# Integrating Geographic Information Systems and Agent-Based Modeling Techniques for Simulating Social and Ecological Processes

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# Agent-Based Simulations of Household Decision Making and Land Use Change near Altamira, Brazil

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## 1 INTRODUCTION

Individuals who influence decisions regarding the use of land, operate within a complex environment comprised of interacting elements that include both natural systems and human institutions. Individually, the elements of the natural and human systems that influence land-use decisions may be very complex. Within natural systems, dynamic processes, such as the hydrological cycle, and the distribution of biophysical resources, such as soil fertility, influence land-use decision making. Elements of an individual's institutional environment can also influence the options and incentives that are available to an individual, and thus the land-use decisions that they make. Understanding the nature of these complex processes and interactions is a nontrivial task. However, agent-based simulation offers researchers a tool to better understand the nature of these complex systems.

The recent development of computer simulation technologies by social scientists has provided a tool for not only predicting social phenomena, but also for better understanding the nature of these human systems. Replicative validity is not the goal of many social simulation efforts. Instead, researchers have focused on developing relatively simple simulations as tools for understanding the properties of social systems and the way in which interactions between actors at the local level results in the emergence of behaviors or phenomena at the global level [8]. In this role, simulation becomes a tool for evaluating assumptions and exercising theories of action [1].

Many of the techniques applied to social simulation can be traced back to earlier developments in the physical or natural sciences. For example, computer simulation has a relatively long history in the natural sciences in applications related to fisheries, forest environments, and watersheds. But recent advances in computer hardware and software technologies have made these technologies accessible to social scientists. Recently, we have seen simulation efforts that have included models of not only the natural system in question, but also the human system with which it interacts. In fields such as anthropology [6, 13, 14] and resource management [3, 5, 27], human systems simulations are being developed which directly address the actions of human individuals or groups as they interact with a natural system.

This approach to simulation is pursued in this chapter. A model of individual human decision making at the household level is linked through a geographical space to a model of ecosystem behavior. The goal of this modeling exercise is to explore the potential of a spatially referenced agent-based model, for understanding how behavior at the local level interacts with natural processes to produce observable phenomena at a higher level. We explore this goal with an application that focuses on the land-use decisions made by individual households within a region of the Amazon rainforest near Altamira, Brazil. The simulation described in this chapter is the product of a pilot effort between the University of Waterloo and Indiana University designed to explore proposed theories of land-use change in this region. Although still preliminary in its scope, this simulation illustrates the potential of such a spatially referenced agent-based approach for better understanding the complex human and natural processes that interact within this region.

The next section of this chapter discusses the history of land use in the Altamira region and outlines the importance of understanding land-use processes at the farm level. Subsequent sections describe the structure of the land-use change in the Amazon (LUCITA) simulation system, and the initial findings that have emerged from an analysis of the model's behavior. A final discussion addresses the strengths and weaknesses of this simulation in the context of land-use change and social simulation research.

## 2 LAND-USE CHANGE IN THE BRAZILIAN AMAZON

The Brazilian Amazon has been experiencing marked changes in the past 30 years [10, 23, 28]. From an area that in 1975 had less than 1 percent of its forest cover removed, the Basin is already 15 percent deforested. Deforestation has proceeded from east to west, along roads and along an "arc of deforestation" along the southern periphery. In these areas, rates of deforestation have been in excess of one percent per year in the past two decades with its peak in



1995 [12]. This massive change in land cover is a result of national decisions to integrate the region into national economic development, by means of a two pronged approach that combined massive road building with colonization and resettlement projects [22, 26]. Attractive subsidies and tax incentives, land title, and access to extension services made moving to the Amazon economically profitable for both large and small landholders.

Before this most recent set of events, the history of land use in the Brazilian Amazon had been characterized by economic development along river banks, which limited occupation to a small portion of the Basin. In the colonial period this took the form of searching for spices, slaves, and some valuable wood species. Under Jesuit tutelage, some of the missions successfully developed cocoa plantations, cattle ranches, and other surplus production, but they collapsed in the eighteenth century following the expulsion of the Jesuits from Brazil. In the national period, the Amazon experienced massive population dislocations to exploit natural rubber (1880–1920), but in which great wealth was achieved by a few at the cost of the many. A shorter-lived rubber boom took place during World War II when the Malaysian rubber plantations' supplies to the Allies were cut off and Brazilian natural rubber was desperately needed. Following these booms, the Amazonian towns stagnated economically, lost population, and persisted by barter and subsistence production.

All this began to change after World War II as nationalist leaders began to see the vast Amazon frontier, accounting for 58 percent of the Brazilian territory, as an important component of achieving world power status. The March to the West began to be seen as a valuable geopolitical objective. With the assumption of power by the military in 1964, implementation of these objectives began to take place very quickly. The Transamazon Highway, running east-west across the Basin, was a particularly important component of this geopolitical plan, and it was backed up with a coordinated plan of incentives to attract both small and large interests to the region.

The showcase for the colonization part of the project was the Altamira Integrated Development Project that began in 1971. From a town of about 1,000 people in 1970, the town grew to over 10,000 in one year [22], and it has continued to grow steadily since then to over 85,000 in the 1990s. Of all the colonization projects along the Transamazon Highway, Altamira was the only one blessed with above-average quality soils, less stagnant water due to a rolling terrain, and therefore less malaria. Communities of 48 homes were built every 10 km to facilitate community life, while still maintaining reasonable distances to the properties. The project was laid out systematically into 100-hectare properties in a rasterized fashion. The layout has come to be called "fishbone pattern" because land was allocated along the main trunk of the highway, as well as along side roads spaced symmetrically every 5 km. Small landholders from throughout Brazil came to the area to claim their properties with over 6,000 families coming in the first decade to the Altamira region. Brazil being a very large country with very different climates and cultural traditions, the immigrants brought with them varied approaches to land use that require that attention be paid to household behavior, rather than assume that they all behave in ethnically equivalent terms.

Farmers from northeast Brazil, accounted for about 30 percent of initial settlers. They came from a land characterized by cyclical droughts, and irrigated agriculture in very small plots along river banks. These proved to be among the most and least educated of the settlers, with a combination of previous landowners of small, irrigated plots and sharecroppers on large properties and plantations. They differed among themselves as much or more than they differed as a group from those of other regions of Brazil. Farmers from the Amazon region accounted for another 30 percent, and they were mostly descendants of rubber tappers, swidden cultivators living along river banks who moved to the roadside properties to get a legal title to land. They were familiar with the local forest species and, with effective ways to recognize good soils, preferred cultivation of manioc and cowpeas as foolproof crops for the area. Another 25 percent came from southern Brazil, and while the government hoped that they would be prime examples of modern agriculture, many of them turned out to be coffee plantation sharecroppers who had left the northeast seeking their fortune in southern Brazil in the previous generation. The remaining group, from the Central-West region, was mostly familiar with cattle ranching at small scale and was seeking to expand their holdings.

From this mix of immigrants the Altamira project started and, over the past 30 years, there has been significant turnover in ownership, with less than 30 percent of the original households remaining on the land. Recent analysis of our data suggests that original households who selected the best soils in the area (i.e., the alfisols) have been remarkably successful in holding on to their land, and that most of those properties have not entered the real estate market to benefit later-arriving settlers [19]. This agent-based simulation benefits from household-level data collected by one of the co-authors in the first three years of settlement [20, 21, 22], and subsequent and more extensive household survey research in 1997–1999 [4, 16, 17, 19]. It also benefits from very intensive studies of land use and land cover analysis, with a focus on the dynamics of secondary succession in the first half of the 1990s [15, 24, 25].

These previous analyses, however, have not undertaken the challenges posed by agent-based modeling within a spatially explicit framework as is proposed here. While the LUCITA simulation system described here is based on these previous analyses, its focus on simulating land-use decisions at the individual household level is inspired by a model outlined in McCracken et al. [16] that focuses on frontier occupation and environmental change as process. This model proposes that land-use changes in the Altamira region should be understood, not only as a result of large-scale, temporally defined effects such as changing credit policies, but also as a product of local household-level effects, such as the age and gender characteristics of farm families. This model maps out a trajectory for families, which relates the type of agricultural practices pursued to a number of factors including the available labor pool within each household. The model describes five stages in the life of a household. In the early stages of household development, limited family labor supplies lead to a reliance on annual crops and associated high rates of deforestation. In the later stages of household development, larger labor and capital resources allow for the development of pastoral lands and/or perennial crops.



Actual trajectories of household agricultural strategies are not as clear as those suggested by the conceptual model [16]. This raises the question of how families make land-use decisions, given the characteristics of their natural environment (such as soils, topography, and water availability), their economic environment (such as distance to markets, credit policies, and commodity prices), and their own households. It is intended that the development of the LUCITA simulation system will eventually provide researchers with an additional tool for exploring these questions. The structure of the initial version of LUCITA, and some observations of its initial behavioral characteristics, are described in the following sections.

## 3 LUCITA MODEL DESIGN

### 3.1 OVERVIEW

The LUCITA model was developed using the Swarm simulation system [18], a set of software libraries written in the Objective-C object-oriented programming language to help facilitate the modeling and simulation of complex adaptive systems. LUCITA is comprised of two submodels that interact with one another through a spatially referenced raster landscape. These two submodels are utilized to capture both the ecological and human dynamics and processes characteristic of the target system. Not only do complex feedback loops exist within each submodel, but also indirectly between the two submodels through the landscape. It is the representation of these intrafeedback and interfeedback loops of the target system that makes the LUCITA model unique from other spatially referenced agent-based models (ABMs).

The basis of the ecological submodel is derived from the KPROG2 model, originally developed by Fearnside [7] to estimate human carrying capacities in regions of the Transamazon Highway. Multiple regression equations for changes in soil characters and the estimation of crop yields were adopted from the KPROG2 model for use in LUCITA. The dynamics associated with changes in soil fertility due to varying agricultural practices and the process of secondary succession could not have been modeled without the multiple regression equations provided by KPROG2. Thus, the ecological submodel is capable of modeling the impacts of deforestation on soil properties, the relationship between soil fertility and successful crop yields, and the effect of soil properties on the rates of natural reforestation.

The human system submodel can be best described by the architecture of an autonomous household agent. Each household agent is representative of a colonist family and is defined by the composition of the family, available family and male labor pools, and available liquid capital. Decision making, with respect to what agricultural land strategy should be adopted for any given patch of land, is governed by a nonevolving classifier system. Land-use strategies, or rules, are represented by binary strings based on principles of genetic algorithms and compete with one another for selection. Those rules that are successful, defined as rules satisfying some type of a threshold level, are rewarded. Ideally, successful rules are reinforced through simulated time and poor rules excluded from future agent decision making. This agent architecture provides a framework to test the conceptual model of household transition [16], where it is hypothesized that as colonist households age in the frontier, decision-making shifts from deforestation intensive strategies, which require minimal labor and capital requirements, and have lower economic returns, to those with high economic returns, that demand less deforested land, but require greater labor and capital inputs.

## 3.2 THE SWARM SIMULATION SYSTEM

The Swarm simulation system, generally referred to simply as Swarm, was originally developed by a team of researchers at the Santa Fe Institute to assist the study of complex adaptive systems [18]. The motivation for the research and development of Swarm was the recognition of the importance of computer models as a research tool, the fact that most researchers are not software engineers and that too much time was being wasted on writing poor software code rather than focusing on research, and the need for a standardized suite of tools to facilitate the development of reproducible computer models. Swarm is a set of software libraries written in Objective-C, an object-oriented programming language, and makes no formal assumptions of the type of model being developed. This implies that Swarm can be used in a wide array of scientific disciplines such as chemistry, economics, and anthropology.

The basic unit of a Swarm simulation is the agent, where an agent is defined as any type of actor within a system that is capable of generating events that are able to impact itself, other agents, or the surrounding environment [18]. Interactions of an agent with itself, other agents, and its surrounding environment are made via discrete events. A Swarm simulation is comprised of a schedule of discrete events defining a series of processes taking place with a collection of agents. Drawing from the object-oriented programming paradigm, a swarm agent is modeled as an object. Any object has both a state and behavior. Object variables are used to describe the state of an object, where the behavior of an object is defined by the class from which it was instantiated.



## 3.3 SPATIAL DATA LANDSCAPE IN GEOGRAPHIC INFORMATION SYSTEMS

The raster landscape is representative of the intensive study area documented in the KPROG2 model [7]. The study area is situated in the vicinity of Agrovila (village) Grande Esperança, in the municipality of Prainha, in the state of Pará. The area is approximately 50 km west of Altamira. The primary reason for selecting this study area was because of the availability of soils data, such as pH. Although the study area differs from the study area documented by Moran [22], from which the source of household behavior data is obtained, it can be argued that the conceptual model of household transition applies to all regions of the Amazon Basin, irrespective of a specific geographic location. For example, given the availability of soils data in the Moran study area, there is no reason why LUCITA could not spatially reference that location.

An area comprised of 236 properties, each 100 hectares in area, is represented by a raster landscape. Properties that are adjacent to the Transamazon Highway have a lot dimension of 500 m by 2000 m and those located off on feeder roads with a lot dimension of 2500 m by 400 m. Each raster cell has a grid resolution of 100 m, representative of an area of 1 hectare. For the purpose of generating a raster landscape, each property lot is assumed to be rectangular in shape. Several property lots in the soils data maps were not rectangular in shape and, therefore, a geometric transformation of the property lots were required so that both the property layout in the data maps matched the property lot generated within the LUCITA model. Given the assumption of rectangular-shaped property lots in the landscape and that the data maps were not to scale, meaning that from a visual analysis, all property lots were not 100 ha in area, digitizing the data maps and subsequently converting them to a raster format for initial soil parameter input into LUCITA was not an option. Instead, a text file, representative of the Swarm landscape, was generated and imported into the ARC/INFO GRID module, where a process of manually adjusting cell values to match the soils data maps was performed. The GRID data layers of pH, carbon, nitrogen, phosphorus, and aluminum, were converted back into a text file for import into the LUCITA model. The untransformed landscape layout, the transformed landscape generated by Swarm as displayed by ARC/INFO GRID, and an example of a soils data map is depicted in figure 1.

For each landscape grid cell, a one-to-one reference exists between a grid cell and an environment object instantiated from an environment class. This implies that for any given household property lot, there exists one hundred environment objects since one property lot is composed of one hundred grid cells. The purposes of an environment object is to provide the spatial grid coordinates of a particular patch of land with respect to the artificial landscape, to differentiate one patch from another through the use of unique internal keys, to store the current land cover for a particular grid cell, to keep a tally of the number of years a grid cell has been used continuously and for what

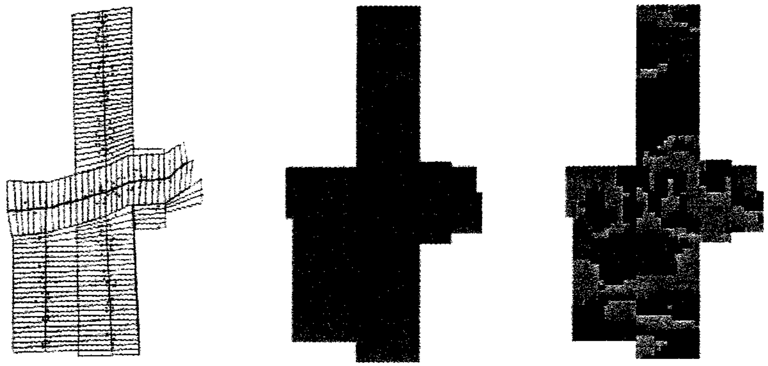

FIGURE 1 Illustration of property lot layout in data maps (left), where dots are representative of sampled areas, the raster layout in ARC/INFO GRID (center), and a sample LUCITA data map (right), in this case representative of pH categories.

land use, and to act as an interface to spatially link a soil object to a grid cell for KPROG2 purposes described in the following section.

During any simulation, the landscape is responsible for tabulating land cover frequencies and for managing the transition of land from one type of land cover to another, while enforcing rules such as the number of maximum years a patch of land may be used in continuous agriculture and the minimum number of years a patch of land must remain in fallow prior to reuse. For instance, manioc, which has a growing season just over a year, renders a patch of land unavailable for use for two years. Accordingly, the landscape will monitor and identify when this patch has satisfied the growing requirements of the manioc land-use strategy and subsequently release the patch of land for future use at the appropriate time event. Similarly, stages of secondary succession, categorized by age, are also defined internally by the landscape. Conceptually, the landscape can be thought of as a land manager, which simply monitors what proportion of land is being used for a particular land use and what state those patches of land should be set to for the next time event.

## 3.4 KPROG2 MULTIPLE REGRESSION EQUATIONS

As mentioned in the previous section, for any given grid cell an environment object exists and it is through a reference in the environment object that a soil object is linked to a grid cell. The KPROG2 multiple regression equations and the parameters required by these equations to model crop yields, soil changes caused by burning, soil changes under land covers that are not burned (i.e., secondary succession), soil changes under pasture, and soil changes as a result of the application of fertilizers and lime, are contained with the definition of



the soil class. The specific soil parameters that are required by the multiple regression equations required for calculating crop yields and soil processes include levels of pH, nitrogen, carbon, phosphorus, and the concentration of aluminum ions.

In slash-and-burn agriculture, a farmer will deforest a patch of land and subsequently burn in an attempt to alter soil conditions to improve crop yields. Three types of land covers are considered by a farmer for clearing and burning and they include virgin forest, secondary forest, and weedland covers. Each of these three land covers has a set of multiple regression equations that describes how the soil parameters are to change if it were to be cleared and burned. Under circumstances where no burning is required, such as land in pasture, land in secondary succession, or land in continuous agricultural use, changes in soil parameters are governed by other sets of multiple regression equations. Maintenance of cacao and black pepper plantations often require the application of fertilizers to raise phosphorus concentrations and lime to reduce the acidity of soil, both critical criteria for good perennial crop yields. Changes in soil parameters resulting from the application of fertilizers and lime is no different than other soil processes that are modeled using a distinct set of multiple regression equations. For instance, the equation used to model changes in nitrogen after a virgin forest burn is described in equation (1) below. A complete review of all the multiple regression equations adopted from the KPROG2 model is documented by Fearnside [7].

Changes in nitrogen are represented by

$$Y = 5.80 \times 10^{-2} - 0.654A + 4.89 \times 10^{-2}B + 2.63 \times 10^{-2}C$$

where

$$\begin{aligned} Y &= \text{nitrogen change (\% dry weight)} \\ A &= \text{initial nitrogen (\% dry weight)} \\ B &= \text{initial carbon (\% dry weight)} \\ C &= \text{initial pH} \end{aligned} \qquad (1)$$

## 3.5 AGENT ARCHITECTURE AND DECISION MAKING

For any given property lot of 100 grid cells on the raster landscape, an instantiation of a household object class exists and is referenced to those cells. Each agent has an internal representation of its environment and itself. An agent has an internal representation of the environment in that each agent is aware of the boundaries of its artificial world within which it exists, the components of that artificial world that it is capable of impacting, and the types of land covers characterizing its immediate surroundings. Further, an agent, using its internal representation of itself, is capable of describing its family composition, both total family members and the number of males in the family, the available capital resources, and the land-use strategies it is capable of implementing.

The behavior of an agent can be described by a set of actions that an agent is capable of executing repeatedly throughout a simulation. In general, these actions tend to deal with the clearing of land, the burning of deforested land, the growing of agricultural crops, and the harvest of crops sown in a given year. In most instances, labor and capital resources are required by these actions. The ability of an agent to identify which patches of land from its property to deforest and burn is determined by a set of clearing preferences defined by the end user at the start of a simulation. Obviously, variations in clearing preferences can affect the rate of deforestation on a given property lot or across the landscape for that matter. For instance, if an agent's first clearing preference is virgin forests prior to any land cover, it can be expected that all virgin forest land will be deforested prior to any other land covers being considered. Following the clearing of a patch of land, an agent must make a decision regarding which crop should be planted based on previous experiences. This decision-making process is governed by a classifier system and is described below. Following a full growing season, crops are harvested and crop yields calculated.

Land-use strategies or rules in LUCITA are encoded as 270-bit (1s and 0s) genetic algorithm strings and are stored in a rule base. Booker et al. [2], Goldberg [9], and Holland [11] provide an overview of genetic algorithms. Each agent has a distinct rule base comprised of eight rules reflecting the land-use strategies for the agricultural crop production of rice, beans, manioc, maize, cacao, and black pepper. The monthly family labor, monthly male labor, and capital requirements of any land-use rule and the action to be triggered given that the requirements of that particular rule are satisfied is encoded in the structure of the 270-bit string. Each monthly family and male labor requirement is translated from base 10 to base 2 and is represented by a series of 10 bits. Therefore, the twelve months of family and male labor requirements for a given land-use rule is encoded in the first 240 bits (i.e., 24 months multiplied by 10 bits/month) of the 270-bit string. The capital requirements for a given land-use rule are encoded no differently than monthly labor requirements; however, a series of 20 bits is required for encoding instead of the previous 10 bits. Small base 10 numbers, characterized by monthly labor requirements, when converted into base 2, requires very few bits. In contrast, large base 10 numbers, characterized by capital requirements, when translated into base 2 strings, requires many more bits for representation. The difference in the number of bits required to encode monthly labor and capital requirements is attributed to the type of values associated with each type of variable. For both monthly labor and capital requirements, an estimate of the greatest possible value for these variables were made, and subsequently translated into base 2 to identify the minimum number of bits that would be required for encoding. The final 10 bits of the 270-bit string are used to represent an effector, or the action to be taken if the conditions of a string are satisfied, and in this



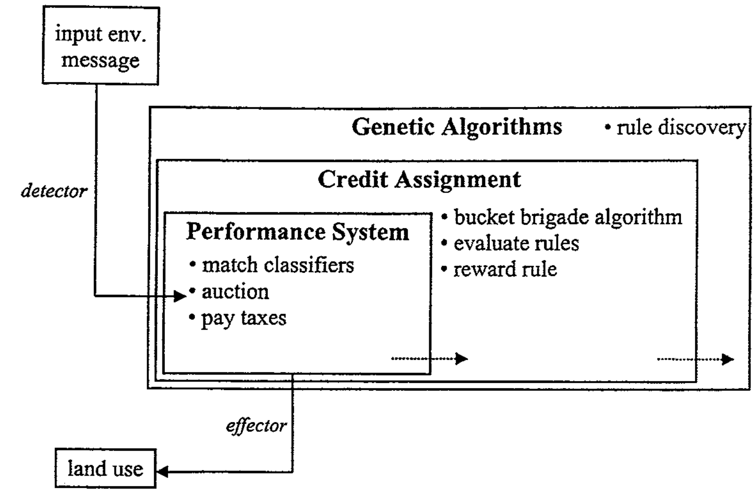


FIGURE 2 General organization of a classifier system used in LUCITA.

case simply represents that type of land-use strategy to be implemented. A strength value is associated with each rule and reflects the fitness of that rule or the effectiveness of that rule. An effective land-use rule, meaning those that generate satisfactory crop yields, should be reinforced through simulated time and should be observed through an increase in strength. A base 2 representation of rules was selected for ease of implementation with the classifier system.

Providing that an agent has enough labor and capital resources to deforest a patch of land for agricultural production, the decision-making process of which of the eight land-use strategies to implement is determined by a classifier system. The classifier system used in LUCITA is designed and implemented following the concepts described by Booker et al. [2]. A classifier system is typically comprised of three components: a performance system, a credit assignment system, and a rule discovery system (fig. 2).

The performance system is responsible for matching rules in the rule base to an encoded message composed of 260 bits, which describes the monthly family labor, monthly male labor, and capital available to an agent at a particular instance in time. The structure of an encoded 260-bit message is no different than the above-described 270-bit rule structure, except for the omission of an effector tag. Those rules that are matched are entered into an auction. A rule is considered to be a match if and only if every monthly labor and capital available to an agent is greater than or equal to the respective monthly labor and capital requirements as defined by that rule. This implies that under circumstances where very labor and capital intensive land-use rules are matched, those rules that are less labor and capital intensive are also matched and entered into the auction. For instance, if an agent can afford to grow cacao, which has high labor and capital requirements, an agent is most likely also capable of growing rice or beans. During the auction process, a matched rule makes a bid based upon its strength. An effective bid is subsequently calculated by simply adding a random value between 0 and 1 to the original bid made by a rule. An effective bid is calculated to avoid the situation where two or more rules have the same fitness and in turn make identical bids. The rule with the greatest effective bid is then selected and used by the agent.

Effective rules in the rule base must be somehow reinforced through time and those that are poor, eventually excluded from the decision-making process. A household agent should have a history of land-use experiences and ideally be able to learn from those experiences and identify those types of land-use strategies that are more effective than others. This process of weeding out effective rules through simulated time can be accomplished by taxing and rewarding those existing rules in a rule base, meaning decrementing or incrementing the strength of a rule. It is the credit assignment system that is responsible for the actual rewarding process. Because only one matching rule can be selected for one patch of land, the bucket-brigade algorithm is not required. In the LUCITA classifier system, at any time event, all rules existing in the rule base must pay a life tax rate (i.e., 1%). Further, rules that match an encoded agent message must pay a bid tax rate to compete in the auction process (i.e., 5%). The winning rule pays its tax in the form of its bid, sometimes 10% of its strength. In general, the effectiveness of the winning rule is evaluated against some criteria, such as the ability of that rule to generate an expected crop yield per hectare. Under circumstances where that winning rule satisfies the defined criteria, it is rewarded and thereby reinforced. However, under circumstances where that rule is deemed ineffective, that particular rule would have paid a significantly larger tax than all other rules, thereby reducing its strength or fitness and affecting its future of being reselected. The dynamics associated with the competition of rules and the reinforcement of effective rules through simulated time will be illustrated in a case scenario of the one-household version of LUCITA.

The functionality of the rule discovery system is not implemented in LUCITA since it cannot be applied to the land-use rules given the nature of the information encoded in the structure of the rules. The purpose of the rule discovery system of a classifier system is to try to evolve new rules by applying genetic operators, such as mutation or crossover, to the most fit rules in a rule base.

In more traditional applications of classifier systems, rule strings are often an encoding of a series of conditions that either evaluates to a true or false state, where a series of conditions triggers some type of response or action. The reason why applying genetic operators to the LUCITA rules would be



inappropriate is because that the conditions of any given rule string does not evaluate to some state of true or false, but rather translates to some specific type of numeric labor or capital value. The defined labor and capital conditions defined by a rule are static and must be satisfied prior to the implementation of any land-use strategy. For instance, it would be incorrect to crossover two rule strings, each representing completely different land-use strategies, since this would imply that the labor and capital requirements for each of these rules are variable which is clearly not the case. Each land-use rule has one and only one set of family labor, male labor, and capital requirements that must be satisfied prior to implementation. For this reason, the classifier system utilized in LUCITA is referred to as a nonevolving classifier system.

## 3.6 SCHEDULING OF EVENTS

For any given simulated year in LUCITA, a series of events is scheduled to simulate the actions of a frontier colonist who practices slash-and-burn agriculture and the associated impacts of those practices on an artificial landscape. In the versions of LUCITA described in this chapter, dynamic scheduling of events is not considered although possible using Swarm. At this present stage of development two versions of LUCITA exist—the one-household version and the landscape version. The one-household version of LUCITA focuses on exploring simulations at a local scale (one property), so as to provide a basic understanding of how an agent makes decisions, how decision making is affected by variability in environmental conditions, what relationships or feedback loops exist between both submodels, etc. In contrast, the landscape version of LUCITA focuses at a regional scale (236 properties), where only the regional land-use trends are of interest. The rationale of this approach is that if the one-household version of LUCITA is explored to a point that local interactions can be explained and understood, then at the regional scale, there is no need to consider local interactions but rather emphasis can be placed on observing the emergence of regional land-use trends. Processes or actions relevant to the KPROG2 submodel and the human system submodel are scheduled as events. The two versions of LUCITA only differ in the number of agents scheduling events and the number of properties affected by agent actions. A flow chart diagram illustrating the scheduling of events is provided in figure 3.

At the start of each year, an event is scheduled to tabulate the frequency of each land cover occurring on the landscape and archived in a data file. At the conclusion of a simulation, this data file can be used to describe the trajectory of land uses both at a local and regional scale, depending on which version of LUCITA was simulated. Following this tabulation, an event is scheduled to identify which patches of land need to be shifted to an alternate land cover based on the transition of land covers internally programmed. The scale of a

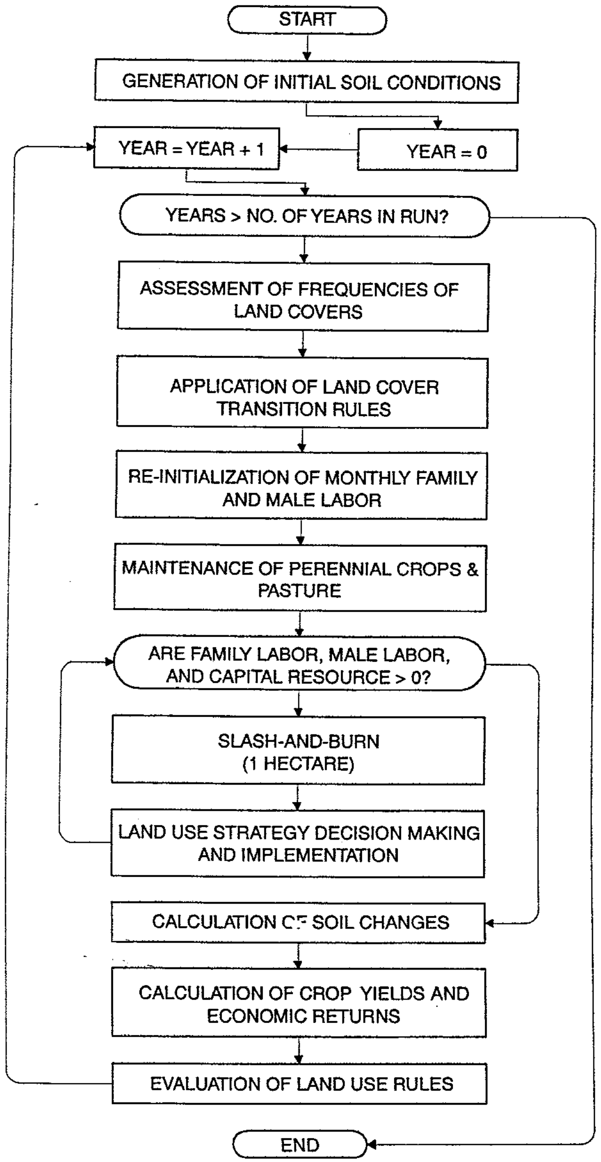


FIGURE 3 Summary flow chart of schedule of events for any given agent and its property lot.



patch of land is always a grid cell, or 1 hectare. The criteria used to determine the transition of one land cover to another is based on the previous land cover of a patch of land and the number of years that patch of land has been in continuous use. For example, a patch of land that has exceeded the maximum number of years of continuous cultivation are processed to a stage of fallow and a patch of land that is some stage of secondary succession is shifted to a further advanced stage of secondary succession.

It is important to note that family and male labor pools are reset at the start of each new year. It is assumed in LUCITA that any given patch of land used for the production of perennial crops or for pasture with or without cattle is maintained prior to any considerations made by an agent to implement a new land-use strategy. Hence, an event is scheduled for each agent to check within its property for patches of land that need to be maintained and to commit the necessary labor and capital resources required by those land uses. Any new land-use strategies are not considered until after this maintenance event is processed.

Providing that labor and capital resources are still available, an event is scheduled for the clearing and burning of one patch of land. An agent will identify, based on its available labor and capital, which of the available three land covers (i.e., virgin forest, secondary forest, and weed) it is capable of burning. The criteria used in selecting a patch of land to be cleared and burned are the clearing preferences defined by an agent, the identified land covers that an agent is capable of clearing, and the patches of land free for use in a given property lot. Land is cleared and burned prior to any consideration by an agent of what type of land use is to be implemented. Following the clearing and burning of a patch of land, the decision-making process of an agent is invoked and with the help of the classifier system, a land-use strategy is recommended and implemented. Under circumstances where there is insufficient labor and capital to implement a land-use strategy after clearing and burning a patch of land, that land is simply abandoned by an agent and enters some early stage of secondary succession. An event of clearing and burning a patch of land, followed by an event for agent decision-making purposes is repeated until either one of the criteria of family labor, male labor, or capital is exhausted.

After the process of land allocation is complete, an event is scheduled to calculate the soil changes for each patch of land in a given property. Not only do soil changes need to be calculated for patches of land that have been cleared and burned for new agricultural land uses, but also for those patches of land undergoing some stage of secondary succession. For any given patch of land under any land cover, a set of KPROG2 multiple regression equations exists to determine the appropriate changes in soil parameters. Using these changes in soil parameters, an event is initiated to calculate crop yields for each and every patch of land in agricultural use. The crop yield for each land-use strategy is evaluated against the expected crop yield for the number of patches used for production to determine the effectiveness of that particular land-use strategy. For any given land-use strategy, providing that the expected crop yield is satisfied, a reward is sent to the classifier system to reward that land-use strategy in the rule base.

## 4 LUCITA SIMULATION RESULTS

### 4.1 EXPLORATORY RESEARCH

The purpose of this section of the chapter is to provide simulation results of two case scenarios for each of the one-household version and the landscape version of LUCITA for a time period of 40 years. The two case scenarios differ in the definition of the land-use clearing preferences. The household parameters were constant for all simulations runs, irrespective of which version of LUCITA was simulated. As described in an above section, the purpose of both versions of LUCITA and the output generated from each version are different; however, from a perspective of how events are scheduled in both versions, they are fundamentally identical. The purpose of the one-household version of LUCITA is to explore the dynamics between an agent and its surrounding environment at a local (property) scale. This is accomplished by generating extensive output data files tracing changes in the environment, changes in labor and capital resources, and the dynamics of decision making using the LUCITA classifier system. The purpose of the landscape version of LUCITA is to observe the emergence of regional land-use trends. For this reason, little output data is generated except for annual land cover frequencies. The landscape version of LUCITA can be considered a container of nested one-household versions.

### 4.2 INITIAL AVAILABLE LABOR AND CAPITAL

The initial available monthly family labor for any given month is calculated by taking the product of the number of family members and the days in a month. Similarly, the initial monthly available male labor for any given month is calculated by taking the product of the number of males in a family and the days in a month. For instance, for a month with 31 days, if a family was composed of four individuals, from which two were of the male gender, the available family labor would be 124 man-days equivalent per hectare and the available male labor would be 62 man-days equivalent per hectare. Issues regarding fertility and mortality within a household are not considered in the two versions of LUCITA. For this simulation, a family size is calibrated to six individuals, from which three are of the male gender. All individuals are assumed to be of a mature age and capable of contributing labor. Initial available monthly family and male labor is summarized in table 1. With respect to initial capital, each household agent is initialized with Cr$0 (Brazilian cruzeiro currency). The initial family composition and initial capital of an agent were arbitrarily selected and were not based on any data sources.



TABLE 1 Number of man-days equivalent of monthly family labor per hectare. Number of man-days equivalent of monthly male labor per hectare.

| Monthly Available Family Labor | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Month | Jan | Feb | March | April | May | June | July | Aug | Sept | Oct | Nov | Dec |
| Family Labor | 186 | 168 | 186 | 180 | 186 | 180 | 186 | 186 | 180 | 186 | 180 | 186 |
| **Monthly Available Male Labor** | | | | | | | | | | | | |
| Month | Jan | Feb | March | April | May | June | July | Aug | Sept | Oct | Nov | Dec |
| Male Labor | 93 | 84 | 93 | 90 | 93 | 90 | 93 | 93 | 90 | 93 | 90 | 93 |

TABLE 2 The pH in initial soil quality generation for 236 property lots in study area. From *Human Carrying Capacity of the Brazilian Rainforest* by P. M. Fearnside © 1986 Columbia University Press. Reprinted by permission of the publisher.

| Class | pH range | Frequency (%) | Mean pH |
|---|---|---|---|
| 1 | < 4.0 | 33.0 | 3.7 |
| 2 | 4.0 – 4.4 | 30.2 | 4.1 |
| 3 | 4.5 – 4.9 | 15.3 | 4.7 |
| 4 | 4.0 – 5.4 | 12.5 | 5.2 |
| 5 | 5.5 – 5.9 | 5.3 | 5.6 |
| 6 | 6.0 – 6.4 | 3.6 | 6.3 |
| 7 | ≥ 6.5 | 0.1 | 7.1 |

### 4.3 INITIAL SOIL CONDITIONS

For the purpose of this simulation, an assumption is made that the soil conditions across a property lot are homogeneous for the one-household version of LUCITA. The mean of the most frequently observed class for each initial soil quality data sampled by Fearnside [7] is assigned to each respective soil parameter. For example, using the initial pH soil quality data for the study area, summarized in table 2, the mean of class 1 is assigned as an initial pH value since that particular class is the most frequently observed.

In the case of the landscape version of LUCITA, the spatial data maps translated from Fearnside [7] were used to calibrate each soil parameter. Therefore, the landscape soil parameters for each of the 236 property lots are spatially variable unlike the homogeneous one-household property lots.

### 4.4 LAND COVERS AND CLEARING PREFERENCES

Nineteen possible land covers exist in LUCITA and are described in table 3. Prior to a simulation run, an agent's clearing preferences must be defined. The land covers that are considered for clearing include virgin forest, weeds, and any patch of land in some stage of secondary succession (i.e., land IDs from 1 through 9 only). Categories of secondary succession are based on the criterion of age only and are defined following the same classification used in

TABLE 3 The nineteen possible land covers in LUCITA.

| Land-Use Code ID | Land Cover |
|---|---|
| 0 | House |
| 1 | Virgin Forest |
| 2 | Weeds & Bare Land (less than 1 year of age) |
| 3 | Secondary Succession 1 (greater than 1 but less than 2 years of age) |
| 4 | Secondary Succession 2 (2 to 3 years of age) |
| 5 | Secondary Succession 3 (4 to 6 years of age) |
| 6 | Secondary Succession 4 (7 to 11 years of age) |
| 7 | Secondary Succession 5 (12 to 16 years of age) |
| 8 | Secondary Succession 6 (17 to 20 years of age) |
| 9 | Secondary Succession 7 (over 20 years of age) |
| 10 | Rice |
| 11 | Beans |
| 12 | Maize |
| 13 | Manioc |
| 14 | Fallow |
| 15 | Cacao |
| 16 | Black Pepper |
| 17 | Pasture without Animals |
| 18 | Pasture with Animals |

the original KPROG2 model. For any simulation, any patch of land can only be used continuously for a maximum cultivation period of two years. When the maximum number of years of continuous cultivation are exceeded, a patch of land must enter a fallow stage for a minimum period of three years prior to reuse. Clearing preferences in combination with whether or not labor and capital requirements are available to slash-and-burn are used to identify which type of patch of land in a given property should be selected for use.

The two case scenarios have different clearing preference definitions, defined in table 4. The first case scenario assumes that an agent's first preference is for mature secondary forests followed by less mature stages of secondary succession and only deforest virgin forest land when no other secondary land covers are available. This scenario is representative of circumstances where frontier colonists recognize the importance of secondary succession in regenerating soil fertility. The second scenario assumes that an agent has some type of an incentive to deforest virgin forests. When virgin forests have been depleted, it is assumed that agents will select to clear the patches of the land that require the least labor and, therefore, preferences range in order from weeds and bare land to secondary succession 7. This scenario is representative of a situation where agents may be influenced by social or economic factors to clear virgin forest lands and do not have an understanding of the impor-



TABLE 4 Definition of land clearing preferences for two case scenarios.

| Scenario 1 | | Scenario 2 | |
|---|---|---|---|
| Order | Land Cover | Order | Land Cover |
| 1 | Secondary Succession 7 (over 20 years of age) | 1 | Virgin Forest |
| 2 | Secondary Succession 6 (17 to 20 years of age) | 2 | Weeds & Bare Land (less than 1 year of age) |
| 3 | Secondary Succession 5 (12 to 16 years of age) | 3 | Secondary Succession 1 (greater than 1 but less than 2 years of age) |
| 4 | Secondary Succession 4 (7 to 11 years of age) | 4 | Secondary Succession 2 (2 to 3 years of age) |
| 5 | Secondary Succession 3 (4 to 6 years of age) | 5 | Secondary Succession 3 (4 to 6 years of age) |
| 6 | Secondary Succession 2 (2 to 3 years of age) | 6 | Secondary Succession 4 (7 to 11 years of age) |
| 7 | Secondary Succession 1 (greater than 1 but less than 2 years of age) | 8 | Secondary Succession 6 (17 to 20 years of age) |
| 8 | Weeds & Bare Land (less than 1 year of age) | 8 | Secondary Succession 6 (17 to 20 years of age) |
| 9 | Virgin Forest | 9 | Secondary Succession 7 (over 20 years of age) |

tance of allowing cultivated land to regenerate through secondary succession to maintain productive soil fertility.

## 4.5 PATCH SELECTION

It is important to note that the type of patch of land identified for clearing is not randomly selected from the property lot. A bubble sort is applied to all patches of land in a property lot to order them in a south-to-north ordering for properties located on feeder roads, and in an east-to-west ordering for properties adjacent the Transamazon Highway (fig. 4). This implies that the direction of clearing is predefined; however, the magnitude of land cleared remains unaffected and remains dependent on labor and capital resources of an agent. Household behavior regarding the spatial location of the selection of land for use is beyond the scope of current versions of LUCITA due to limited data and knowledge. The ordering of property lots also has implications with respect to spatial patterns of deforestation, but it is important to note that in these early stages of LUCITA, the spatial pattern of deforestation is not as important as the trajectory of household land uses through simulated time.

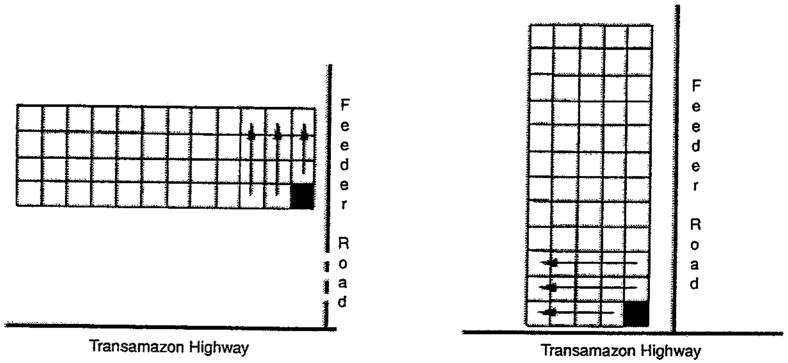


FIGURE 4 The direction that free patches of land are searched by an agent on property lots off on feeder roads (left) and on property lots adjacent the Transamazon Highway (right) for slash-and-burn agriculture. Black grid represents location of house.

## 4.6 CLASSIFIER SYSTEM PARAMETERS AND REWARD CRITERIA

Any rule contained in an agent's rule base must pay a life tax of 0.5% of its existing rule strength. Rules that are matched based on the available labor and capital possessed by an agent must pay a bid tax rate of 1% of its existing rule strength to be considered in the auction process. The winning rule from the auction process must, in turn, pay 5% of its existing strength when selected for implementation. Classifier system parameters are constant for all simulation runs.

Ideally, effective rules should be reinforced through time. Annual cash-crop strategy rules are rewarded when the expected yield for all patches of land in a given annual cash-crop rule is satisfied. For instance, if the expected yield for rice is 1500 kg/ha and 5 hectares of land are used for crop production of rice by an agent, the annual cash crop rice rule is only rewarded if 7500 kg for the 5 hectares of land is produced. The actual reward value is calculated by adding the total bid amount made for all the hectares of land use for that successful land use, plus half of that total. No data is available for perennial crops and, given the soil condition of the study area, even with liming and fertilizing, it is often difficult to produce satisfactory yields. For this reason, a perennial crop rule is assumed to be successful or effective if it produces a yield greater than 0. The reward value is calculated in the same fashion as that of annual cash crops. Pasture land uses are not evaluated as to their effectiveness and are therefore never rewarded. The rational for this approach is that pasture land uses in most instances are always implemented when little labor or capital remains after implementing other land uses. Therefore, pasture land uses will



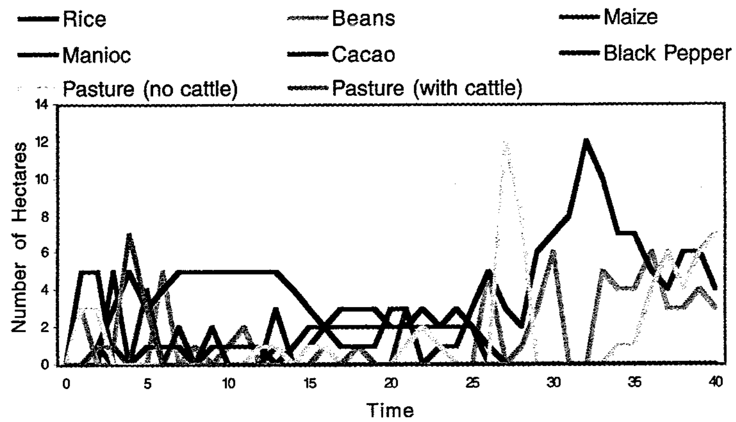


FIGURE 5 Land-use frequencies for scenario 1 using the one-household version of LUCITA.

most likely be implemented more frequently than others resulting in pasture land uses emerging as dominating land uses. Instead, pasture land uses are allowed to compete for selection; however, when selected such uses are not reinforced since pasture land use is often implemented to deplete all labor or capital resources of an agent before moving on to the next time step.

## 4.7 SCENARIO 1: ONE-HOUSEHOLD VERSION OF LUCITA RESULTS

The results from simulating scenario 1 are presented in figure 5. Virgin forest-land, stages of weeds, and all stages of secondary succession are not depicted in the graph for scaling reasons. Only 29% of the original forest were cleared for agricultural and pasture use. During the first seven years, all land-use rules can be seen to compete. This time period, where an agent experiments with rules, is somewhat shorter than expected. Maize and bean crops can be seen to be the first crops produced, followed by black pepper, rice, cacao, and maize. It is interesting to note that sufficient labor and capital are available as early as year 1 to implement perennial crop rules.

Both pasture land uses are similarly implemented early in this time period, as expected, as very little labor and capital are required by these land uses. It is important to emphasize that pasture land uses compete in the auction process, but do not earn rewards since no criteria is available to evaluate if they are effective or not. This implies that pasture land uses are only implemented when very little labor remains following the implementation or maintenance of other crop rules.

From year 7 through to year 24, cacao establishes itself as the dominating land-use rule because of a combination of the fact that it possesses the highest strength and because it is assumed that any patch of land in perennial use or pasture is maintained for the maximum cultivation period prior to any consideration of the implementation of new land-use rules. Other crops are implemented less frequently as illustrated under the cacao trend line.

By year 26, cacao noticeably ceases to be the dominating land use. This event can be explained by the decrease in soil fertility in the patches of land used. Based on the clearing preferences, land uses cycle on only 29 patches of land from the one-hundred-patch property lot as seen in snapshots of the simulation presented in figure 9. The most advanced stage of secondary succession that is ever reached with these land patches prior to being recleared is the secondary succession 3. By analyzing the crop-yield data file, cacao crop yields are shown to be negative, implying that a decrease in soil fertility has occurred, resulting is those land patches no longer being productive for the production of cacao. An examination of the multiple soil data files of the patches of land in use reveal that pH levels decreased to a very low value.

Following this decline in cacao production, most of the land is implemented in the pasture with no cattle land use. This surge of the pasture with no cattle land use can be explained by observing the previous year's land use. Manioc, beans, cacao, and black pepper are produced in year 26, and because of manioc's two-year growing season and the assumption that perennial crops are maintained for the maximum cultivation period, most of the labor for the subsequent year is already committed to maintenance of these crops. The little remaining labor is sufficient only for the implementation of the pasture with no cattle land use resulting in the surge of that land use.

Come year 28, maize and bean land uses emerge as the dominating land-use trends, complemented by the pasture with no cattle land use. These two annual cash crops emerge as the dominating land uses because of their ability to produce on soils with poor fertility. By examining the crop production data files, it is revealed that while other land uses began to generate negative crop productions near the same time of the decline of cacao production, maize and beans continued to produce crops.

In summary, it appears that how clearing preferences are defined may affect soil fertility, in turn affecting the production of crops. In this scenario, a stage is reached when soil fertility drops to a point where many land uses are no longer able to produce crops. The maize and bean land uses simply emerge as the most effective land uses at the end of the simulation because of their ability to produce under low soil fertility. Based on the definition of the clearing preferences for this scenario, an agent is incapable of deforesting all virgin forests on its property lot and only does so when no other alternative is available. Therefore clearing preference in this scenario plays a large role in the emergence of effective land uses and the magnitude of virgin forest deforestation.



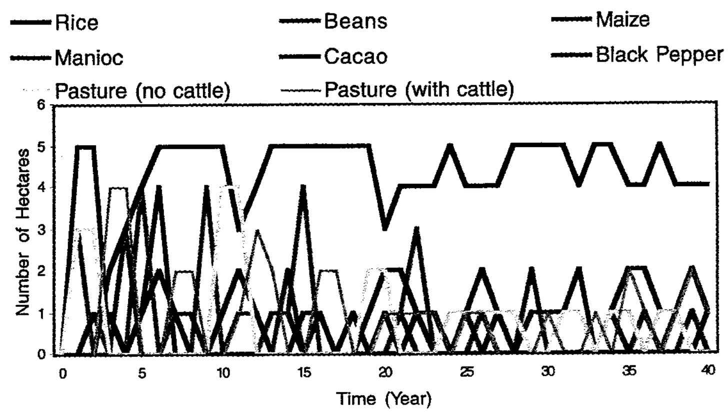


FIGURE 6 Land-use frequencies for scenario 2 using the one-household version of LUCITA.

## 4.8 SCENARIO 2: ONE-HOUSEHOLD VERSION OF LUCITA RESULTS

Simulation results for scenario 2 are presented in figures 6 and 10. Like scenario 1, virgin forests, weeds, and stages of secondary succession land uses are not displayed for scaling reasons. Virgin forests are completely depleted by year 17 and mature secondary forests fully regenerated by year 20. Land-use trends are very similar to scenario 1. A common trend in both scenarios is the dominance of the cacao land-use rule early in the simulation. Other rules continue to compete for implementation as shown under the cacao trend line, but cacao is the most frequent land use implemented and maintained on the property lot.

The first seven years of the simulation are similar to scenario 1 where results of the experimentation of land-use rules only differ from scenario 1 in the order of the experimentation chosen by an agent. Black pepper is only produced during years 2 to 4 and is never produced again in the simulation. This event can be explained in terms of the dominance of the cacao land use. Both cacao and black pepper have high labor and capital requirements. Given that cacao has the highest strength and wins most bids, when no sufficient labor or capital remains for implementation of the cacao land use, then, in turn, any consideration of implementation of black pepper is excluded because of the similar labor and capital requirements. All land uses, excluding black pepper, continue to compete throughout the simulation.

Cacao continues to be the dominating land use throughout scenario 2, in contrast to scenario 1, because of the definition of clearing preferences. A clearing preference for virgin forest is emphasized throughout the simulation and, as a result, patches of land are rarely recleared for use since new land is continuously deforested. This implies that soil fertility remains consistently high and, in turn, is capable of maintaining the soil conditions for cacao production unlike in scenario 1 where a decrease in soil fertility occurred. With the maintenance of cacao production, meaning that the cacao land use was being reinforced through time, little opportunity was available for other land uses to dominate.

In summary, scenario 2 further reinforces the importance of clearing preferences in affecting the emergence of dominating land uses and the magnitude of deforestation. Further, at the end of the simulation, mature secondary forests regenerate to cover 77% of the original primary forest extent. In comparison to scenario 1, 71% of the original virgin forest was left undisturbed. Comparing the amount of forest cover in both scenarios, irrespective of the type of forest cover, suggests an agent, based on its description of family composition and capital, can only sustainably manage one quarter of its property lot.

### 4.9 SCENARIO 1 AND SCENARIO 2: LANDSCAPE VERSION OF LUCITA RESULTS

The landscape version of LUCITA generates regional land-use trends based on a spatially explicit soil landscape. Land-use results from simulating scenario 1 and scenario 2 using the landscape version of LUCITA are presented in figure 7 and figure 8, respectively. Snapshots of both landscape scenarios are depicted in figures 11 and 12.

Regional land-use trends are very similar to those at the local property scale for scenario 1. Virgin forests, weeds, and secondary stages of succession are once again omitted from figure 7 for scaling reasons. From the total virgin forest extent, 66% remains undisturbed and is very close to the 71% at the local scale. The most advanced stage of secondary succession reached is stage 4. Cacao emerges as the dominant land-use trend for approximately the same duration as that of the local scale. Manioc and pasture with no cattle land uses emerge as the dominating land-use trends near the end of the simulation. Instead of the bean land-use trend also emerging near the end of the simulation, like in the case of the local scale simulation, maize emerges as the third dominant land-use trend. Granted that the clearing preferences were identical for simulations using each version, the slightly different land-use trends in the landscape results must be affected by the spatial variability of the soil data characterizing the landscape. Higher or lower soil fertility in particular regions of the landscape may lead to increases or decreases in crop production, which in turn may affect the evaluation of rule strengths. The general similar trends can be explained by the generation of initial soil quality for the local scale property lot, where the most frequent soil value of each parameter observed on the landscape were assigned to the property lot's soil parameters.



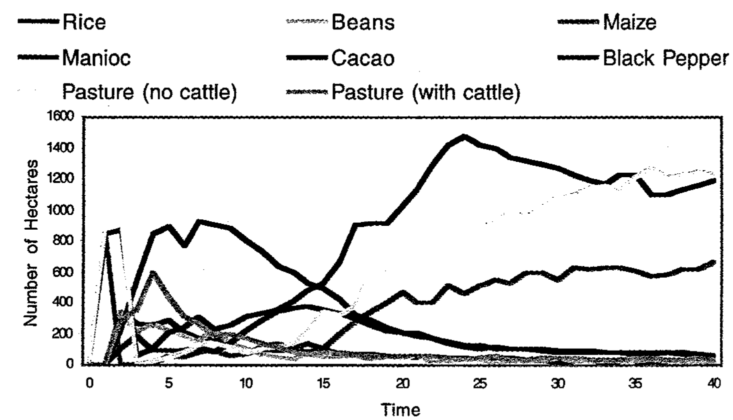


FIGURE 7 Land-use frequencies for scenario 1 using the landscape version of LUCITA.

In scenario 2 for the landscape, depicted in figure 8, general land-use trends are nearly identical to those at the local scale. Once more, only crop and pasture land uses are depicted in the graph. Virgin forest depletion occurs at year 33, much later than year 17 at the local scale. Mature secondary forests begin regenerating at year 21, one year later than the case at the local scale. Figure 8 shows the dominance of the cacao land use early in the simulation to the end of the simulation. Other rules continue to compete as shown under the cacao trend line and match the trends at the local scale results. Following depletion of primary forest cover, mature secondary forests regenerate to cover 75% of the original virgin forest extent, almost identical to the value obtained at the local scale. Despite the spatial soil variability of the landscape, the land clearing preferences ensures that cacao is continuously implemented only on fertile soil and, so long as soil fertility is adequate for cacao production, it will continue to dominate.

## 5 DISCUSSION

An examination of the results presented in this chapter reveals both the strengths and limitations of LUCITA, and the need for additional data collection within the Altamira study area. This section examines the replicative validity of the simulations, as compared to the observed situation in Altamira, and explains some of the behavioral anomalies of the simulations. These observations point to the need for additional data collection on the natural, institutional, and demographic and behavioral characteristics of the region.

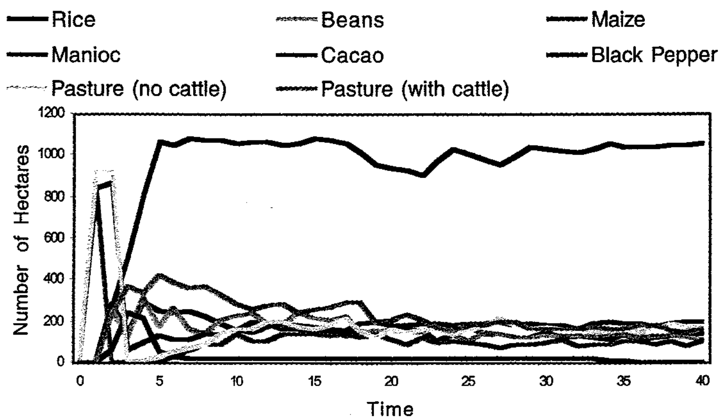


FIGURE 8 Land-use frequencies for scenario 2 using the landscape version of LUCITA.

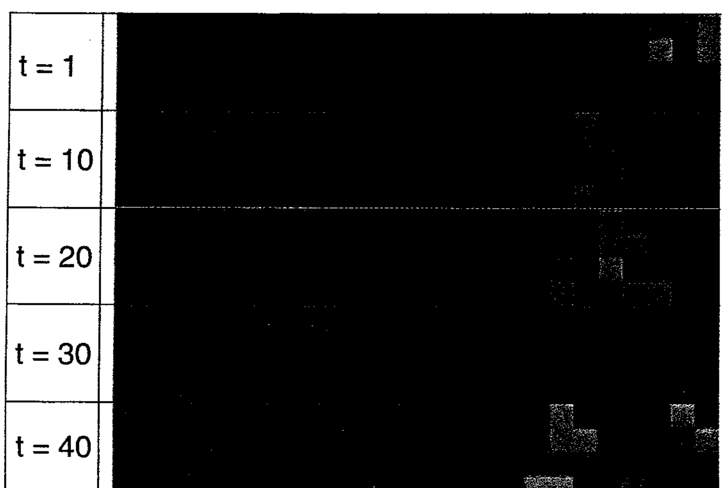


FIGURE 9 Snapshots of scenario 1 simulation using one-household version of LUCITA.



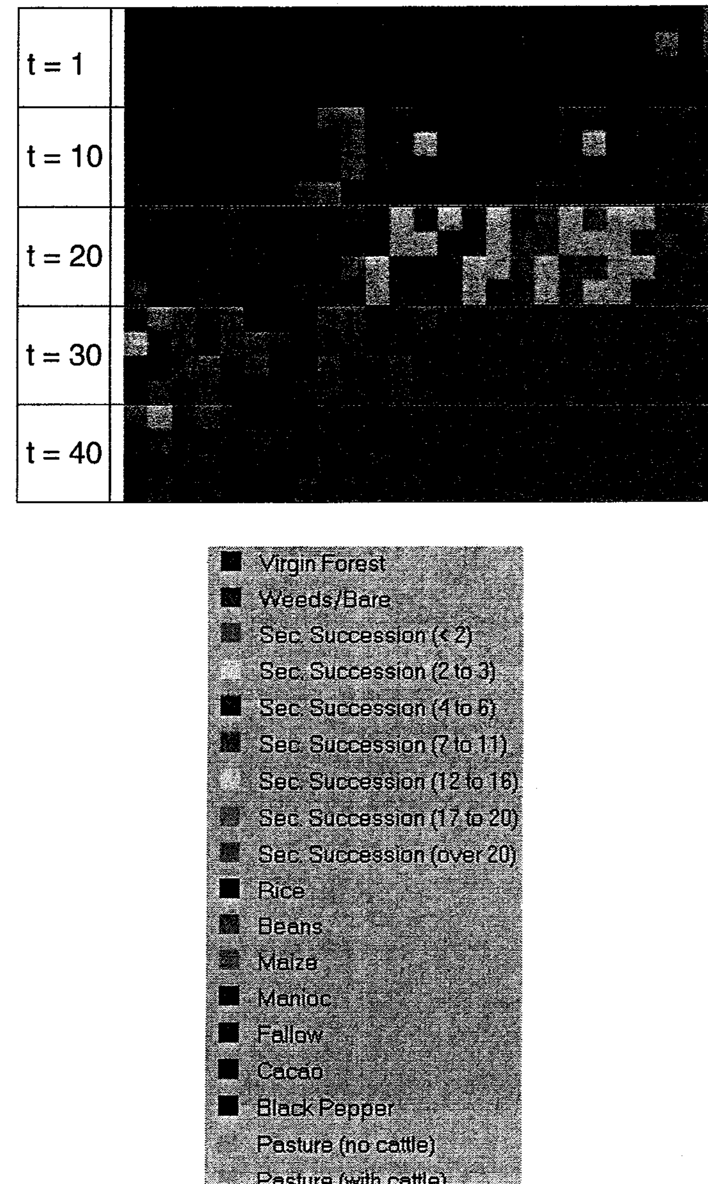


FIGURE 10 Snapshots of scenario 2 simulation using one-household version of LUCITA.

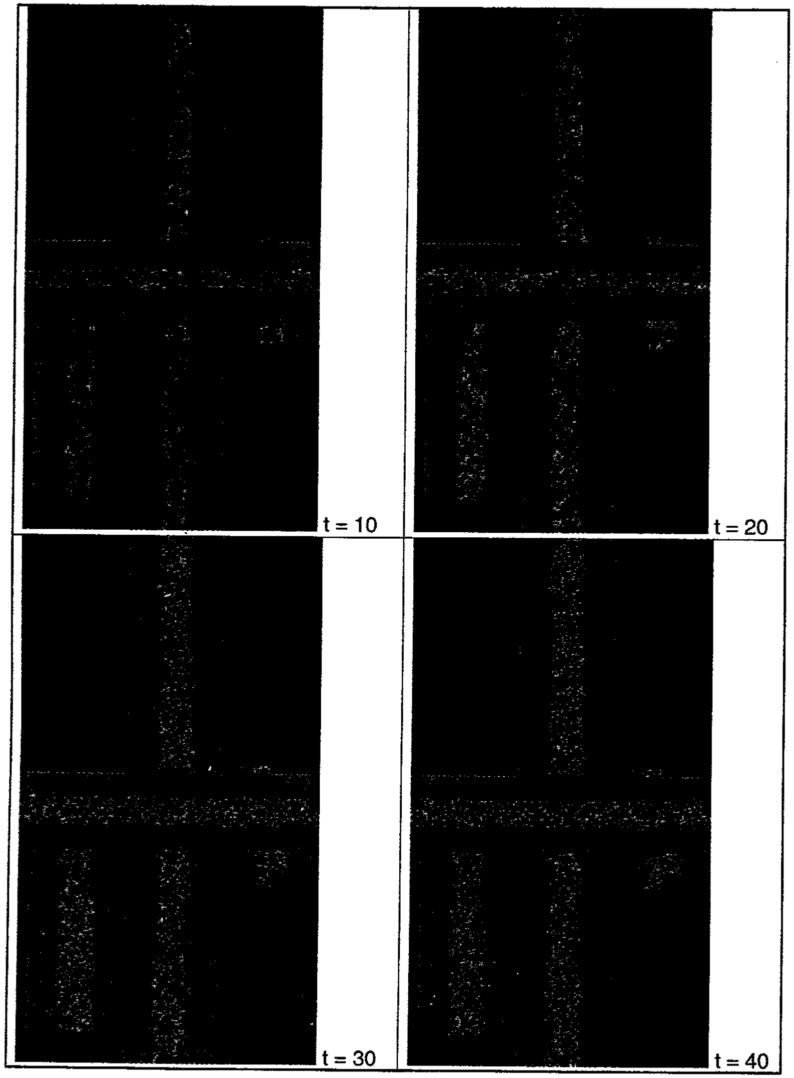


FIGURE 11 Snapshots of scenario 1 simulation using landscape version of LUCITA. Legend in Figure 10.



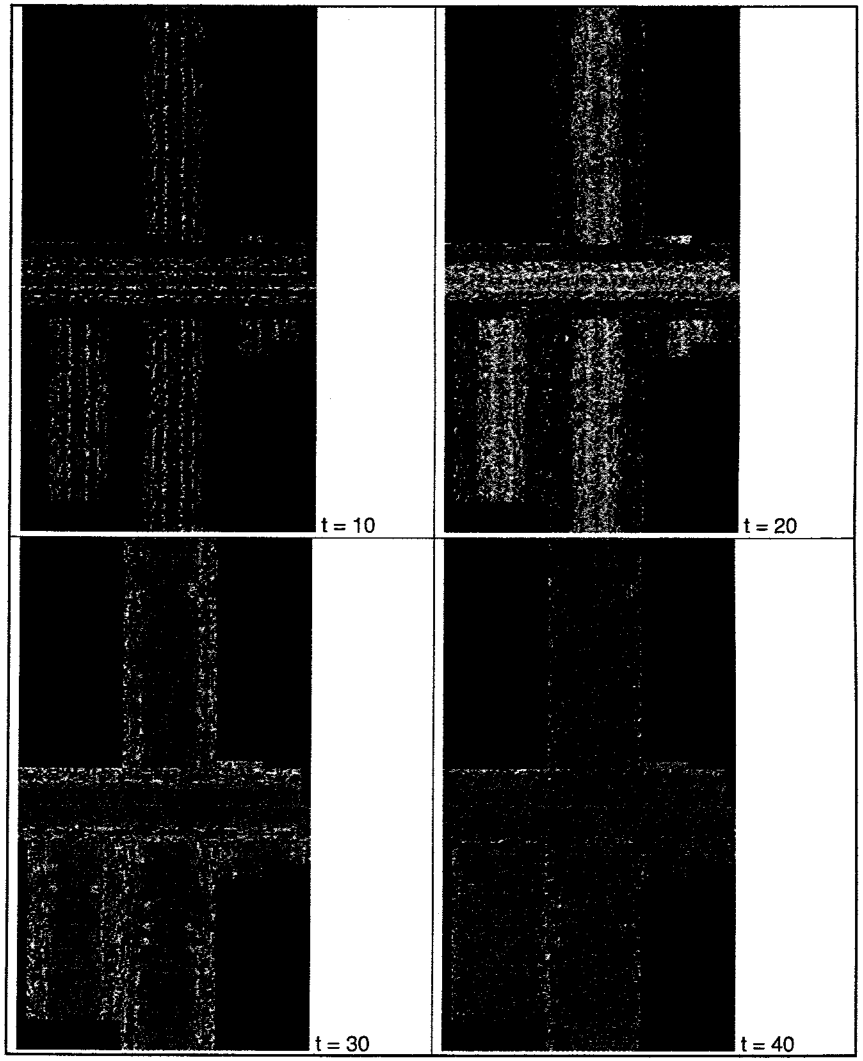


FIGURE 12 Snapshots of scenario 2 simulation using landscape version of LUCITA. Legend in Figure 10.

The land-use trajectories generated from scenario 1 and scenario 2 using both versions of LUCITA do not resemble the trajectory proposed in the conceptual model of household transition outlined in McCracken et al. [16] for several reasons, the most important being the definition of the reward criteria used to evaluate the effectiveness of rules following implementation by an agent. In general applications of classifier systems, at any given time step, one rule is selected, evaluated, and reinforced prior to the next time step where a new rule is selected. In the case of LUCITA, at any time step, several rules can be selected and implemented depending on an agent's available labor and capital resources. Emphasis is placed on the word "selected," meaning that we are not referring to the matching of rules to an environmental message encoded by an agent representing its available labor and capital, but rather those rules that actually win a distinct auction process in the performance system of a classifier system. Those rules that are selected are not rewarded, nor evaluated until all decision making has been completed at the end of a time step for the simple reason that, during a growing year, a farmer does not know if the production of a particular crop is successful until the end of the growing season. Rewarding a rule before all decision making has been completed will, in effect, bias decision making toward effective rules selected early on, since their rule strength will be reinforced before other rules have an opportunity to be tested within that same time step.

The adoption of an approach where a set of rules are not evaluated and rewarded until all decision making has been completed introduces several problems, which has emerged from the simulation of both scenarios presented in this chapter, ultimately affecting land-use trajectories. Selected rules must pay a bid value depending on the defined bid ratio; however, because rule strengths cannot be modified until all decision making has been completed, these bid amounts must be archived in some type of a data structure. Similarly, reward payments must be archived to prevent changes in rule strengths. A problem that has emerged in the LUCITA simulations is that, if a land use is implemented on more than one patch of land and is evaluated as an ineffective rule, its rule strength is often depreciated to a strength below previously identified less effective rules. This is because, for each implementation of a land-use rule, a bid is paid based on the defined bid ratio. The more times a land use is implemented during a given time step, the larger the paid bid amount and, if the land-use rule is evaluated to be ineffective, there is no recovery of the paid bid through rewards.

Based on the definition of the reward criteria for land-use rules in the existing version of LUCITA, a land-use rule cannot be evaluated as partially effective. A rule either pays its total bid amount or is rewarded the paid bid amount plus a percentage. There is no consideration of the spatial variability of crop yields in the existing version of LUCITA and, hence partial recovery of a proportion of total paid bids by a land-use rule is not possible. For instance, an extremely successful crop yield on one hectare of land may compensate for poor yields on another two hectares and yet still achieve the total expected crop yield for three hectares of land, ultimately resulting in the reinforcement of the rule. Consider that same situation, but in this case the total expected yield for three hectares of land is not achieved; despite the expected yield for one hectare of land being satisfied, the rule itself is not reinforced. Therefore, as mentioned above, rules that are implemented on several patches of land can lose a large proportion of its rule strength if evaluated as ineffective based on the definition of the reward criteria and the lack of consideration of the spatial variability of crop yields. Given the general poor initial soil qualities and the rapid decrease in soil fertility following slash-and-burn, many hectares are unable to achieve the expected crop yields. In turn, this inability to achieve expected crop yields is reflected by a continuous net decrease of rule strengths toward zero as opposed to a dichotomy of rules emerging, comprised of effective and noneffective rules.

Simulated land-use trajectories are also affected by how the labor and capital requirements of a land use are defined, and in turn determining which ones can be implemented by an agent. A general idea of the conceptual transition of households is that, when a household arrives to the frontier, that household on average has very little liquid capital and, hence, can only pursue a subset of the total available land-use rules, which often excludes perennial crop production. What has emerged from the simulations is that agents are often capable of beginning to implement perennial land-use rules as early as the second production year since enough liquid capital has been produced in the first year of crop production. The general idea of the transition of households is modeled correctly since, during the first time step, we observe no competition of perennial crop rules and mostly only annual cash crop rules and pasture land-use rules. This suggests that a discrepancy exists in how net income from the sale of crops is calculated. Because of a lack of data describing the costs or expenses of a household family on an annual basis, it was assumed that from the total annual income generated from crop sales, 75% of the income was lost to expenses, such as medicine, transportation, and crop seed costs. The capital requirements for each land-use rule defined in the genetic algorithm strings only factor in building materials and chemical costs for maintenance. The ability of an agent to implement perennial crop rules as early as the second year is attributed to the above assumption of net income given the unavailability of data. In the LUCITA simulations presented in this chapter, capital was not a constraint for decision making as the conceptual model suggests since agents were acquiring capital at an exponential rate despite the deduction of 75% of income, but rather labor, specifically male labor, was the limiting factor in determining how many and what land uses could be implemented in a given time step. With more detailed information regarding colonist expenses, net income should be able to be better calculated, resulting in less-biased land-use trajectories.

## 6 CONCLUSIONS

These weaknesses of LUCITA have important effects on the land-use trends that were simulated for both scenarios. However, the replicative validity of the existing versions of LUCITA was not a priority at this stage. Instead, the utility of using agent-based modeling techniques integrated with geographic information systems (GIS) spatial data is explored in this chapter. In this regard, LUCITA has the potential for a high degree of structural validity. It approached the study of land-use change from the bottom up, addressing the behavior of the individual households that make land-use decisions and allowing overall landscape patterns to emerge as a result of the many actions of these individuals. The goal was never to test or explore the conceptual model of household transition, but rather to develop a model that considered both the ecological domain and the human domain and how they interact with each other. Further, the development of this preliminary simulation system highlighted the need for additional data collection efforts within the Altamira region, designed specifically to support simulation development. The modeling and simulation efforts described here relied on data that was originally collected for other purposes. Additional data collection efforts specific to simulation development would focus on collecting biophysical information such as soils, topography, and drainage patterns. Additional data on economic factors such as the history of credit policies, crop prices, and economic conditions, which have not yet been implemented, as well as frontier family demographic and behavioral characteristics, such as the cultural and behavioral factors that influence land-use decision making, would also be required.

Natural resource management modeling efforts in many instances consider the ecological domain and the human domain in isolation, or at best simulate the actions of one domain while holding the characteristics of the other constant. However, given the complex interactions that exist within each domain and between each domain, integrated modeling approaches are needed and must be developed. Such an approach will assist researchers in better understanding the complex nature of the interactions between human and natural systems. There are very few attempts similar to LUCITA, where two submodels interacting through a spatially explicit landscape with adaptive agents exist in the literature. It is hoped that this chapter presents a preliminary methodology that other researchers can use as a starting point and learn from some of the challenges that we have presented from our results and discussion of the simulations.

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