the simulation period 1985-2008 is $66/ton, which translates to about $1650/ha assuming an average miscanthus yield of 25 ton/ha; and when the miscanthus price multiple is 0.8, $132/ton or $3300/ha. (Note that these averages are based on historical prices and have not been inflation adjusted to any particular year.) In comparison,
Khanna et al. (2008) estimated the breakeven price of cultivating miscanthus to be about $59/ton, $1475/ha, in 2003 dollars considering the opportunity costs of land.

From Figure 6-8, it can be seen that the miscanthus acreage is less likely to change much with time when the farmers are cautious than when they are bold, and when the miscanthus price multiple is higher than when it is lower. Further, when the miscanthus price multiple is low, the bold farmers are more easily influenced by price fluctuations than when the price ratio is high.

From Figure 6-8, it can be further observed that the bold farmers are quicker to adopt miscanthus (a new crop to them) than the cautious farmers. In looking at the individual decisions of the farmers, it can be seen that bold farmers, should they choose to begin cultivating miscanthus, are more likely to do so for all their plots at once. On the other hand, cautious farmers tend to plant miscanthus first on their plots of marginal land (which are smaller than their plots of normal cropland), then only after some time, on their second (normal) plots and after even more time, on their third plots (also normal). This difference in behavior is due to differences in their levels of risk aversion. At the start of the simulation period, the bold and cautious farmers are equally uncertain of the price and production cost of miscanthus. However, due to their higher aversion to risk, the cautious farmers are less willing to commit all their land at once to miscanthus but will do so only after they have gained some experience and reduced their uncertainties. This observation is consistent with Scherr (1995) who reported that risk averse farmers in Western Kenya tend to adopt new practices in incremental steps, usually by starting with a small piece of land.

It is also noted from the individual decisions of the farmers that, should they decide to cultivate miscanthus, they will maintain their miscanthus crops for 14 to 18 years before replanting or switching to corn or soybean. Recall from Section 4.1.1 that, in this study, it is assumed that a miscanthus stand can continue yielding a crop for up to twenty years but its yields will start to decline after the fifteenth year. This explains the 14-18 year range observed in the results.

The differences in miscanthus crop lifetime among farmers are due largely (though not entirely) to their differences in foresight (the number of years they see into the future). As shown in Table 6-3, shortsighted farmers tend to maintain their miscanthus crops for a longer time after their yields start to decline. In contrast, especially when miscanthus prices are high, longsighted
farmers tend to terminate their waning miscanthus crops sooner rather than later to make way for fresh batches of miscanthus. This is true for both the cautious and bold populations of farmers.

The farmers' foresight levels also influence their decisions to cultivate miscanthus in the first place. Table 6-4 gives the average number of new miscanthus cultivations per plot of land as a function of farmer foresight and the miscanthus price multiple. As seen in the table, the shorter a farmer's foresight, the less likely he is to start a new miscanthus cultivation, due to the high initial capital required and zero yield in its first year of cultivation. Shortsighted farmers are unwilling to bear that initial loss, especially when the miscanthus price multiple is low. In fact, for this particular case study, none of the farmers, whether bold or cautious, with foresights shorter than three years decide to cultivate miscanthus, even when the miscanthus price multiple is set quite high.

### Table 6-3: Average lifetime of a miscanthus cultivation in years as a function of the miscanthus price multiple

<table>
<thead>
<tr>
<th>Foresight (year)</th>
<th>Miscanthus Price Multiple</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cautious Farmers</td>
</tr>
<tr>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td>2</td>
<td>--</td>
</tr>
<tr>
<td>3</td>
<td>18.00</td>
</tr>
<tr>
<td>4</td>
<td>16.90</td>
</tr>
<tr>
<td>5</td>
<td>15.98</td>
</tr>
</tbody>
</table>

### Table 6-4: Average number of new miscanthus cultivations per plot of land throughout the simulation period 1985-2008 as a function of the miscanthus price multiple

<table>
<thead>
<tr>
<th>Foresight (year)</th>
<th>Miscanthus Price Multiple</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cautious Farmers</td>
</tr>
<tr>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
</tr>
</tbody>
</table>
6.2.5 Scenario E: Carbon trading and miscanthus price

In this scenario, the farmers are offered both carbon and miscanthus prices (as defined in Sections 6.2.3 and 6.2.4). Eight combinations of carbon and miscanthus prices are examined: there are four sub-scenarios of carbon prices (as defined in Figure 6-4 and thereafter, identified by their starting prices in 1985) for each of two sub-scenarios of miscanthus prices. In the first sub-scenario of miscanthus prices, the price of miscanthus is set at 0.4 times the average of corn and soybean prices and in the second, 0.5. Refer to Figure 6-9 for the results.

![Graph](image_url)

Figure 6-9: Time-averages of the aggregate of the bold (o) and cautious (▲) farmers’ decisions under Scenario E for the different sub-scenarios of carbon prices as given in Figure 6-4 and where the miscanthus price multiple is 0 (—), 0.4 (—) and 0.5 (▬).
From the figure, it can be seen that miscanthus price is a bigger influence than carbon price on the decisions of the farmers, whether bold or cautious. As shown in the figure, for a fixed miscanthus price multiple, the time averages of the aggregate of the farmers' decisions do not change significantly with the price of carbon. On the other hand, for any of the four sub-scenarios of carbon prices, the aggregate of the farmers' decisions changes quite significantly as the miscanthus price multiple is changed.

The reason for this relative insensitivity to carbon price is that, while carbon trading pays the farmers for cultivating miscanthus, it also pays them for practicing conservation tillage when cultivating corn or soybean. Thus, any incremental profit from carbon trading when cultivating one crop is comparable to that when cultivating another. This is true even though the carbon payment for conservation tillage is less than that for cultivating miscanthus; for the carbon price scenarios considered here, the savings in fuel and labor from the former are sufficient to make up for this difference in revenue.

6.2.6 Scenario F: Nitrogen subsidy, carbon trading and miscanthus price

Under this scenario, the farmers are offered the nitrogen fertilizer reduction subsidy and carbon and miscanthus prices. There are altogether 48 combinations (i.e., scenarios) of the subsidy and carbon and miscanthus prices: four sub-scenarios of carbon prices (as defined in Figure 6-4 and hereafter, identified by their starting prices in 1985), for each of two sub-scenarios of miscanthus prices, for each of four sub-scenarios of the nitrogen subsidy. In the sub-scenarios of miscanthus prices, the price of miscanthus is set at 0.4 and 0.5 times the average of corn and soybean prices, respectively. In the sub-scenarios of the nitrogen subsidy, the subsidy is fixed at 500, 1000, 1500 and 2000 $/ton-N, respectively. Refer to Figure 6-10 for the simulation results.
Figure 6-10: Time-averages of the aggregate of the bold (o) and cautious (▲) farmers’ decisions under Scenario F for the different sub-scenarios of carbon prices as given in Figure 6-4 and where the miscanthus price multiple is 0 (—), 0.4 (—) and 0.5 (▬) and where the nitrogen subsidy (Pnit,n) is 500, 1000, 1500 and 2000 $/ton-N.
It can be seen that carbon price is not as influential on the farmers' decisions as the nitrogen subsidy and miscanthus price. As shown in Figure 6-10, for a given combination of the nitrogen subsidy and miscanthus prices, the farmers' decisions do not change significantly with carbon price. In comparison, for any of the four sub-scenarios of carbon prices, changes in the farmers' decisions with the nitrogen subsidy and miscanthus price are more obvious.

By comparing Figure 6-10 and Figure 6-2 (which shows the results for Scenario B where only the nitrogen subsidy is offered), it can be observed that non-zero carbon and miscanthus prices do not change the primary effect of the nitrogen subsidy on the farmers' decisions, viz., to reduce their nitrogen fertilizer use by planting more soybean and less corn, although, as Figure 6-10 shows, this effect is somewhat diminished when miscanthus price is high. This means that, in terms of its immediate objective, to reduce the farmers' nitrogen fertilizer use, the nitrogen subsidy is less effective when miscanthus price is high. This however, does not necessarily mean that it is less effective in terms of its ultimate objective, to reduce nitrogen run off, when miscanthus price is high, since miscanthus cultivation is seen to produce less nitrogen run off than the conventional corn and soybean in rotation (refer to Section 6.3 for more detail).

Similarly, the primary effect of a market for miscanthus on the farmers' decisions, viz., to switch from corn and soybean to miscanthus, do not change when the nitrogen subsidy and carbon price are non-zero. Note however, that when the nitrogen subsidy is high, for any one of the two sub-scenarios of miscanthus prices, the farmers are slightly less prone to converting to miscanthus than when the nitrogen subsidy is low. This is because when the nitrogen subsidy is high, there is even larger incentive for the farmers to cultivate soybean (which has zero nitrogen fertilization) as compared to miscanthus (which in this study, is assumed to require a nitrogen fertilizer application rate of 0.090 to 0.108 ton-N/ha/yr depending on the number of years since establishment).

**6.3 Water Quality (Nitrate Load) Effects**

To estimate the effects of the nitrogen subsidy, carbon trading and miscanthus price on nitrate load, the farmers' decision data presented above are entered into the SWAT model of the Salt Creek watershed developed in Chapter 3 to simulate stream nitrate load at the watershed outlet under various scenarios. Table 6-5 through Table 6-9 below give the results for Scenarios
B to F in terms of gross nitrate load as well as percent reduction in nitrate load from the status quo (Scenario A). The figures in the tables represent the most likely values of nitrate load, given the calibration uncertainties of the SWAT model of the Salt Creek watershed as characterized using GLUE (refer to Chapter 3).

As can be seen from the tables, the nitrogen fertilizer reduction subsidy can be expected to bring about reductions in nitrate load. For the levels of the nitrogen subsidy examined here, the subsidy can potentially result in reductions of about 3 to 15% (refer to Table 6-5). The reductions are due to the farmers favoring soybean (which does not require any nitrogen fertilizer input) over corn (which is a fertilizer-intensive crop) with higher nitrogen prices.

Demand for miscanthus as a bioenergy crop can also be expected to lead to nitrate load reductions (refer to Table 6-7). A miscanthus price that is pegged at 40% of the average of corn and soybean prices (weight basis) will result in a nitrate load reduction of about 14% if the farmers are cautious and 20% if they are bold, while increasing the miscanthus price to 50% and 60% of average corn and soybean prices will result in reductions ranging from 30 to 36% and 35 to 36%, respectively. The reductions are from the farmers switching from corn and soybean to miscanthus. With miscanthus, the nitrogen balance is such that the amount of nitrogen removed from the system with harvesting, in comparison with the amount of new nitrogen applied to the system with fertilization, is greater than with corn or soybean (with soybean, even though there is no nitrogen fertilization, there is still new nitrogen entering the system via fixation). This is true despite miscanthus having a lower nitrogen content; due to its higher yield, the total amount of nitrogen removed in harvest is comparable to that for corn.

Unlike the nitrogen subsidy and miscanthus price, however, carbon trading (by itself, without a price for miscanthus) is unlikely to lead to any reduction in nitrate load and may even cause it to increase slightly (refer to Table 6-6). Carbon trading will cause the farmers to practice conservation tillage on a larger scale, which will result in less surface runoff but more subsurface infiltration. As a large percentage of the watershed is tile drained, this may cause more of the nitrogen in the soil to leach out into the tiles and into receiving waters. This observation of the relative insensitivity of nitrogen loss from fields to tillage method is consistent with findings of Mitsch et al. (1999), who summarized several empirical studies to show that conservation tillage, depending on local conditions, may cause nitrogen loss either to increase or decrease slightly. Carbon trading will also cause the farmers to practice grass planting which reduces nitrate
runoff; however, for all the carbon price scenarios considered in this study, the amount of land converted to uncultivated grass is not enough to result in any significant net decrease in nitrate load at the watershed outlet.

When there is carbon trading and a market value for miscanthus, Table 6-8 indicates that considerable reductions in nitrate load can be expected, especially if the miscanthus price is high. Note though, that it is that price, rather than the incentive provided by carbon trading, that is the principal driver behind the land use changes leading to the nitrate load reductions.

Similarly, when there is the nitrogen subsidy, carbon trading and a market value for miscanthus (refer to Table 6-9), its price and the nitrogen subsidy are bigger drivers of nitrate load reduction than carbon price. However, the effect of the nitrogen subsidy on nitrate load reduction is less evident for the bold farmers than for the cautious farmers. The effect of the nitrogen subsidy on nitrate load is also less pronounced when miscanthus price is higher than when it is lower.

From the results presented above it can be seen that different market or incentive programs are not equal in their effectiveness in inducing large-scale land use changes with the ultimate purpose of reducing nitrate load in surface waters. For the particular scenarios examined in this study, it can be concluded that probably the most effective means of achieving any significant reduction in nitrate load is to have a market value for miscanthus (or other similar perennial bioenergy crops). Nitrogen fertilizer reduction subsidies can also lead to nitrate load reductions, but probably not as effectively as a Miscanthus market.

Consider the recommendation by EPA SAB (2007) to reduce the nitrogen load entering the Gulf of Mexico by 45% to mitigate the hypoxia problem in the Gulf. According to the results in Table 6-5 to Table 6-9, none of the policy scenarios examined in this study are capable of achieving this target; the only scenarios capable of achieving close to this target, i.e. a greater than 30% reduction, are the ones where there exists a market value for miscanthus that is 50% (or higher) of the average of corn and soybean prices. For the simulation period used in this study (1985-2008), this translates to an average price of miscanthus of about $82.50/ton.
Table 6-5: Average nitrate load and percent nitrate load reduction over 1985-2008 under Scenario B as functions of the nitrogen subsidy

<table>
<thead>
<tr>
<th>Nitrogen price, $P_{nit,n}$ ($/ton-N)$</th>
<th>Nitrate load ($10^3$ ton-N/yr)</th>
<th>Nitrate load reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cautious</td>
<td>Bold</td>
</tr>
<tr>
<td>0</td>
<td>9.64</td>
<td>9.94</td>
</tr>
<tr>
<td>500</td>
<td>9.35</td>
<td>9.64</td>
</tr>
<tr>
<td>1000</td>
<td>9.10</td>
<td>9.10</td>
</tr>
<tr>
<td>1500</td>
<td>8.57</td>
<td>8.70</td>
</tr>
<tr>
<td>2000</td>
<td>8.15</td>
<td>8.39</td>
</tr>
</tbody>
</table>

Table 6-6: Average nitrate load and percent nitrate load reduction over 1985-2008 under Scenario C as functions of carbon price

<table>
<thead>
<tr>
<th>1985 carbon price ($/ton-CO2e)$</th>
<th>Nitrate load ($10^3$ ton-N/yr)</th>
<th>Nitrate load reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cautious</td>
<td>Bold</td>
</tr>
<tr>
<td>0</td>
<td>9.64</td>
<td>9.94</td>
</tr>
<tr>
<td>13</td>
<td>9.64</td>
<td>9.94</td>
</tr>
<tr>
<td>17</td>
<td>9.73</td>
<td>9.95</td>
</tr>
<tr>
<td>28</td>
<td>9.77</td>
<td>9.94</td>
</tr>
<tr>
<td>33</td>
<td>9.78</td>
<td>9.93</td>
</tr>
</tbody>
</table>

Table 6-7: Average nitrate load and percent nitrate load reduction over 1985-2008 under Scenario D as functions of miscanthus price

<table>
<thead>
<tr>
<th>Miscanthus price multiple</th>
<th>Nitrate load ($10^3$ ton-N/yr)</th>
<th>Nitrate load reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cautious</td>
<td>Bold</td>
</tr>
<tr>
<td>0</td>
<td>9.64</td>
<td>9.94</td>
</tr>
<tr>
<td>0.3</td>
<td>9.64</td>
<td>9.93</td>
</tr>
<tr>
<td>0.4</td>
<td>8.31</td>
<td>8.01</td>
</tr>
<tr>
<td>0.5</td>
<td>6.75</td>
<td>6.39</td>
</tr>
<tr>
<td>0.6</td>
<td>6.25</td>
<td>6.32</td>
</tr>
</tbody>
</table>
Table 6-8: Average nitrate load and percent nitrate load reduction over 1985-2008 under Scenario E as functions of carbon and miscanthus prices

<table>
<thead>
<tr>
<th>1985 carbon price ($/ton-CO2e)</th>
<th>Nitrate load (10^3 ton-N/yr)</th>
<th>Nitrate load reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MPM=0^1</td>
<td>MPM=0.4^1</td>
</tr>
<tr>
<td></td>
<td>Caut^2</td>
<td>Bold</td>
</tr>
<tr>
<td>0</td>
<td>9.64</td>
<td>9.94</td>
</tr>
<tr>
<td>13</td>
<td>9.64</td>
<td>9.94</td>
</tr>
<tr>
<td>17</td>
<td>9.73</td>
<td>9.95</td>
</tr>
<tr>
<td>28</td>
<td>9.77</td>
<td>9.94</td>
</tr>
<tr>
<td>33</td>
<td>9.78</td>
<td>9.93</td>
</tr>
</tbody>
</table>

^1 MPM is miscanthus price multiple
^2 Caut is cautious

Table 6-9: Average nitrate load and percent nitrate load reduction over 1985-2008 under Scenario F as functions of the nitrogen subsidy and carbon and miscanthus prices

<table>
<thead>
<tr>
<th>1985 carbon price ($/ton-CO2e)</th>
<th>Nitrate load (10^3 ton-N/yr)</th>
<th>Nitrate load reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MPM=0^1</td>
<td>MPM=0.4^1</td>
</tr>
<tr>
<td></td>
<td>Caut^2</td>
<td>Bold</td>
</tr>
<tr>
<td>13 Nitrogen subsidy = 0500 $/ton-N</td>
<td>8.85</td>
<td>8.97</td>
</tr>
<tr>
<td>17</td>
<td>8.79</td>
<td>9.03</td>
</tr>
<tr>
<td>28</td>
<td>8.90</td>
<td>9.08</td>
</tr>
<tr>
<td>33</td>
<td>8.88</td>
<td>9.07</td>
</tr>
<tr>
<td>13 Nitrogen subsidy = 1000 $/ton-N</td>
<td>8.33</td>
<td>8.58</td>
</tr>
<tr>
<td>17</td>
<td>8.27</td>
<td>8.61</td>
</tr>
<tr>
<td>28</td>
<td>8.26</td>
<td>8.57</td>
</tr>
<tr>
<td>33</td>
<td>8.25</td>
<td>8.58</td>
</tr>
<tr>
<td>13 Nitrogen subsidy = 1500 $/ton-N</td>
<td>7.81</td>
<td>8.06</td>
</tr>
<tr>
<td>17</td>
<td>7.80</td>
<td>8.06</td>
</tr>
<tr>
<td>28</td>
<td>7.72</td>
<td>8.11</td>
</tr>
<tr>
<td>33</td>
<td>7.83</td>
<td>8.10</td>
</tr>
</tbody>
</table>

^1 MPM is miscanthus price multiple
^2 Caut is cautious
In comparison, Nelson et al. (2006), who made a case study of a watershed in northeast Kansas with switchgrass (another potential second-generation bioenergy crop that has received much attention), estimated that a switchgrass price of $33-38.5/ton will result in a nitrate load reduction of about 35%, assuming an average switchgrass yield of 10.4 ton/ha. This gives switchgrass a sale value of $343.2-400.4/ha. The current study, however, estimates that a 30% reduction in nitrate load requires an average miscanthus sale value of $1155/ha in the second year after establishment and double of that in the third year and onward. There are several salient differences between the two studies that may explain this discrepancy. Nelson et al. (2006) based their analysis on a single set of prices and costs, while the current study is based on time-series of prices and costs. Further, yields in Kansas are different than in Illinois due to differences in climate and soil type. The study also did not consider the risk aversion of farmers nor the initial delay in returns when cultivating switchgrass. Nevertheless, both studies indicate that an expanding market for miscanthus or switchgrass improves water quality.

6.4 Cost, Income and Crop Acreage Tradeoffs

As discussed in the previous section, the nitrogen subsidy and a market value for miscanthus, though not carbon trading, will lead to significant nitrate load reductions in surface waters if the nitrogen subsidy and price of miscanthus are sufficiently high. However, such programs, whose success depends on farmers making large-scale land use changes, are not without tradeoffs. Policy makers should be aware of the tradeoffs between nitrate load reduction and farmers' cost and income, as well as crop acreages of these programs.

Refer to the left column of graphs in Figure 6-11 for the tradeoffs between nitrate load reduction and the farmers' average physical cost for Scenarios B to F. Here, physical cost is defined as the cost of labor, energy, supplies, machinery and other physical materials necessary for crop production. It is of interest as a measure of the cost of nitrogen abatement. As shown in the graphs, generally, achieving a high nitrate load reduction means increasing the farmers' overall cost of crop production. An exception to this is the case of the nitrogen subsidy (Scenario B), under which lower cost is associated with lower nitrate load.

For Scenarios C to F, the higher physical cost that comes with higher nitrate load reductions is mainly due to the farmers switching from corn and soybean to miscanthus, which
has a higher cost of production. As for Scenario B, the lower physical cost that comes with higher nitrate load reductions is mainly due to the farmers planting more soybean and less corn (soybean has a lower cost of production than corn).

Refer also to the right column of graphs in Figure 6-11 for the tradeoffs between nitrate load reduction and the farmers' average income. For all scenarios, higher nitrate load reductions also mean higher incomes for the farmers. This is desirable as it shows then that market programs to reduce nitrate load incorporating nitrogen subsidies and/or a price for second-generation bioenergy crops will be directly beneficial to farmers. More specifically, Figure 6-11 shows that any combination of the nitrogen subsidy and carbon and miscanthus prices that will produce more than a 30% reduction in nitrate load will also increase the farmers' average income to over $800/ha from about $400/ha.

Refer now to Figure 6-12 for the tradeoffs between nitrate load reduction and crop acreages, which affect food, feed and bioenergy feedstock supplies. From the graphs in the first column of the figure, it can be seen that to achieve at least a 30% reduction in nitrate load, the watershed in corn must be reduced to less than 30% in corn from about 55% (which is the status quo (Scenario A) if the farmers are cautious) or 60% (which is the status quo if the farmers are bold). In some of the cases, the portion of the watershed in corn may even shrink to less than 20%.

Similarly, from the graphs in the second column Figure 6-12, it can be seen that for all the scenarios where there is at least a 30% reduction in nitrate load, the portion of the watershed in soybean will also decrease. For the scenarios where there is no nitrogen subsidy, the portion of watershed in soybean will fall to about 20% or less. And where there is the nitrogen subsidy (and at least a 30% reduction in nitrate load), the fall in soybean acreage can be expected to be less severe, to about 20 to 40%, depending on the nitrogen subsidy.

On the other hand, to achieve at least a 30% reduction in nitrate load, the portion of the watershed in miscanthus will have to rise to 50 to 75%, depending on the combination of the nitrogen subsidy and carbon and miscanthus prices, and whether the farmers are cautious or bold. The fraction of the watershed in miscanthus tends to be greater when the nitrogen subsidy is zero or lower, and smaller where it is higher.
Table 6-11: Tradeoffs between nitrate load reduction and farmers' cost and income under Scenarios B to F for the bold (o) and cautious (▲) populations of farmers.
Figure 6-12: Tradeoffs between nitrate load reduction and corn, soybean and miscanthus acreages under Scenarios B to F for the bold (○) and cautious (▲) populations of farmers.
7. FINAL REMARKS

This dissertation develops and applies an agent-based model of farmers’ crop selection decisions under various policy incentives, to estimate the effects of those decisions on water quality, namely stream nitrate load. The model takes into consideration the farmers’ potential switch from conventional crops, i.e. corn and soybean, to miscanthus, a second-generation bioenergy crop. This switch may occur in response to policy changes reflecting concern for global warming and energy independence. This dissertation takes an integrated hydrologic-agronomic-economic modeling approach. To the best of the author’s knowledge, this is one of the first studies to take such an approach in the area of bioenergy development for the specific case of miscanthus (which looks promising as the ideal second-generation bioenergy crop). It is hoped that policy-makers will find the results here useful for the better understanding of market instruments for nutrient management, as well as of the environmental effects of a market demand for second-generation bioenergy crops. Refer to the following subsections for a summary of the work done and discussions on major findings and policy recommendations, as well as the limitations of the study and possible future work.

7.1 Summary

An agent-based model of farmers' crop and best management practice (BMP) decisions under the influence of a nitrogen fertilizer reduction subsidy, and carbon and miscanthus prices is developed. Agent-based modeling (ABM) is a relatively novel approach to modeling water quality policy problems that are usually modeled by imposing on the system some least cost, or maximum utility, equilibrium. The least cost equilibrium approach is valid only if assuming rational behavior, perfect information, zero transaction costs and static conditions. The ABM approach, which formulates the system from the perspectives of the individual agent, is arguably more realistic as it gives the modeler greater flexibility not to make the assumptions of the conventional least cost equilibrium approach. At the same time, the data needs of ABM exceed those of the conventional approach to a considerable degree.

The agent-based model is linked to a Soil and Water Assessment Tool (SWAT) model of the Salt Creek watershed in East-Central Illinois to simulate the interactions between agents
(farmers) and the environment. The model is calibrated and validated using the Generalized Likelihood Uncertainty Estimation (GLUE) method for daily stream flow at four locations within the watershed, annual corn and soybean yields and monthly stream nitrate load at the watershed outlet. Work has also been done to parameterize the crop growth component in SWAT for miscanthus. (Even though SWAT comes with a database of default parameters for a number of crops, the values for miscanthus are unavailable, as it is a relatively new crop.) Once ready, the model is used to generate crop yield data to feed to the agent-based model. It is also used to simulate stream nitrate load as a function of the farmers' crop management decisions as predicted by the agent-based model.

The agent-based model is applied to fifty hypothetical farmers in the Salt Creek watershed in East-Central Illinois. The farmers are heterogeneous in terms of their initial perceptions of prices, costs and yields, and how they update those perceptions with time. They are heterogeneous in terms of their land areas, fractions of marginal land, economies of scale, yields, time discount rates, foresights, and risk aversions as well. The farmers are also interacting in terms of their knowledge of initially unfamiliar activities, i.e. carbon trading, conservation tillage and miscanthus cultivation. Their uncertainties of the costs and benefits of these activities are reduced as their neighbors or they themselves experiment and gain experience.

In the agent-based model, each farmer is represented by a dynamic programming model with the objective to maximize his sum of discounted utilities over time. The farmer's decisions depend on his expectations and uncertainties of future prices, costs, yields and weather variables. His decisions also depend on his current state, which in turn, is subject to the past states and decisions of the farmer. At the beginning of every year, the farmer has to decide on the best combination of crops (corn, soybean and miscanthus) and BMPs (conservation tillage and grass planting). To maximize utility, he has to find the right balance between potential gains from crop sales, carbon trading and nitrogen subsidies and potential losses from fertilizer and other production costs.

The farmers' expectations and uncertainties of future conditions are updated with new observations according to a Bayesian algorithm. The Bayesian algorithm weights existing beliefs against new observations. The parameters in the Bayesian algorithm are set differently for different farmers such that each is unique in his processing of new information. However, due to a lack of empirical data, it is not possible to know the values of these parameters that adequately
represent reality. Therefore, for the purposes of this study, two extremes of behavior are defined: cautious and bold. For farmers that are cautious, their Bayesian parameters are set such that they are slow to adjust their expectations in response to new observations but quick to reduce their forecast confidence when new observations fail to match expectations. On the other hand, for farmers that are bold, their Bayesian parameters are set such that they are quick to adjust their expectations with new observations but slow to reduce their forecast confidence when there are unexpected changes in the system. Cautious and bold farmers are also dissimilar in their levels of risk aversion; cautious farmers are more risk averse than bold farmers.

Results are obtained for various scenarios of the nitrogen fertilizer reduction subsidy and carbon and miscanthus prices. For each scenario, two sets of simulations are carried out; one for a population of fifty cautious farmers and another for a population of fifty bold farmers. The effects of the nitrogen subsidy and carbon and miscanthus prices on the farmers' decisions, and consequently, stream nitrate load are examined and discussed. The tradeoffs between nitrate load reduction and farmer cost and income, as well as crop acreages, are also analyzed. Major findings are reiterated and discussed in the following subsection.

7.2 Major Findings and Recommendations

From the results, it can be seen that the different market instruments are not equal in their effectiveness in inducing large-scale land use changes with the ultimate purpose of reducing nitrate load in surface waters. For the scenarios examined, the most effective means of achieving a significant reduction in nitrate load is to have a market demand for miscanthus. The nitrogen fertilizer reduction subsidy is also effective. (Miscanthus price has a larger effect on nitrate load than the nitrogen subsidy because the former encourages miscanthus cultivation while the latter soybean cultivation. With miscanthus, the amount of nitrogen removed from the system with harvesting, in comparison with the amount of new nitrogen entering the system, is greater than with corn or soybean.) However, carbon trading is unlikely to lead to any major change in nitrate load for the case study watershed.

Of all the combinations of the nitrogen subsidy and carbon and miscanthus prices examined, the only ones that are capable of producing a 30% reduction in nitrate load (EPA SAB (2007) recommends a 45% reduction to mitigate the hypoxia problem in the Gulf of Mexico;
however, none of the policy scenarios examined is able to achieve this target) are those where there is a market value for miscanthus that is about 50% of the average of corn and soybean prices. For the simulation period used in this study (1985-2008), this translates to an average price of miscanthus of about $82.50/ton. In reality though, miscanthus prices may never reach levels that are high enough to induce sufficiently large land use changes. As farmers switch to miscanthus (or other second-generation bioenergy crops), it will be partially, if not fully, at the expense of conventional crops. This will cause their supplies to decrease and consequently, prices to rise. The final state of the system may be such that miscanthus prices are much less than 50% of the average of corn and soybean prices.

Where miscanthus prices are low, reductions in nitrate load can be improved by offering farmers a subsidy for decreasing their fertilizer application rates. For example, when miscanthus prices are about 40% of the average of corn and soybean prices, a $2000/ton-N subsidy should result in a 20.8-22.6% reduction in nitrate load, which is an improvement over the 13.8-19.4% that can be expected without the subsidy.

In this study, carbon trading is found to be unlikely to lead to any significant reduction in nitrate load and may even cause it to increase slightly. This is because it will cause farmers to practice conservation tillage on a larger scale, resulting in less surface runoff but more subsurface infiltration. As a large percentage of the watershed is tile drained, this may cause more of the nitrogen in the soil to leach out into the tiles and into receiving waters. Further, even though carbon trading does also provide incentive for grass planting, however, for all the carbon price scenarios considered in this study, the amount of land converted to uncultivated grass is insignificant.

Note that the findings here do not mean that carbon trading will not lead to nitrate load reductions in areas elsewhere where there is no tile drainage. Indeed, Wu and Tanaka (2005) have estimated, in a case study of the Upper Mississippi River Basin, that incentive payments for conservation tillage would be effective in reducing stream nitrate concentration. Greenhalgh and Sauer (2003) found similar results for the entire Mississippi River Basin. Further, in other places where land characteristics are different from those in the Midwest, farmers may be more prone to grass planting to claim carbon credits. Wu and Tanaka (2005) predicted that to convert land producing corn and soybean (which is the case of the Salt Creek watershed) to uncultivated
grass, incentive payments 1.5 to 2.5 times greater than those for land producing hay or other crops are required.

Note also that whatever policy instrument is used to bring on large-scale land use changes with the ultimate purpose of reducing stream nitrate load, there will be tradeoffs. Probably the largest tradeoff is the decline in land allocated to corn and soybean. Results indicate that, for this particular case study, to achieve at least a 30% reduction in nitrate load relative to a conventional corn-soybean rotation, the fraction of the watershed in corn must be reduced to less than 30%, and in soybean to 10-40%, depending on the combination of the nitrogen subsidy and carbon and miscanthus prices. This decline in corn and soybean acreages diminishes food and feed supplies. The corresponding increase in miscanthus acreage is also likely to cause reductions in stream flows, especially hot weather low flows, since evapotanspiration for miscanthus is significantly greater than for corn and soybean due to its longer growing season (Hickman et al., 2010). If such changes are unacceptable, then policy makers should consider perhaps, interception strategies that do not entail any change in current practices but rely on intercepting and treating nutrient-rich runoff to reduce nitrate load. One interception strategy is the use of constructed wetlands placed at strategic locations within the watershed (Kovacic et al., 2000; Ng and Eheart, 2008). Another is the use of denitrifying bioreactors filled with wood chips or other organic materials to capture tile-drainage effluent (Blowes et al., 1994; Robertson and Merkley, 2009; Chun et al., 2010).

Thus, it is shown that ABM is able to produce results that are meaningful, which demonstrates its suitability to modeling water quality policy scenarios. It is also able to provide insights not possible using the least cost equilibrium approach. For example, it is able to predict how differences in the way farmers process new information affect their forecasts of future conditions and hence, decisions. It also appears able to predict patterns of their adoption of new technologies (in this case, conservation tillage and miscanthus cultivation). Its predictions, while empirically untested, appear plausible and consistent with general behavior by farmers.

7.3 Limitations and Future Work

A large part of ABM is in defining the individual agents. Their characteristics, actions, interactions, learning etc. need to be clearly specified. It is however, not straightforward to define
the agents in a credible and accurate manner if the purpose is to model real agents; the data and knowledge requirements for such a task are significant. The problem is even more difficult when modeling social systems where empirical data are often lacking. In the present work, to model farmers’ decision-making, rational behavior is assumed, which may not be entirely valid. Even though ABM does allow for the incorporation of non-rational behavior, this work does not take advantage of that. This is primarily because of the lack of empirical data that can be used to deduce farmers' actual thought processes to develop more realistic rules that are able to account for the non-economic factors behind farmers’ motivations, such as the reasons why in reality, many farmers do not practice conservation tillage, and similarly, why they may not cultivate miscanthus in the future on a large scale, even if conditions are such that these activities are economically optimal. It should be acknowledged that farmers face many barriers to adopting new crops or practices that are not easily defined, e.g. conflicting information, increased complexity, incompatibility with other aspects of farm management and personal objectives, high implementation costs and capital outlay etc. (Vanclay and Lawrence, 1994).

Another major assumption that may not be entirely valid is the assumption that farmers adjust their perceptions of the world according to a Bayesian algorithm. While others (Feder and O'Mara, 1982; Foltz, 2004) have made the same assumption, there is little empirical evidence to suggest that this is indeed how real farmers update their beliefs with new information, or even more fundamentally, that those beliefs can be expressed as probability distributions. Again, this assumption has been made due to the lack of empirical data that can be used to define more realistic updating algorithms.

Thus, for future work, it is worthwhile to conduct interviews and/or role-playing games involving real farmers to obtain empirical data on their decision-making and learning processes. This idea of conducting interviews and role-playing games to deduce real behavior is not new and has been done before (Castella et al., 2005). Empirical data from historical records, if available, may also be useful for providing a retrospective view of farmers' behavior. For example, historical data on farmers’ adoption of hybrid seeds or other new technologies can be analyzed to gain insights, especially on risk, uncertainty and learning (e.g. Smale and Heisey, 1993; Sarkar, 1998). This is an opportunity for interdisciplinary work between economists, psychologists, sociologists and engineers. Economists and other social scientists are adept at performing experiments and analyzing data (whether from experiments or historical sources).
involving human subjects where observations are often subjective and noisy. Engineers have very limited experience in these but are skilled at integrating the results of those experiments into a larger model of the system, which may include a sub-model of the physical environment.

For future work, it may also be meaningful to model the long-term effects of the nitrogen fertilizer reduction subsidy. In the short term, as discussed in Chapter 6, the subsidy will cause farmers to reduce their fertilizer use, leading to an overall decrease in nitrogen runoff. However, in the long term, the subsidy may attract farmers to cultivate previously uncultivated land (Baumol and Oates, 1975), leading to an overall increase in nitrogen runoff, although such activity could easily be specifically declared ineligible for the subsidy. It may also be meaningful to assess the effects of a nitrogen fertilizer use tax, which should have the same short-term effects as the subsidy but without the same long-term effects. Taxes, especially on farmers, however, are generally not politically feasible. It would also be interesting to model and assess the effects of a nitrogen fertilizer cap-and-trade program. Unlike the subsidy or tax, in the cap-and-trade program, the overall use of nitrogen fertilizer, and hence, nitrogen runoff, is fixed regardless of the total area of cropland.

As mentioned above in Chapter 4, it is not within the scope of the current work to consider the effects of pests and diseases on yields, which increase farmers’ uncertainty and complicate their decision-making. Nonetheless, it may be of future interest to do so, perhaps, in the context of climate change, which is likely to introduce new pests and diseases to the region (Patterson et al., 1999), rendering existing strategies of controlling them obsolete. Also mentioned above, in Chapter 5, the current work does not consider the general equilibrium effects of the nitrogen subsidy, and carbon and miscanthus prices. The subsidy and prices will cause large-scale land use changes which will conceivably, affect crop supplies and as a result, crop prices. The current work does not consider this secondary effect. It may be interesting, for the future, to link the current model to models of the corn, soybean and miscanthus markets to capture the interdependence between prices and land use.

Future work should also include an uncertainty analysis of user-provided model parameters. In this study, model parameters such as the farmers’ risk aversions, foresights, fractions of marginal land, time discount rates and initial perceptions of yields, prices, costs and the weather are somewhat randomly selected. It is quite possible that results may be quite different if another set of parameters had been used. A more comprehensive approach would be
to run the model multiple times for different random parameter sets and base the final conclusions of the study on multiple sets of results, rather than on a single set of results as in the current case. The computational cost of taking this approach, however, is expensive and time-consuming. Such an analysis is left for the future and is recommended to be carried out together with a sensitivity analysis of the model parameters to give a more complete picture of the problem.

It is also useful to repeat the study for other watersheds of different climates, soils and crop choices. The results here are specific to the Salt Creek watershed and can probably be extrapolated to other agricultural watersheds in the area. However, it is uncertain if they are applicable to other watersheds that are significantly dissimilar in soil, slope, climate, etc.
REFERENCES


