Agent Based Modeling of Human and Natural Systems and their interactions

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***Abstract*— This paper provides an overview of the simulation of interacting models that combine forest and landscape dynamics with human values and decision-making. It also explores mathematically complex interaction and feedback relationships of integrated models. We attempt to generalize results by application of models to several hierarchical scales across scales and cultures.**

***Keywords*— Equation Based Modeling, Agent Based Modeling, Swarm, Biocomplexity.**

1 Understanding Biocomplexity

Biocomplexity is a new area of multi- and interdisciplinary scientific research focusing on the interactions of various kinds of dynamic living systems. The US National Science Foundation (NSF) has recently designated biocomplexity research as new funding priority. One salient form of biocomplexity is the dynamic interaction between biotic communities, their associated ecosystems, and their human inhabitants, which NSF categorizes as *Coupled Natural and Human Systems*. The authors are members of a multidisciplinary team of researchers, funded by NSF, based at the University of North Texas in collaboration with colleagues at Yale University and Rice University in the United States and the Universidad de Los Andes and the Universidad Experimental de Guayana in Venezuela. We are studying the dynamic interaction between vegetation cover, ecosystem function, and human behavior in two sites in Texas and two in Venezuela.

The field of Biocomplexity addresses the interaction between living systems and their environment. Essentially, the two major role players in biocomplexity are: the humans and the natural environment around them. Thus, biocomplexity is the complex interaction between the interdependent human and natural systems. This interaction has compelling influences and can cause positive or negative effects. Biocomplexity, as a research area, seeks to understand these interactions and the goal is to be able to predict the effects of these interactions. From individual cells to ecosystems, these systems exhibit properties that are interdependent and have reciprocal effects. Currently, only few ecosystems are free of extensive human influence. However, the way human activity affects such systems and their corresponding effects on human behavior is poorly understood.

1.1 The Goal of Coupled Natural and Human Systems Research

The central goal of our research is to build reliable computer models to understand and predict the effects of human decisions on vegetation cover, the effects of changed vegetation cover on ecosystem function, and the feedback-looped effects of changed vegatation cover and ecosystem function on subsequent human decisions. We hope that simulation of these dynamics will enable environmentalists, geographers, and policy makers to anticipate the future environmental and social consequences of present land-use decisions and therefore to make better informed choices. Using these predictions, one can find ways that complement and enrich natural systems functioning rather than degrade and diminish them. It will thus facilitate a more informed analysis of the long-term consequences of private and public policies on the natural systems in which human systems are embedded and with which they interact.

1.2 Our Approach

To provide a comprehensive solution to the above problem, we focused on modeling and analyzing the dynamic relationships between:

1. Composition and structure of forested ecosystems at varying scales.
2. Functional attributes of those ecosystems.
3. Human behaviors affecting those systems driven by human values and perceptions.

The results obtained by coupling the human systems model with the natural systems model and their dynamic interactions helps in making conclusive decisions. Figure 1 shows a block diagram of the human and natural systems and their interactions. In this figure, I_1 through I_4 represent the different interfaces. This is important for compatibility issues. Moreover, "HS" and "NS" stand for the human and natural systems, respectively.

We model the anthropogenic disturbance and stressors with multi-agent simulation methods and utility functions (see Fig. 1). Then analyzing the feedback coming from the natural system before making new decisions. This study will enable residents of the study areas, natural resource managers, and other parties to engage in environmental policy debates and ultimately make better-informed environmental policy choices.

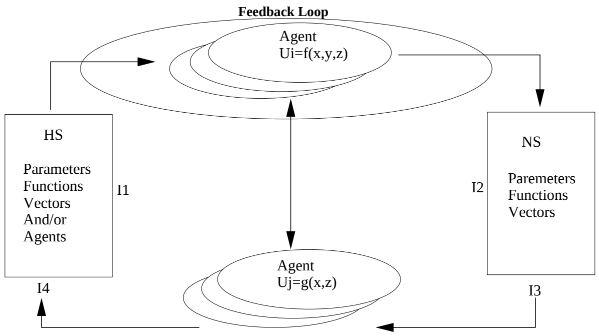

Figure 1: Modeling Systems

The focus of this research is to build a model of the human and natural system interaction. We are trying to convert the complex effects of both the systems into a computer-based model that can be easily perceivable by us. This model will predict the long-term effects of nature on human, based on our current effect on nature. To model these systems, we are choosing an agent based modeling approach. In this approach, all the players in the model are agents. We study the characteristics and effect of each of these agents. Then we study their combined effect and try to predict the outcome based on the study.

1.3 Modeling Coupled Natural and Human Systems

Modeling forest dynamics has a fairly long and familiar history going back to the 1970s. Our team will model land cover using FACET to model individual tree growth and MOSAIC [9] [10] [11] [12] to scale up to the landscape level. Changes in almost all aspects of ecosystem function register a signal in water dynamics and water quality. For example, clearcutting a forest and converting it to or a pasture, subdivision, or strip mall will result in increased flashiness in streams, increased suspended solids, and possibly increased nutrients and the production of chlorophyl. Such phenomena indicate changes in such ecosystem functions as nutrient retention and cycling, soil stability, and primary productivity. Therefore, hydrological models will be used to model ecosystem function. To model the human systems that will be linked to both the land-cover and hydrological models, we have chosen to use agent based models, more particularly Swarm [3] [5] [7]. To provide the data to build various kinds of agents we are conducting research to identify the values that drive human decisions using various survey techniques, conjoint analysis prominent among them.

In order to model a complex system, we have to understand the collective behavior of all of its components. We are specially interested in the components that influence the environment.

2 Agent Based Modeling

Before we formally introduce agent based modeling, we breifly introduce agents and some of their fundamental characteristics.

2.1 Agents

Broadly speaking, agents are entities that perceive their environment, incorporate perceptions, and remember and reason about facts. Agents then adopt beliefs, goals, and intentions and execute corresponding actions to change the state of the environment. Agents have the following charecterstics [6] (see Fig. 2):

- **Memory or state:** internal data representations.
- **Perceptions:** means for modifying internal data representations.
- **Behaviors:** means for modifying their environments.
- **Intelligent reaction:** adaptation to dynamics of the system.
- **Cooperation:** knowledge sharing, common strategies negotiation.
- **Autonomy:** execution of actions without external intervention.
- **Goal-directed:** action to achieve defined tasks.

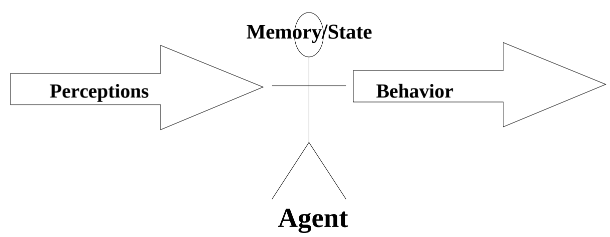

Figure 2: An Agent

A very famous example of an agent is the "Clippy" - paper-clip from Microsoft Office.

2.2 Types of Agents

One type of agent [1] is a program that performs actions on behalf of the user. For example, there can be an agent that searches airlines to find the best price for an airline schedule. Similarly, there can be a calendar agent that communicates with other calendar agents to schedule meetings and appointments. An agent perceives its environment and makes a decision (behavior) based on his analysis (see Fig 2).

Another type of agent [2] is the distributed problem solving agent. With this type of agent, usually there are dozens or hundreds (or many more) copies of a program spread over a network to solve a problem. Agents can be responsible for managing network traffic. Sometimes, each agent is assigned a small calculation and after some delay, the results from all agents are combined.

Another common type of agent is the agent designed for simulations. Each item in the simulation is an agent. Each agent has some code that gives it instructions on how to behave in the simulation. For instance, we can simulate traffic [4] and represent each car by a different agent.

2.3 Characteristics of Agent Based Modeling

Agent based modeling [4] is a new approach to system modeling and simulation. The basic unit of activity in such a system is the agent. Usually, a model contains many agents (at least tens, occasionally many thousands) and its outcomes are determined by the interactions of the agents. Agent based models are most popular in domains that are characterized by a high degree of localization and distribution.

In our attempt of modeling the human system, we consider a single human being as our primary entity. We then group individuals to form larger groups and they are categorized based on their interests. This gives us a hierarchy of agent types and we use Swarm's hierarchical modeling capabilities [3] [5] [7] (see Fig. 3) to implement this model. Moreover, in our model, we are also interested in an agent's action and how that action effects the environment. In later sections, we discuss and introduce a formal mathematical model that serves this purpose.

2.4 Relationship to Similar Models

Why agent based modelling? In this section, we describe some of the similar modeling techniques that have been used in the past for system modeling and simulation. We will look at some of the drawbacks in these models and how we can use agent based models to overcome these hurdles. It is crucial to understand that an agent based model complements and enhances these traditional approaches. The original intent is not to supplement them in any way. Moreover, we will also compare and contrast agent based models with another mathematical approach, equation based models [8].

2.4.1 Some Issues

Some of the traditional mathematical methods are Ordinary Differential Equations (ODE), Partial Differential Equations (PDE), and statistical approaches. In the context of modeling, these methods have the following drawbacks [5].

- These methods can describe the macroscopic properties of a system that are already known, but they fail to explain the origin of these properties. (e.g. rate constants)
- Such systems cannot be easily extrapolated to situations where the assumptions behind the equations no longer hold. (e.g. Hookes law $F = -kx$)
- These models are not capable of handling discontinuous systems properly.
- Finally, these models cannot handle heterogenity in polpulations accurately.

2.4.2 Agent Based Modeling versus Equation Based Modeling

The distinction [8] between an agent based model and an equation based model is of great interest in domains where both techniques can be applied appropriately. It is important for system modelers and simulators to understand the different capabilities of these two approaches so that they can make ethically sound decisions. Both approaches build a model for any given scenario and then executes the model on a computer. Let us define the two techniques and illustrate their capabilities using an example.

In **Equation Based Modeling**, the model consists of a set of equations. The model execution consists of evaluating these equations. An equation based model identifies system variables and evaluates and integrates the sets of equations. In **Agent Based Modeling**, the model consists of a set of agents who represent different individuals and entities of the system. The model execution consists of emulating the behavior of these agents. Typically, an agent has a fixed schedule of actions but it can be interepted by an external influence or by an action of another agent in the system.

Equation based models are usually useful for systems that can be modeled centrally. For example, an approach based on Ordinary Differential Equations (ODE) has been used for modeling industrial supply networks at processes level. On the contrary, Agent based models are usually useful for domains that are characterized by a high degree of localization and distribution. For example, agent based models have been used successfully for urban planning [4]. Integration of equation based modeling tools into agent based modeling can be a powerful way to study selection in systems with complex dynamics. For example, individual components (agents) may be modeled through equation based models.

2.5 Swarm: A Toolkit

Swarm [3] [5] [7] is a tool which is used to implement agent-based models. It is a software package for multi-agent simulation of complex systems, originally developed at the Santa Fe Institute.

2.5.1 Basic Facts About Swarm

Swarm [7] is a collection of software libraries which provide support for simulation programming. Some of it's prominent features are as follows.

- In the Swarm system, the basic unit of simulation is the swarm, a collection of agents executing a schedule of actions.
- Swarm supports *hierarchical modeling* (see Fig. 3) approaches whereby agents can be composed of swarms of other agents in nested structures.
- Swarm provides object-oriented libraries of reusable components for building models and analyzing, displaying, and controlling experiments on those models.
- **Swarm Output:** The Swarm system supports a variety of generic methods for tapping data from components of the system, combining those data through statistical filters and displaying them with generic visualization objects or saving them to files.
- As in all simulations, the Swarm system allows us to change a few parameters so we can observe how the change affects things.
- Swarm supports *Discrete Event Simulation.* Agents are created and their communication is controlled by scheduling mechanisms. In a typical simulation, agents proceed by updating/modifying their internal state (variables) and they are asked to report to the observer swarm layer of the simulation (see Fig. 3).

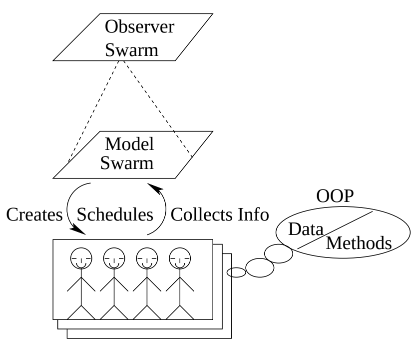

Figure 3: Swarm Hierarchical Modeling - Different Layers of Swarm

3 A Simple Model

3.1 Landowners - An Abstract Model

In order to model the complex human system, a basic model has been developed which consists of a single agent. This agent is a landowner. In the following paragraphs, we develop a formal mathematical model in which we strive to depict an agent's (landowner's) actions. The enviroment and other external influences are also considered.

Let A $(a_1, a_2, \ldots, a_n)$ represent the set of actions available to individual landowners. These actions include those available when landowners perceive a threat to their vicinity (environment). For example, an individual can perform no action, protest individually or organize into associations.

Landowners are assumed to view the state of their vicinity (environment) by evaluating it with respect to a set of factors $(F_1, F_2, \ldots, F_n)$. For example, one factor is the intensity of residential development in their neighbourhood. Each factor is assumed to have a finite number of possible levels, reperesented by $(f_1, f_2, \ldots, f_n)$. Therefore, at any time, landowners perceive their environment to be in a state characterized by a n-tuple of factor levels. A typical landowner perception of the environment is given by $F_1{=}f_1, j_1,\ F_2{=}f_2, j_2,\ \ldots\ ,\ F_n{=}f_n, j_n$.

Given a preceived threat to their environment or a proposed action by another agent, landowners evaluate the potential consequences of that threat and selects an action by constructing a probability measure on the possible future state of the environment. Denote this probability measure by $p(t, a_i)$.

The preferences and value trade-offs of landowners for different states is expressed by a utility function. Moreover, to account for the trade-offs between the desire for various environmental states and the costs associated with the actions necessary to achieve or maintain these states, each landowner is assumed to have a utility function. For example, if $u(a_i, f_1, ..., f_n) > u(a_j, g_1, ..., g_n)$, then the landowner prefers action-state pair $u(a_i, f_1, ..., f_n)$ over $u(a_j, g_1, ..., g_n)$.

Given a threat t, a landowner evaluates the value of an action with respect to it's expected utility.

$$u(a \mid t) = \sum_{f_1,\ldots,f_n} u(a, f_1, ..., f_n) * p(t, a)(f_1, ..., f_n)$$

Figure 4 shows an influence diagram for a sample decision model.

3.2 An Example

In this section, we examine a sample scenario in biocomplexity and we try to model it using agent based modeling.

In our toy model, we have only two agents. They are represented by A_1 and A_2. A_1 is the government and it has the authority to issue lumber cutting permits. A_2 is a lumber company. Figure 5 shows a block diagram of our model. In the figure, "HS" and "NS" stand for the human and natural systems, respectively.

A_1 tries to control forest fragmentation as prescribed by the government guidlines and regulations. A_2 tries to increase the number of permits so it can maximize it's personal revenue. Clearly, these two agents fall into two very different catagories. They both have very conflicting goals. A_1 tries to minimize and control forest fragmentation by issuing a limited number of permits. At the same time, it

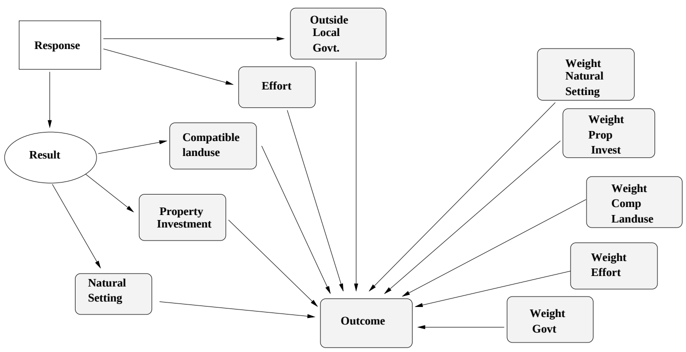

Figure 4: An Example Decision Model

wants to maximize employment of the region for acquiring local support. If A_1 issues more permits, A_2 can hire more people and consequently, there will be less unemployment but at the same time, there will be more forest fragmentation.

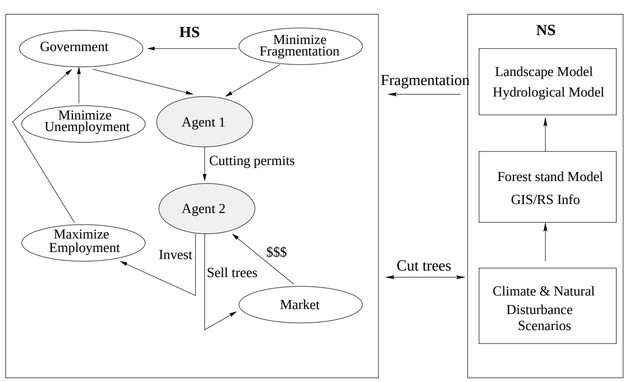

Figure 5: Human and Natural Systems

3.3 An Example Implementation

The preferences and value trade-offs of an agent are represented by a *preference structure*. In the example discussed above (in section 3.2), we can envision the two agents (A_1 and A_2) having different preference structures. Preference is a loosely defined concept [13], so to choose one behavior over others, a numerical utility function is usually defined (see section 3.1).

In the following code sections, a preference structure of an agent is created. The random nature of the code allows for greater flexibility when creating preference structures for different agent types. The second code section defines a new class for storing a value for each preference attribute.

Code Section 1

```
// AgentPreference.java
// Inputs the preference structure of an agent

import swarm.Globals;
import swarm.defobj.Zone;
import swarm.objectbase.SwarmObjectImpl;
import java.io.*;
import java.util.*;

public class AgentPreference extends SwarmObjectImpl
{
  // some variables
  private int totalElements;
  private int preferredElements;
  private Vector preferenceTable;

  // constructor
  public AgentPreference(int totalElements)
  {
    this.totalElements = totalElements;
    // randomizing the preferences
    preferredElements = 1 + (int) (Math.random() *
        totalElements);

    // giving weight to each element
    int totalWeight = 100;
    int eachWeight = totalWeight/preferredElements;

    //initializing the preferences
    preferenceTable = new Vector();
    // PreferenceStructure class defined below
    PreferenceStructure ps;
    for(int i = 0; i<totalElements; i++)
    {
      ps = new PreferenceStructure(i, 0);
      preferenceTable.addElement(ps);
    }

    for(int i = 0; i <preferredElements; i++)
    {
      if(i == preferredElements-1)
      {
        ps = new PreferenceStructure(i, totalWeight);
        preferenceTable.set(i,ps);
        continue;

      }

      // randomly adding weight to each element
      int thisWeight = 1 + (int) (Math.random() *
         eachWeight * 1.5);
      ps = new PreferenceStructure(i, thisWeight);
      preferenceTable.set(i,ps);

      totalWeight = totalWeight - thisWeight;
      eachWeight = totalWeight/(preferredElements -
        (i+1));
    }
  }

  public String toString()
  {
    return totalElements + ":" + preferredElements +
        ":" + preferenceTable.toString();
  }

  public Vector getPreferenceTable()
  {
    return preferenceTable;
  }

}
```

From the above implementation, it is clear that we can create a preference structure for a single agent using this simple algorithm. In future, we plan to extend the present model and introduce several more agents. Due to the ran-

Code Section 2

```
// class for storing the preferences
class PreferenceStructure
{
  private int elementNumber;
  private int preferenceValue;

  public PreferenceStructure(int elementNumber,
       int preferenceValue)
  {
    this.elementNumber = elementNumber;
    this.preferenceValue = preferenceValue;
  }

  public String toString()
  {
    return elementNumber + ":" + preferenceValue;
  }

  public int getPreferenceValue()
  {
    return preferenceValue;
  }
}
```

domness of the current algorithm, we can use this same implementation to create preference structures for different agents in the hierarchical model. We have developed some toy models using the Swarm toolkit [3] [5] [7]. We believe that once we have a well-built model of the human system, we should be able to implement it using the various facilities provided by Swarm.

4 Conclusions and Future Work

Agent based modeling closely approximates the person-environment context where environment, behavior, and agents form an inseparable whole, where any change in the complex system has effects upon the rest of the system. Agent based modeling allows researchers to investigate complex adaptive systems and allows them to create artificial worlds that model activity in the natural world. Using Swarm, an agent based modeling tool, researchers design a series of rules to govern those (artificial) worlds and then send players, i.e., agents, to live under those guidlines.

In this paper, we have presented a preliminary agent based model of the human system. At the same time, an attempt had been made to investigate the interactions between the human and natural systems. We do realize that some questions have been left unanswered but we do anticipate future work on these issues. One of them is the representation of external threats that trigger the simulation. In our current implementation and algorithm, we consider only one agent and different set of rules that govern the behavior of this agent. In future, however, we would like to introduce multiple agents to our modeling. In addition to this, we will also develop an agent negotiation protocol that will help them come to a common decision and we will observe their aggregate effect on the environment.

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