An Agent-Based Model of Multifunctional Agricultural Landscape Using Genetic Algorithms

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Abstract

Landowner characteristics influence his/her willingness to change landuse practices to provide more or less environmental benefits. However, most studies of agricultural/environmental polices identify landowners as homogenous. And, the primary cause of failure of many environmental and other polices is the lack of knowledge on how humans may respond to polices based on changes in their behavior (Stern, 1993). From socioeconomic theory and empirical research, landowners can be identified as individuals who make agricultural landuse decisions independently based on their objectives. Identifying possible classes of landowners, assessing how each would potentially respond to policy alternatives, and the resulting pattern of land uses in a watershed or a riparian corridor would be very useful to policy makers as they evaluated alternatives. Agricultural landscapes are important producers of ecosystem services. The mix of ecosystem services and commodity outputs of an agricultural landscape depends on the spatial pattern of land uses emerging from individual land use decisions. However, many empirical studies show that the production of ecosystem services from agricultural landscapes is declining. This is consistent with research conducted over the last few decades showing there is a narrow range of social circumstances under which landowners are willing to make investments in the present to achieve public benefits in the future through investing in natural capital resulting in public goods which are frequently produced as ecosystem services.

In this study an agent-based model within a watershed planning context is used to analyze the tradeoffs involved in producing a number of ecosystem services and agricultural commodities given price and policy scenarios while assuming three different types of agents in terms of their goals. The agents represent landowners who have been divided into a number of different groups based on their goals and the size of their farm operations. The multi-agent-based model is developed using a heuristic search and optimization technique called genetic algorithm (GA) (Holland), which belongs to a broader class of evolutionary algorithms. GAs exhibit three properties (1) they start with a population of solution, (2) they explore the solution space through recombination and mutation and (3) they evaluate individual solutions based on their appropriate fitness value(s), for example given profit maximizing agents this would be gross margin. A GA is a heuristic stochastic search and optimization method, which works by mimicking the evolutionary principles and chromosomal processing in natural genetics. The three economic agents that are modeled are based on variations in their objective functions and constraints. This study will help in identifying the tradeoffs associated with various agents in the provision of ecosystem services and agricultural commodities. The agent model developed here will help policy and decision maker identify the various agents within the watershed and assess various policy options based on that information. The study will also help to understand the interaction and feedback between the agents and their environment associated with various policy initiatives. The results of the study indicate that the agent model correctly predicts the actual landuse landcover map by 75 percent.

Key words: Multifunctional agriculture, Agent based modeling, Genetic Algorithm.

Introduction

Landowner (agent) characteristics are one of the major sets of factors that influence a landowner's willingness to change landuse practices to provide more or less environmental benefits (Lockeretz, 1990; Loftus and Kraft, 2003). However, most studies of agricultural/environmental polices fail to include landowners as a factor influencing policy. And, the primary cause of failure of many environmental and other polices is the lack of knowledge on how human may respond to polices based on changes in their behavior (Stern, 1993). From economic and social theory and empirical research farm landowners can be identified as heterogeneous individuals who make agricultural landuse decisions independently based on their objectives (Maybery et al., 2005). Identifying possible classes of landowners (agents), assessing how each would potentially respond to policy alternatives, and the resulting pattern of land uses in a watershed or a riparian corridor would be very useful to policy makers as they evaluated alternatives.

Multifunctional agricultural landscapes are potentially important producers of ecosystem services, e.g., enhanced water quality, nutrient recycling, reduced sedimentation, carbon sequestration, and enhanced wildlife habitat, in addition to traditional agricultural commodities. The product mix of ecosystem services and commodity outputs from an agricultural landscape depends on the spatial pattern of land uses emerging from individual land use decision, called the economies of configuration by Gottfried et al., (1996). However, many empirical studies show that the production of ecosystem services on agricultural landscapes is in decline. This is consistent with social research conducted over the last few decades showing there is a narrow range of social circumstances under which farmers or landowners are willing to make personal investments in the present to achieve public benefits in the future through investing in natural capital (Firey 1963), i.e., investments that result in the greater production of ecosystem services. These services are frequently public goods from which the landowner derives virtually no income.

Understanding the links among agricultural/environmental policies, human decision making through land use choices, and environmental outcome can help design policies that directly affect incentives pertaining to land use and management. Consequently, in this study an agent-based model within a watershed-planning context is used to analyze the tradeoffs involved in producing a number of ecosystem services and agricultural commodities given a number of price and policy scenarios while assuming three different types of agents or landowners in terms of their goals. Most of the previous simulation studies used traditional mathematical programming methods lack the capability of modeling complex, human-decision- making process of feedback and interaction of agents with the environment and among themselves, and they also lack in spatial specificity (Berger 2001).

Parker et al., (2003), defined agents as autonomous entities that have limited knowledge and information, which are nothing but simple subroutines of a computer program. Agents are goal directed; can sense the environment and act upon it; can react to policy and market conditions; and are capable of interaction with other agents and a common environment (Woolridge and Jennings, 1995). In this study, agents represent landowners who have been divided into a number of different groups based on their goals, biophysical variables such as soil crop productivity, and the size of their farm operations. In this research a multi-agent-based model that capture multiple farmer behavior is developed by using a heustric search and optimization technique called genetic algorithm (GA) (Holland, 1975), which belongs to a broader class of evolutionary algorithms (EA).

Research Goal

This research develops a multi-agent based model that accurately captures multiple farmer typology behaviors in making land use decisions that invariably affects the production suits of multifunctional commodities from an agricultural landscape. This study also analyzes the multi-agent-based model, in the decision making process, on the possible economic and environmental outcome for policy scenarios such as change in agricultural/ environmental policies such as soil conservation. Finally the study tests the robustness of the developed agent-model in accurately capturing the variations in the decision-making process of various farmer agents due to variations in endogenous (e.g. agents value) and exogenous factors (e.g. market price) compared to the actual land use land cover map.

Study Area

The study area is the Big Creek watershed (Figure1) of the Cache River basin in southern Illinois, which covers and area of 1944km^2. Large quantities of sediment from the upper reaches of the basin are being deposited in aquatic and wetland habitat found in the Lower Cache River, threatening to eliminate the high quality natural communities that inspired the designation of this area as a State Natural Area and Land and Water Reserve, a National Natural Landmark, an Important Bird Area, and a Wetland of International Importance (RAMSAR Wetland). Land use changes in the Big Creek watershed (land clearing, drainage efforts) have significantly increased the discharge (flow volume and velocity) of this tributary (Demissie et al. 1990), resulting in excessive sediment suspended and transported in the water column during periods of high flow. Along with the need to enhance ecosystem quality, there is also a political and economic need to maintain a viable agricultural sector. The region is an impoverished area with few linkages to surrounding regions and minimal infrastructure to support non-farm activities (Beaulieu et al., 1998).

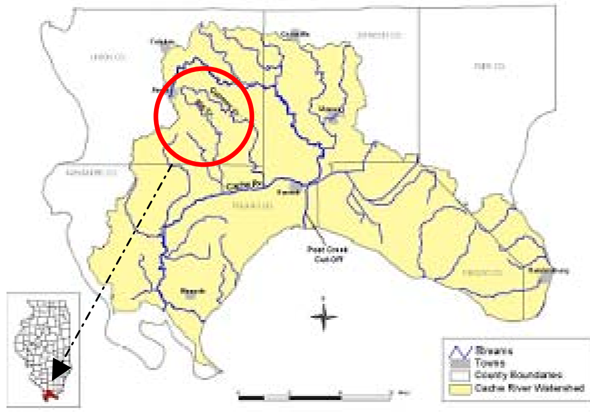


Figure1: Map of study area.

The landscape supports a variety of agricultural related enterprises with grain, cattle, and vegetable producing operations being the most prominent. Study conducted by Beck et al., 1995 have established that land use changes associated with maintaining and enhancing the Cache watershed are not inherently damaging to the local economy.

AGENTS

The theoretical principles of agriculture location theory based on market forces used by Von Thünen (Ponsard 1983) to explain the agricultural land use land cover changes that underpin most of traditional geographic land use land cover model does not capture the anthropocentric and biophysical complexity associated with land use change. Recently, studies have shown that complexity associated with biophysical variables (e.g. slope, soil type, and erosion), economic factors, and anthropogenic factors (e.g. value, cultural and objectives) in addition to market factors are important elements in the explaining agricultural land use land cover change. Most of the traditional economic and geographic studies tried to separate the two entities associated with land use change of human decision-making and environmental consequences into two separate models**.** Until lately, socioeconomic research of human decision-making ignored the spatial component of the environment human agents were acting on, while the environmental modeling completed ignored the human element on landuse land cover change (Irwin and Geoghegan 2001). But the agent-based models for agent environment interactions are spatially explicit due to their integration with spatial models such as GIS or cellular automata (CA). One of the major failures associated with current environmental management is the failure of non-inclusion of human-decision making in natural resource management. So there is an increased focus on research towards integration of human systems and their influence of environmental outcomes. According to Deadman et al., (2000) understanding the linkages and complexities between human and natural systems is central to the development of effective natural resource policy.

Recent research studies in the modeling of human decision-making (Berger 2001; Parker et al., 2003) and its effects on environment have successfully explored the benefits of using agent-based models compared to traditional mathematical models such as differential equations and transition probability matrices. The traditional process-based models or statistical models do not include human decision-making as a driver of landuse change, which many recent studies show play a major role in landuse change. Even though this agent-based research on human decision-making is in the rudimentary stage of the developmental process, various studies have shown that it has enormous potential. Compared to traditional mathematical models, an agent- based model helps to represent human decision-making process explicitly. An agent-based model for environmental management consists of two things: a spatial process based model to capture and analyze the complex biophysical variables, and an agent-based model to account for the complex human decision-making process (Berger 2001). An agent can represent any autonomous entity such as atoms, biological cell or a human being, but in this research context of agricultural land use management, the agent represents a farmer or a farm manager who combines his/her knowledge, values, relevant policy and market conditions, information on biophysical variables such as soil quality, crop productivity, and slope, and resources availability such as land, labor, and machinery availability to make agricultural land use choices that define an agricultural landscape.

Ferber (1989) defined agents as follows:

"A real or abstract entity that is able to act on itself and its environment; which has partial representation of its environment; which can, in a multi-agent universe, communicate with other agents; and who's behavior is a result of its observations, its knowledge, and its interactions with the other agents (p 249)."

An agent-based model can be used to represent a simple homogenous agent or complex, multiple agents. A multi-agent- based model involves multiple heterogeneous agents interacting with the environment, which can be a market, a political institution, a watershed or a farm. According to Bonabeau (2002) the benefits of agents based modeling in human decision-making compared to traditional models are that (1) agent-based models are flexible, (2) agent-based models captures emergent phenomenon, and (3) the models incorporate real world systems involving complex human decision making. The flexibility of the agent-based model helps it to integrate various complexities associated with human decision-making as well as the complexity associated with environmental process (Parker et al., 2003; Berger et al., 2001). Various studies on agent-based model on agent environment interactions have shown that, the agent-based models can be used: as a computational laboratory to explore human environment interactions and feedbacks; to represent complexity related to socioeconomic decision-making; helps to represent emergent phenomenon; to integrate human environmental systems; and for scenario analysis related to land use land cover change (Berger 2001).

Agents interact with the environment and also among themselves. Agent-agent interaction involves imitation, information diffusion, coalition, and buying and selling. However agent environmental interaction, is the main focus of this particular study involves agent's influence on an agricultural landscape in the form of soil erosion, water quality impacts, and deforestation. Agents can also interact with each other while providing valuable feedback regarding landuse patterns (Torrens and Benenson, 2005). But for this study the spatial autocorrelation of landuse choices among agents was statistically insignificant. According to Sengupta (forthcoming) the agent-based decision-making appears to be a spatially variable process rather than a spatial diffusion process. One of the reasons for this can be the advances in the technologies of communication that diminishes the influence of neighbors on an individual landowner's landuse choice.

Recent studies on agent-based models have shown that these models can be used to capture human decision making with a high degree of success compared to traditional models when the interactions between the agents are complex, nonlinear, discontinuous, and discrete, or when there are multiple heterogeneous agents acting independently, or when the agents represents complex behavior such as adaptation and learning (Bonabeau 2002). Most of the traditional economic studies model human actors only as utility maximizing agents (Ormerod 1995) with unfettered information and knowledge and with the brainpower to comprehend all information. However, this is against the norm of most human psychological studies that argue most human makes decisions based on cognitive limitations and bounded rationality (Simon 1957). Bounded rational agents rather than trying to find an optimal solution that fully anticipate the future states of the system of which they are part, make inductive, discrete, and evolving choices that move them towards achieving goals or levels of aspiration (Simon, 1997; Rabin 1998). So, traditional economic models can be misleading if considered to represent the real world phenomenon with multiple human agents having multiple social behaviors like the one under study.

A survey done by Kraft et al., (1989), in the study area was used to identify three different types of landowners, technologically-adopting commercial farms or profit maximizer; landowners showing satisficing behavior a la Simon; and conservationists, whose first and foremost goal was to conserve natural resources. These agents were spatially distributed across the watershed based on an algorithm written in avenue scripts (ArcView 3.2) that takes into account crop productivity and soil erosion. The distribution is consistent with the previous studies by Kraft et al., (1989) and Tim Loftus and Kraft (2003), in that large commercial farm occupy majority of the highly productive and low erosive lands, while smaller or rural lifestyle farmers (satisficer) mostly occupy less productive and highly erosive lands. Maybery et al., 2005, in their study in Australia also identified three different types of landowners (profit maximizer, rural life style, and conservationist) similar to one done at the Big Creek watershed.

Genetic algorithms (GAs) have been frequently used in economics to study the social behaviors of human agents with respect to their economic decision-making. Studies by Riechmann (1999); Arifovic (1994) have shown that GA can generate human behavior consistent with the experimental data obtained with actual human subjects. In most of the agent-based studies using GAs, economist have used it to model heterogeneous agents to optimize a given objective. In this study an agent-based model of various typologies of farmer decision-making abilities is modeled using a single objective GA. The advantage of using GA over other classical optimization techniques such as direct (linear programming) and gradient based (non-linear programming) method is that, it is well suited to solve complex problems (e.g. non-convex, discontinuous) such as human decision making (Parker et al., 2003), its global perspective in finding optimal or near optimal solutions (Debb 2001, Nicklow et al., 2004, Nicklow 2000), and its inherent parallel processing ability (Debb 2001) which are essential criteria for multi agent-based models.

A genetic algorithm (GA) is a subset of EAs that applies the principle of biological genetics, including natural selection. GA was first described by Holland (1975), which applies the principle of the "survival of the fittest" to a population of competing individuals or solutions within a given environment technically called the search space. The major difference between GAs and the other classical optimization techniques is that the GA works with a population of possible solutions, on the other hand classical optimization techniques work with a single solution. An individual solution in a population of solutions is equivalent to a natural chromosome. Just as a natural chromosome completely specifies the genetic characteristics of a human being, an artificial chromosome in GAs completely specifies the values of various decision variables representing a decision or a solution.

The steps involved in a GA are similar to the process that occurs in biological genetics. The GA starts with a randomly generated number of solution samples, collectively called the population, within the feasible search space. Each of these samples, called a chromosome, is defined by a sequence of decision variables known as genes. The representation of GA genes can be in binary strings of ones and zeros of user specified length, or real value numbers or integers. Each chromosome in the initial population is assigned a measure of fitness, based on the objective function value. These chromosomes are referred to as species of the first generation. For a maximization problem, the higher the fitness values, the higher the chance for survival. The next step is the selection of chromosomes, to create the next generation. For this the chromosome of the first generation would be ranked in ascending order of their fitness value for a minimization problem, and in descending order of their fitness for a maximization problem. Chromosomes with the highest fitness value will be given a higher probability to obtain a mate, so as to produce offspring that may better fit the environment. This process of selecting mates is called selection. Once mates are selected, genes of corresponding mates, or parents, are systematically exchanged with the conception that the resulting solutions or offsprings will have higher fitness values. The process of creating new individuals by systematically assigning genes of chosen mates to the new individuals is known as crossover. The new chromosomes replace the old chromosomes, which have low fitness values.

The process of selection and crossover do not inject new genes, so the solution can converge to a local optimum. As a remedy of this concern, a process called mutation is performed. Among individuals of a current generation, the algorithm conducts a random selection of chromosomes, often a user-specified percent of individuals in the generation, as well as a random selection of gene sequences or gene locations within the chromosomes. Mutation allows GAs to search a wide search space and prevents the premature convergence to local optimum. In a binary coded GA, mutation is achieved through a local perturbation, i.e., by replacing 0 with 1 or vise versa. The process of selection, crossover, and mutation is repeated for many generations with the objective of reaching the global optimal solution after a sufficient number of generations. The convergence criterion could be a maximum number of generations to be allowed or stability of statistics such as mean and/or variance of the population fitness values from generation to generation. The flow chart below (figure 2) shows the progression of GAs.

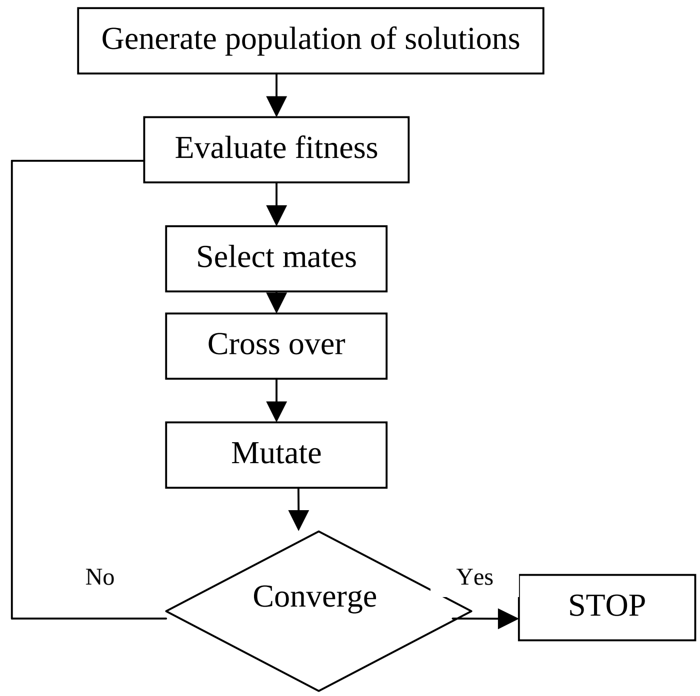


Figure2: Flow Chart of a single objective genetic algorithm

The three economic agents that are modeled are based on variations in their objective functions and constraints. For the profit maximizing landowner the objective function will be to maximize farm profit, for a conservationist the objective function will be minimization of soil loss, while the satisficing landowner is modeled using a goal programming approach that tries to minimize the soil loss subject to a satisfaction level or aspiration level (Simon 1957). The constraints considered are the labor and machinery requirement for various size farms within the watershed, environmental constraints such as soil loss, and season of planting.

Data

A 10m by 10m resolution DEM for the watershed area was obtained from Natural Resource Conservation Service (NRCS), which was used to calculate the average slope. A

30m by 30m pixel based land use maps for the watershed, for the years 1999 to 2004, were obtained from National Agricultural Statistics Service (NASS), which was used to identify the actual land use cover for the study area during those years. And a 30m by 30m resolution soil map from SSURGO-NRCS was obtained which is used to classify soil types within the watershed. Field delineation of the Big Creek watershed was done using the imagery acquired from the 2004 National Agricultural Imagery Program (NAIP). About 2098 fields were delineated for the Big Creek Watershed, out of that 1284 fields were in agricultural land use, pasture or CRP, rest of the fields were in forest, urban, water and other miscellaneous land use. Of approximately 34,000 acres in the Big Creek watershed, about 16043 acres were being used for agricultural purposes (cropping and grassland) in 2002 (figure3); the average acreage of these farming units was 245 acres. A clustering routine available in the ARC/INFO software package was used to allocate these 16043 acres into 92 farming units, based on the special tabulation of the census of agriculture.

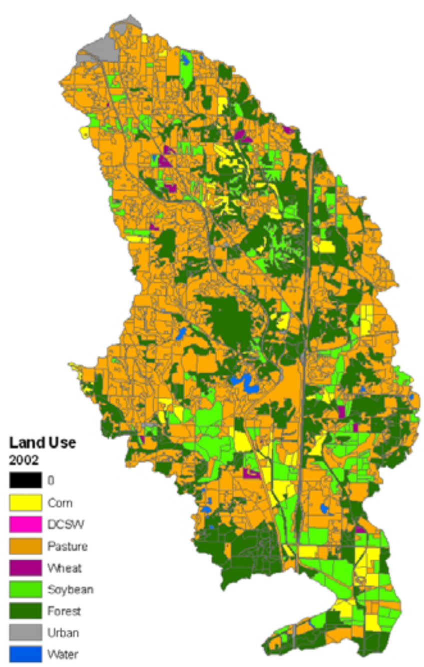


Figure 3. Landuse for year 2001

The construction of these faux farms was necessary because accurate property boundaries were not available. The farms were classified into large (>350 acres), medium (140-350 acres) and small farms (<140 acres).

The landuse for the study area for the year 2005 were primarily a mix of cropland (25.8%), pasture (42.5%) which includes hay, grasslands, and CRP, forests (28.6%), and the rest under urban and water uses. Farms in the watershed range in size from 4 acres to 580 acres with a mean of 213 acres. The labor and machinery availability was based on farm size, large farm were assumed to have one and quarter labor units available, while medium and small farms were assumed to have one full labor available for the farm. The machinery size for large farm was assumed to be big, meaning less percent of an hour required to cover an acre of farm compared to medium and small farms that have small size machinery. The landuse alternatives included crops such as corn, soybean, and alfalfa hay, grasslands, and CRP. Conservation management included tillage type such as conservational and no-till.

The crop yield for each field is the weighted average soil specific crop yields for that field. The market price for agent-based model is the five-year average market for various crops from year 2000 to 2005. The historic landuse that is used to jump-start the model is from the year 2001, since NASS had a separate classification for CRP. The crop rotation penalties associated with two-year rotation is based on previous studies and from the *Illinois Agronomic Handbook* (2005).

Methodology

In this study an agent-based model for various farmer typologies interacting with the agricultural landscape that provide multifunctional commodity outputs is developed by integrating genetic algorithm (GA) with geographical information systems (GIS). This model is an advanced version of the Kraft and Toohill (1984) representative farm model. The three economic agents that will be modeled will be based on variation in the objective function and constraints. For profit maximizing land owner the objective function will be to maximize gross margin (profit), while for conservationist the objective function will be minimization of soil loss, and for satisfying landowner the objective function will be to minimize the soil loss but subject to a goal or satisfaction level or aspiration level constraint (Simon 1957). The resource constraints considered are the labor and machinery requirement for various size farms within the watershed.

The agents' complex decision making processes are modeled as independent GA agents that respond to socioeconomic driving forces such as profit maximizations or conservation, resource availability such as labor and machinery, environmental policy such as soil conservation, and prior landuse. Depending on the agent type each agent will start with a population of potential land use choices (solutions/chromosomes) based on an actual landuse for the prior year. The historical landuse for the year 2001 was chosen as the prior year landuse since conservation reserve program was included as a separate classification only for the year 2001. The historical landuse map is shown in the figure X. The very heart of the genetic algorithm is the selection and reproduction operator. The selection operator selects the best land management alternative for a particular agent type based on binary tournament selection. In a binary tournament selection two land use alternatives are picked at random, and one with the higher fitness score wins. Selection process ends once all the parents for reproduction are selected through the binary tournament selection process. The fitness of an agent depends on his/her objective function. So for a profit-maximizing agent the land use management alternative that maximizes the gross margin will be have a better chance of being selected as a parent compared to a land use management alternative that has a lower gross margin. While for a conservationist higher fitness values are given to those land use management alternatives that has the lowest soil loss, and for a satisficer higher fitness is given those land use alternatives that minimizes soil loss and also have the goal constraint satisfied.

Once the parents are selected they under go crossover, which is the exchange of information between two parents to produce offsprings. The crossover probability determines the percent of parents that will undergo crossover, and the rest will be copied on to the next generation. Reproduction means the process of deriving new land use alternatives from the old population. So the process of selection and crossover will weed out those landuse alternatives that perform relatively low based on a particular agents objective, copy the successful alternative landuse strategy through crossover, and take it to the next generation. Repeated selection and crossover can move the search algorithm to a local optimum, so a mutation operation is performed which extents the search space. Mutation can create a random land use management alternative that has never been used before. Mutation operator in single objective GA depends on the mutation probability. Mutation probability determines the percent of population that will undergo mutation. The whole process is repeated until the user specified number of generations is reached. The final solution obtained for each agent will be the optimal land use management alternative that optimizes each agent's objective.

The framework of agent model methodology is shown in figure 4. Agent distribution to various farms within the watershed is predetermined based on crop productivity and soil erosion. The distribution of the three agents across the watershed is shown in Figure 5. Farms with high crop productivity index and with low and medium soil erosion were assigned to profit maximizers and those farms with low crop productivity and high erosion were assigned to conservationist. The rest of the farms were randomly assigned to satisficers, profit maximizers and conservationist. Based on the agent distribution for Big Creek watershed, 44% of the farms where profit maximizers, and the rest 56% is split evenly between satisficers and conservationist, which was consistent with the previous study done by Kraft et al., (1989). Based on area 46% were profit maximizers, while 30% and 24% of the watershed were satisficers and conservationist respectively.

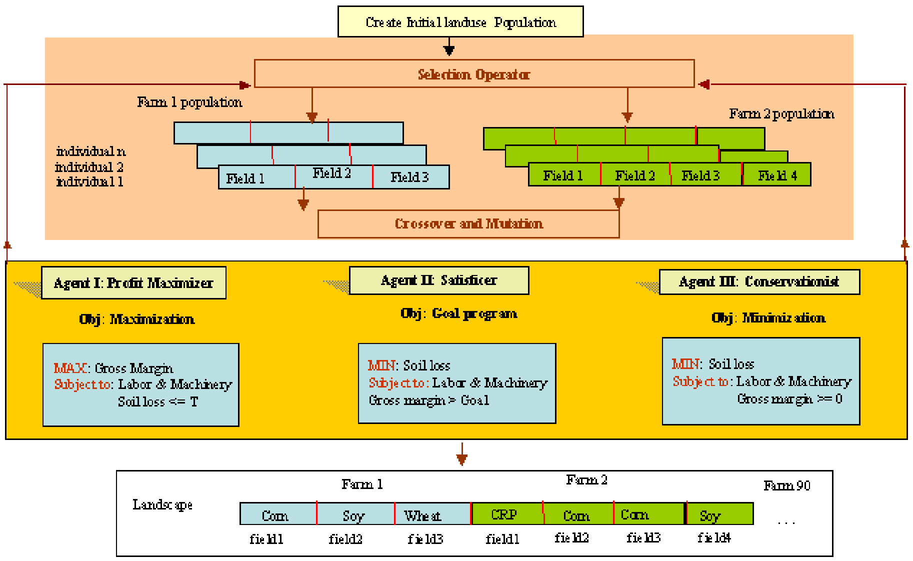


Figure 4: Framework of Agent based model

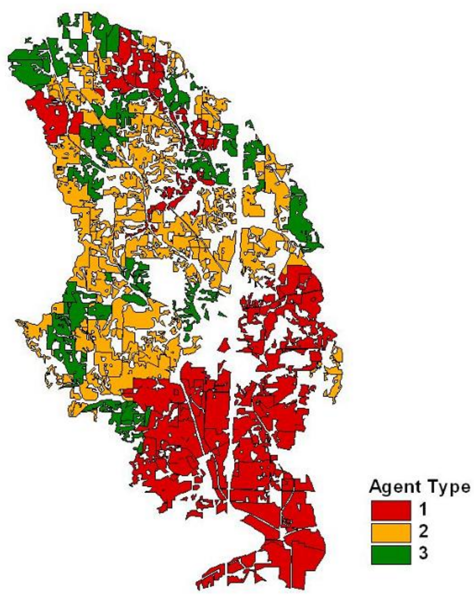


Figure5: Agent typology Distribution

The agent based model starts by randomly generating user specified number of initial solutions for a single farm from the watershed. The decision variables for the agents are the landuse, tillage type and planting time, which are represented by unique real numbers. Based on the combinations of landuse, tillage type, and planting time there were 43 different decision variables, which is shown in table 1. The agent model randomly generates a decision alternative from the 43 different alternatives for each field within in the farm and then for each individual within the population. During random generation of initial population the model make sure that, if the particular field was enrolled in CRP the previous year, the field remains in CRP the next year. Each farm individual of the population represents a particular decision strategy or alternative for that farm agent. Next the fitness of each individual within the population is calculated to determine the best decision strategy for that agent. Here the fitness function is the objective function. The objective functions (state variable) for the agent model vary depending on the typology of farm agent and based on the prior landuse. For a profit maximizing agent the objective function is calculated as follows:

$$\textit{Maximize } Z = \sum_{k=1}^{n}\sum_{J=1}^{m} a_k (f_{kj} P_j - C_j)$$

Subject to

$$\sum_{k=1}^{n} X_{kj} \leq T$$

$$\sum_{i=1}^{I} r_j \leq R$$

$$X_{kj} ; R_j \geq 0$$

where:

Z = gross margin maximizing objective function.

i = index of farm.

j = index of crop cover types (corn, soybean, hay, CRP, grass pasture).

a_{k} = area of field k.

f_{kj} = soil crop productivity of field k for cover type j .

p_j = price for cover type j.

c_j = variable cost of production per unit area for cover type j.

x_{kj} = soil loss for farm field k from cover type j.

n = total number of fields for farm i.

k = index of farm fields

m = land uses considered.

r_{j} = labor and machinery requirement for cover type j.

T= amount of soil loss in tons.

R= amount of labor and machinery available for farm i.

The objective function for a profit-maximizing farm is to maximize the farm gross margin[♣] subject to soil loss conservation and resource constraints such as labor and machinery. If the farm agent is a satisficer the objective function is calculated as follows:

[♣] *Gross margin represents the short-term profit for a firm or enterprise, which is the calculated by deducting variable cost of production from the gross revenue.*

$$Minimize\ S = soil\ loss$$

Subject to

$$\sum_{k=1}^{n}\sum_{j=1}^{m} a_k \left(f_{kj} P_j - C_j \right) \geq G$$

$$\sum_{i=1}^{n} r_j \leq R$$

$$G; R_j; d_i \geq 0$$

where:

S = minimizing soil loss.

i = index of farm.

j = index of crop cover types (corn, soybean, hay, CRP, grass).

$a_{k\,=}$ area of field k.

f_{kj} = soil crop productivity of field k for cover type j .

p_j = price for cover type j.

c_j = variable cost of production per unit area for cover type j.

N = total number of profit maximizing farms.

n = total number of fields within each farm.

k = index of farm fields

m = land uses considered.

G = goal or the aspiration level.

$r_{j=}$ labor and machinery requirement for cover type j.

R= amount of labor and machinery available for farm i.

For a satisficer farm agent the objective is to minimize the soil loss subject to a goal constraint G. The goal or aspiration level of a satisficing agent is a random value between one third and three fourth of the profit maximizing level depending on the size of the farm. The objective function is also subject to a resource constraint of labor and machinery. Soil loss calculation for a farm is described below. While for an agent type conservationist the objective function is calculated as follows:

$$Minimize\ C = soil\ loss$$

Subject to

$$\sum_{k=1}^{n}\sum_{J=1}^{m} a_k (f_{kj} P_j - C_j)_i \geq 0$$

$$\sum_{i=1}^{n} r_j \leq R$$

$$X_{kj} ; R_j \geq 0$$

where:

C= conservationist objective function.

i = index of farm.

j = index of crop cover types (corn, soybean, wheat, hay, CRP, double crop).

$a_{k\,=}$ area of field i.

f_{kj} = soil crop productivity of field i for cover type j .

p_j = price for cover type j.

c_j = variable cost of production per unit area for cover type j.

x_{kj} = soil loss for farm field i from cover type j.

N = total number of profit maximizing farms.

n = total number of fields within each farm.

k = index of farm fields

m = land uses considered.

$r_{j=}$ labor and machinery requirement for cover type j.

R= amount of labor and machinery available per farm.

The objective of conservationist is to first and foremost minimize soil loss subject to gross margin constraint greater than zero, and also labor and machinery constraints. The fitness function for the farm varies depending on agent typology.

The Soil loss constraint is calculated using the USLE soil loss equation (Wischmeier and Smith, 1978) for each farm field based on the weighted average of all soil type properties. The equation for USLE is:

$$USLE = R \times K \times LS \times C \times P$$

where: USLE is the average annual soil loss in tons per acre,

R is the rainfall factor,

K is the soil erodability factor,

LS is the length and steepness of slope factor,

C is the cropping and management factor,

P is the conservation practice factor.

The LS factor for the Big Creek watershed is derived from the 10m x 10m digital elevation model (DEM), K factor for each soil type is obtained from the NRCS-SSURGO. The crop management factor C varied based on tillage operation, crop, and timing of tillage activity. For example, the C factors for corn were estimated at 0.18 for conservation tillage fall-plowed, and 0.05 for no-till. The conservation factor P, was held constant at 0.85 across all farm fields.

The objective function value is calculated based on the farm agent type. Once the objective function calculation is over, the individuals of the population are ranked based on the objective function value. For a profit-maximizing farm, a feasible individual with the

Table1: Landuse codes

Landuse code	Description	Real number
ALF1	Alfalfa Hay	1
CNT1	Corn-notill-planting1	2
CVF1	Corn-conservation till Fall planting1	3
CVS1	Corn-conservation till-spring planting1	4
CNT2	Corn-notill-planting2	5
CNT3	Corn-notill-planting3	6
CNT4	Corn-notill-planting4	7
CNT5	Corn-notill-planting5	8
CNT6	Corn-notill-planting6	9
CVF2	Corn-conservation till Fall planting 2	10
CVF3	Corn-conservation till Fall planting 3	11
CVF4	Corn-conservation till Fall planting 4	12
CVF5	Corn-conservation till Fall planting 5	13
CVF6	Corn-conservation till Fall planting 6	14
CVF7	Corn-conservation till Fall planting 7	15
CVF8	Corn-conservation till Fall planting 8	16
CVS2	Corn-conservation till-spring planting 2	17
CVS3	Corn-conservation till-spring planting 3	18
CVS4	Corn-conservation till-spring planting 4	19
CVS5	Corn-conservation till-spring planting 5	20
CVS6	Corn-conservation till-spring planting 6	21
CVS7	Corn-conservation till-spring planting 7	22
CVS8	Corn-conservation till-spring planting 8	23
SNT1	Soybean-notill-planting1	24
SVF1	Soybean-conservation till Fall planting1	25
SVS1	Soybean-conservation till-spring planting1	26
SVF2	Soybean-conservation till Fall planting 2	27
SVF3	Soybean-conservation till Fall planting 3	28
SVF4	Soybean-conservation till Fall planting 4	29
SVF5	Soybean-conservation till Fall planting 5	30
SVF6	Soybean-conservation till Fall planting 6	31
SVS2	Soybean-conservation till-spring planting 2	32
SVS3	Soybean-conservation till-spring planting 3	33
SVS4	Soybean-conservation till-spring planting 4	34
SVS5	Soybean-conservation till-spring planting 5	35
SVS6	Soybean-conservation till-spring planting 6	36
SNT2	Soybean-no till-planting 2	37
SNT3	Soybean-no till-planting 3	38
SNT4	Soybean-no till-planting 4	39
SNT5	Soybean-no till-planting 5	40
SNT6	Soybean-no till-planting 6	41
PCR1	Conservation Reserve Program	42
GLM1	Grass Lands	43

highest gross margin among all population members is ranked first. For unfeasible solutions one with the lowest penalty is selected when compared with unfeasible solutions in the population. While for conservationists and satisficers landuse management strategies that minimizes soil loss and that are feasible are ranked higher compared to landuse management alternative that have high soil erosion. Once the fitness function associated with all the population members of that farm are rank ordered, the agent model undergo various GA operations such as selection, crossover and mutation for the user specified number of generation. After the user specified number of generation is reached the individual that is ranked the highest represent the optimal solution. For a farm, the optimal solution represents the best landuse management strategy based on agent type, soil conservation policy, resource availability for that farm and other exogenous factors such as market price for various crops and CRP rental rates.

Once the agent model has finished running for one farm, it selects the next farm from the watershed and undergoes the same process until the agent model runs for all 90 farms are completed. Once the independent runs for each farm are completed the agent model undergoes an aggregation process of compiling the optimal landuse management strategy associated with each farm to form a watershed landscape based on the optimal decision strategy made by each agents acting independently. The multi agent-based model is run for 300 generations and 200 population members, with crossover probability and mutation probability of 0.6 and 0.2 respectively. The agent-based model took 12 minutes to complete a single run.

According to Veldkamp and Lambin (2001), one of the important prerequisites for a landuse change model is its ability to validate future landuse changes. Validation refers to the estimation of model accuracy consistent with the intended application of the model.

The model validations are done based on the remote sensing data for the study region available through NASS. The agent-based model for agricultural land use management developed in this study plays an important role in the understanding of agricultural landuse change as a result of variations in the drivers of landuse change, such as agricultural policy. The model can be validated based on the quantity of agricultural landuse change occurring on the landscape and also based on the spatial patterns or locations of landuse change. The validation of the agent model runs are done based on error matrices calculated on a field-by-field basis for the study area. The error matrices will provide information on how various agents chooses landuses based on policy, biophysical variables, his/her objectives and other exogenous variables such as price, compared to the actual landuse map. The higher the percent correct prediction indicates the model captures the inherent drivers of agricultural landuse change.

While the model verification represents how well the agent model capture the inherent real world process. Verification of the agent model is done by running and analyzing by using just profit maximizing agents. Agent model must be able to predict the reality accurately based on a theoretical and empirical basis such as average gross margin, spatial pattern of landuse change, and soil loss. The agents model has been verified by reproducing the past landscape for example 2002 landscape under average market prices for the past 5 years, policies and 2001 landuse by running multiple agents and also by single profit maximizing agents.

Results and Discussion.

The multi agent model utilized 1000 population members and ran for 500 generation with a crossover and mutation probability of 0.7 and 0.2 respectively. The model run took twelve minutes. The multi agent model predicts the landuse pattern for the year 2002 based on agent objectives, market prices, soil conservation policy, and prior landuse for the year 2001. The agricultural landscape output is shown in figure 6. The map legend shows the landuse and tillage options for the various fields within the watershed. The landuse type forest, urban, and water, which was not the part of the agent decision-making, was added back at the end to form the watershed landscape. The average farm gross margin was $39,206, where profit-maximizing farms netted an average gross margin of $67,143, while satisficers and conservationist had $37,070 and $27,450 respectively. The gross margin distribution for various farms within the watershed is shown in figure 7. Most of the farms with high gross margins are located on the bottom part of the watershed which is flat and fertile croplands, while the low gross margins are distributed on the top part of the watershed where the land is rolling and is highly suited for pastureland. The agent model predicted cropland of 4,378 acres that included corn and soybean uses and no-

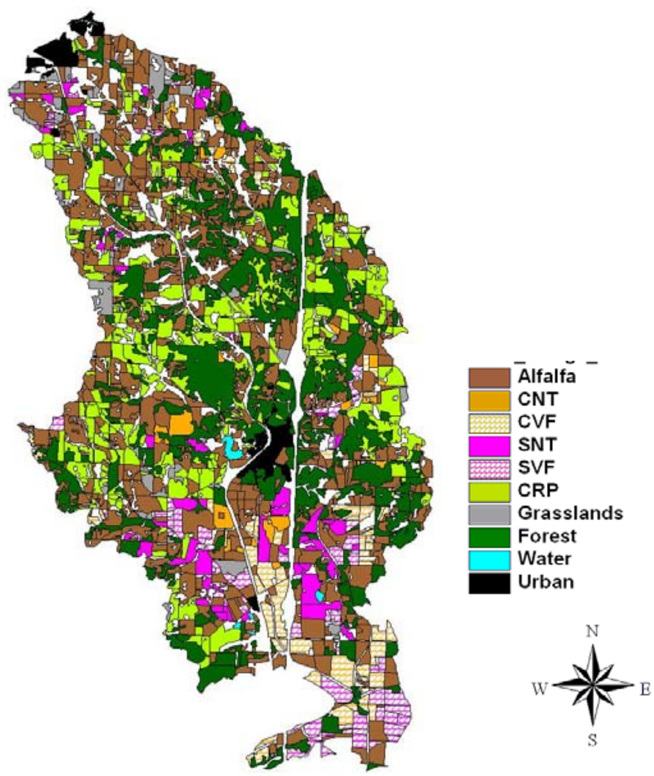


Figure 6: Model output for year 2002

till acres of 1,647 and conservation till acres of 2,731. The model output had 10,828 acres in pasture, which included alfalfa hay and grasslands and CRP of 4940 acres. The model had no constraints on the amount of CRP land that a farm could enroll.

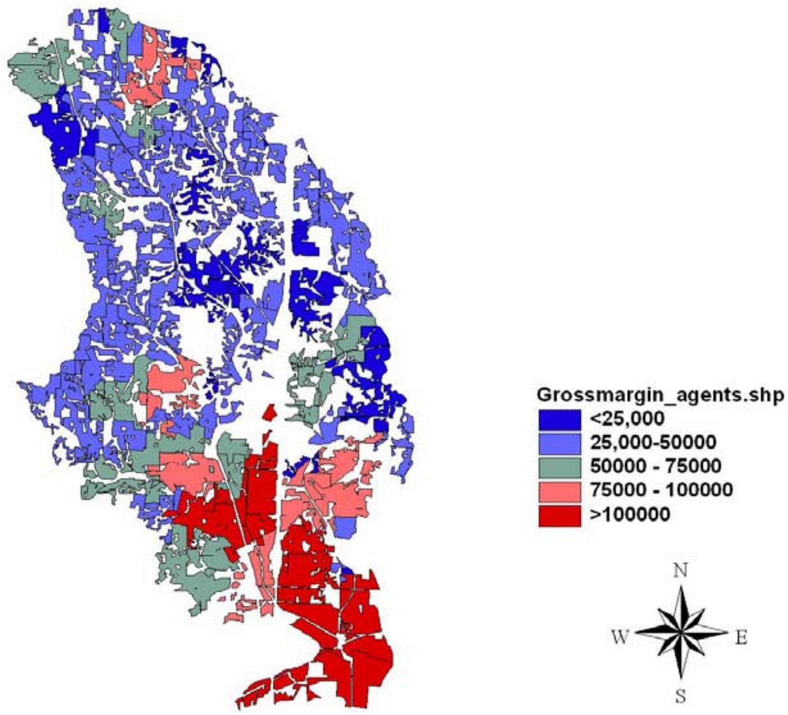


Figure 7: Gross margin distribution associated with farms

The validation of the agent model is done by comparing the model-generated landcover with the landuse landcover map for the year 2002. The validation of the agent model with the actual landuse is done using an error matrix. For error matrix calculation the landuse classification was reduced to just two classes of cropland and pasture. Since the error in distinguishing corn from soybean was relatively high for the actual landuse map the landuses corn and soybean fields were combined to form the cropland, while CRP, alfalfa hay and grasslands were combined to form the pasture landuse. The validation on a field-by-field basis shows the model 75 percent correctly predicts the actual landuse landcover map. The error matrix for the model is shown in table 2. The table shows that the model is little bit over predicting the landuse pasture and under predicting the cropland.

Agent Model

2002	Cropland	Pasture	
Cropland	129	129	258
Pasture	194	840	1034
	323	969	
	Correct prediction: 75 %		

Actual

Table2. Error Matrix

Figure 8 shows the model correctness and errors associated with predictions. The field in red and yellow represents the correct prediction of pasture and croplands respectively. While the fields in green represents the regions of crop under prediction, and the fields in blue represents the regions of pasture under prediction, by the agent model. The error map based on agent types (figure 9) shows that satisficer and conservationist is being 81 and 85 percent correctly predicted while profit maximizer is being 67 percent correctly predicted. This validates the presence of heterogeneous agent types in the watershed other than just profit maximizer, which traditional economic models used to study human behavior. The verification of agent-model was done by comparing the predictability of the multi-agent model with a single-agent model of profit maximizers. The results show that assumption of just profit maximizers in the watershed gives a false impression of reality. The single-agent model correctly predicted only 60 percent of the fields within the watershed, which is 15% less correctly predicted than compared to the multi-agent based model.

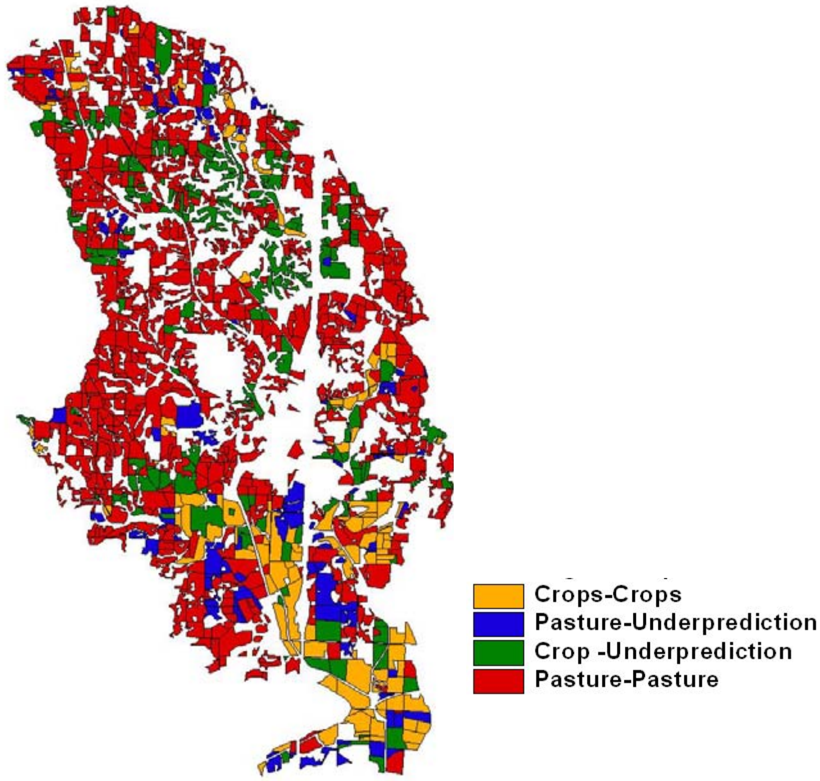
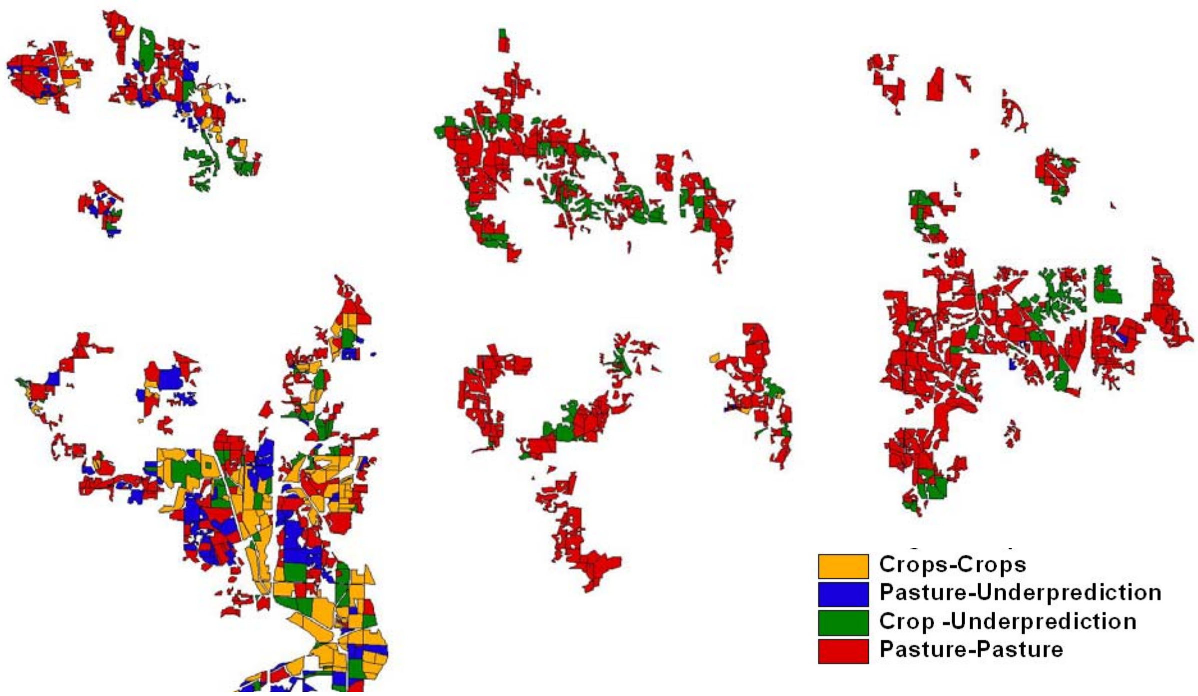


Figure 8: Error map associated with agent run.



Profit Maximizers Satisficers Conservationist

Figure9: Error Map based on agent type

The study can be used analyze the multifunctional nature of agriculture in providing both commodity as well as non-commodity outputs (ecosystem services). Figure 6 shows the various landuse choices selected by farmers based on their objectives subjected to relevant market and policy conditions. The results indicate the optimal landuse choices for various farm agents responding to market conditions of prices, soil conservation policy, biophysical factors such as crop productivity and soil erosion, and available resources such as labor and machinery. Table 3 shows the break down of commodity and non-commodity output acres based on the types of agents. Profit-maximizing agents have half of their land under commodity crops of corn and soybean, while satisficers and conservationist have their land mostly under alfalfa hay and CRP. The results of the study show that satisficers and conservationist are the major providers of various ecosystem services, which is captured indirectly by the amount of CRP acres and hay land. Here CRP and lands along with no-till conservation practices represents the production of various ecosystem services such as water quality, soil retention, wildlife habitat or carbon sequestration, which are available at the current CRP rental rates to farmers enrolled in the program. However in this paper, only soil loss was used as proxy for ecosystem services, but further development of the model is currently going on to include an index that captures multiple ecosystem services of alternative landuses and riparian buffers.

Based on the study we have found that predicting landuse decisions based upon just profit maximization can be improved upon by utilizing multiple agents with profit-maximizers concentrated on the highly productive and less erosive lands, while conservationist and satisficing farmers are distributed on less productive and more erosive agricultural lands. The modeling environment is currently being used to study different policy and price scenarios.

Conclusion:

One of the main goal of modeling human-environmental interaction is to provide scientific information to policy makers and stakeholders that will aid in their planning and decision making process (Berger and Schreinemachers, 2006). The agent model developed here will help policy and decision maker identify the various agents within the watershed and assess various policy options based on that information. The study also helped to understand the

Table 3: Commodity and no-commodity outputs

Economic Results			
	Profit Maximizer	Satisficer	Conservationist
INCOME (Gross Margin) ($)			
Total	2,685,747	937,876	613,935
Average (per farm)	67,143	37,072	27,459
ACRES			
Total	9,229	5,745	4,711
Corn/Soybean	4,212	747	57
Conservation	2,899	0	0
No-till	1,449	747	57
Alfalfa Hay	4,854	3,270	2,478
CRP	0	1,728	2,176

interaction and feedback between the agents and their environment associated with various policy initiatives. The agent-based model developed here can be used as a tool to predict future landuse decisions resulting from varying market conditions and policies which will have a drastic influence in the provision of commodity outputs as well as various ecosystem services that are critical for human welfare. The results of these modeling activities can be used as a decision tools by policy makers to guide the policies that target various agents on the landscape resulting in production suites of commodities and ecosystem services contributing to human welfare.

The utilization of the genetic algorithm in modeling human behaviors provided added flexibility when compared to traditional optimization methods. The use of GA to model multiple agents out performed the previous study of single agent (profit maximizers) done using linear programming (Lant et al., 2005). Future development of the model is required in the area of scenario analysis over multiple years.

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