# Multi-agent CHANS: BDI Farmer Intentions and Decision Making

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**Abstract.** This paper extends previous works on multi-agent-based simulation models of Coupled Human and Natural Systems (CHANS), by introducing a farmer agent model capable of interact with environmental, economic, and spatial variables in the context of supply and demand of environmental services. Emphasis is made on how the Farmer Agent implements the BDI framework (Believes, Desires, and Intentions) at its core. Also, insights about its decision-making mechanism based on fuzzy logic are provided. Preliminary results are shown in terms of modulating variables such as knowledge, money, well-being, energy, and productivity.

**Keywords:** Complex-environmental systems · Multi-agent systems · Emotional BDI · Multi-agent simulation · BDI agent · Fuzzy logic

## 1 Introduction

The incorporation of models of human decision-making processes in social simulations is a powerfull strategy to understand the effects of human adaptive behavior on global simulation outcomes. In Coupled Human and Natural Systems (CHANS) systems, the focus consist in jointly model humans with communities and their interactions with the territory, following realistic observed patterns, in order to enhance the comprehension of human decisions regarding ecology and how these decisions can be formalized in models created by Schluter et al. [12]. However, this type of modeling is complex due to the multifactorial nature of the human decision-making process concerning ecology, as it involves economic aspects, non-economic benefits, social influence, social impact, emotions, uncertainty, knowledge about the environment, spatial location within the ecosystem, among other factors [5]. There are two predominant approaches to include the individual's decision processes in CHANS simulation models: bio-economic and agent-based models. Bio-economic models focus their attention on investigating questions related to optimal decision making as a function of


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temporal variability in natural resource dynamics. Probabilistic and risk estimation techniques, uncertainty analysis, among others, are used. In addition, these models seek to represent the concepts derived from ecological economics, which, according to Schluter, allows a more realistic modeling of ecological dynamics and the ethical aspects involved in the sustainability of non-renewable resources.

In contrast to the focus on the study of risk in bio-economic models, agent-based models (ABM) allow modeling the social interactions between multiple entities immersed in the simulation, while incorporating decision-making models. In this way, an approximation towards models of human behavior is possible, since agents representing human beings can "actively reevaluate their beliefs, values and functioning to adapt to unexpected environmental changes" [3]. Indeed, systematic literature reviews identify different categories of agent-based decision-making models applied in social simulation: production rule systems, psychologically and neurologically inspired models, BDI models and derivatives [9], normative and cognitive models [2]. An example of psychologically inspired decision-making architectures in CHANS is the one proposed by Malawska and Topping, with a focus on incomplete rationality. Each farmer agent is assigned one of the following objectives: profit-maximizing, yield maximizing, environmentally friendly. Additionally, each agent is assigned one of the following harvesting schemes each year: deliberation, repetition, imitation, or social comparison. The deliberation decision mode is based on a simplified form of micro-economic optimization. The architecture includes a rule to switch to a deliberation strategy if the price of a crop varies by 20% [6].

The objective of this work is to explore in-depth the BDI farmer agent presented in a previous work [8], to explain in more detail the decision-making mechanism as well as preliminary results regarding the modulation of variables such as knowledge, money, emotion, well-being, energy, and productivity. Thus, the structure of the paper is as follows. Section 2 presents the state of the art giving a context on social simulation and the BDI paradigm, whilst details of the interaction of the farmer agent with the Multi-agent-System (MAS) are given in Sect. 3. Meanwhile, the architecture of the model are presented in Sect. 4 and the specific details about the decision-making mechanism are highlighted in Sect. 5. The final two sections were left for results and conclusions.

## 2 Social Simulation and BDI Architectures

Despite considerable work applying classical dynamical systems models in ecology, agent-based models have demonstrated advantages in CHANS simulations, particularly in land use applications. For instance, Matthews et al. [7], compiled the main advantages described in the literature on the use of ABM for land use modeling, highlighting the following: the ability to couple social and environmental models, incorporate the influence on environmental management of micro-level decision processes, study emerging collective responses to environmental management policies, ability to model decision making at different levels (individuals and organizations), model adaptive behavior at the individual and system level. In this same work, the authors distinguish five categories related to land use, in which ABM models have been performed, namely: policy planning and analysis, participatory modeling, characterization of spatial patterns of land use or settlements, evaluation of concepts derived from social sciences, and explaining land use functions.

Agent-based models exhibit distinguishable characteristics like the search for the fulfillment of predefined objectives and the structured representations of the processes involved in the decision-making mechanism. In fact, rational agents can incorporate a mental state that allows them to make decisions according to contextual situations. This ability of ABMs can be modeled through BDI paradigm (Believes, Desires and Intentions) [9], showing interesting results in the context of social simulation because its capability to represent complex human behavior as Adam's work stated [1].

In addition, other desirable features of social simulation-oriented ABMs are posited as the following: (i) getting the agent to modulate its decision-making process by incorporating a representation of emotions in its mental state (emotions can determine the agent's ability to want to do things and work to achieve them), consistent with recognized psychological theories to bring the agent closer to bounded rationality; (ii) incorporating the representation of uncertainty in decision-making; (iii) maximizing cooperation and coordination between agents; (iv) adding a module that allows the agent to evaluate social norms and cultural values; (v) getting the agent to modulate its decision-making process through individual and collective learning. This last point is emphasized since it is desirable to model the effect that the community has on individual and collective decision-making. In this way, the concept of the social fabric and the effect of collective action on an agent's decision-making could be incorporated.

## 3 Multi-agent Farmer Interaction Model

This section will describe the multi-agent system and the interactions of the farmer with the other implemented entities. To define the design and behavior of the entities, the AOPOA methodology [10] was applied (this is an approach for agent-based programming with a organizational orientation of recursive decomposition of roles and goals), resulting in the generation of roles or sub-roles of agents, events, objectives, abilities, resources, and tasks of the multi-agent system. Being the entity Farmer as the main agent in the simulation, its role and the interactions it has with the other entities in the simulation will be detailed below.

### 3.1 General Vision of MAS

In the simulation developed, eight major roles interact (farmer, consumer, market, farm, associations, disturbances, private) as represented in the Fig. 1. These roles are decomposed into sub-roles, some implemented with BESA [4] or BESA-BDI agents and others as cellular automata in the case of land use and cover

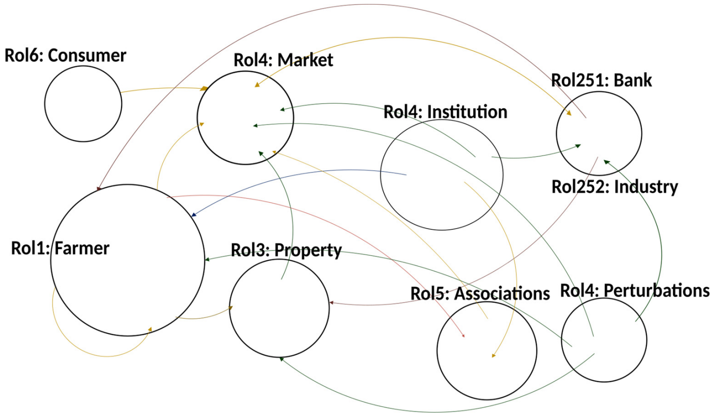



**Fig. 1.** Multi-agent CHANS SimSAC, Roles and high-level interaction flow.

(plant and/or mineral), water, air, and temperature, these will not be addressed in this article. BESA it's a Java library used to build multi-agent systems, ready for extensions like BDI and others, made by researchers in the Pontificia Universidad Javeriana. Next, the interactions of the Farmer Agent with the other entities in the simulation will be detailed.

### 3.2 Farmer Interactions

The farmer agent was implemented with a BESA-BDI architecture, whose goals are to maximize its welfare and the optimization of benefits when developing its productive activities. Throughout the simulation, the farmer can play a sub-role as an agricultural, mining, livestock, or ecosystem services producer. To achieve its goals, the agent must interact with the other entities that are part of the simulation, it interacts directly with six of the eight entities in the model and with itself, in the Table 1 the agent with whom it interacts and the description of the possible interaction are listed.

The simulation model takes into account social, economic, and environmental interactions, among others, to achieve the prioritized goals. Social interactions can achieve associativity among peers. It is also possible to observe how institution-type entities can exert influence through training and modify the beliefs of the Farmer agents, achieving incentives and improving their welfare.

## 4 Farmer's BDI Goal Model

The architecture of the model shows how a BESA-BDI agent (Farmer), based on a fuzzy reasoning system, incorporates its beliefs, desires, and intentions based on the interaction processes among the other agents, starting with those closest to it or having common interests, through its role. These can also change

**Table 1.** Multi-agent CHANS SimSAC - role descriptions

| Agent | Description |
|---|---|
| Farmer | Demand or supply of products |
| Property | Soil exploitation or conservation |
| Market | Demand or supply of products or services and this in turn sells it to consumers |
| Institution | Receives environmental or regulatory influences, in addition to the supply of public services |
| Association | Product demand or supply |
| Bank | Make or collect loans |
| Industry | Demand for or supply of products or services |
| Perturbation | Receives negative or positive influences from the environment |

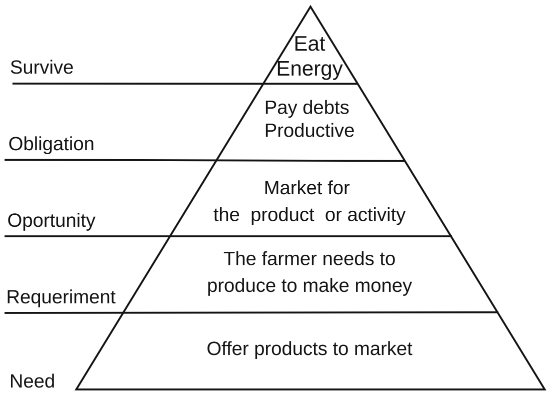



**Fig. 2.** Hierarchical pyramid of BDI goals

with the interaction with other external agents such as the market, institution, associations, industry, or banks. These can modify the BDIs of the financier agent based on the interaction and the financier's objectives, which change as he interacts, incorporating data and information to act, either with other agents in the same role or in a different one, or to perform actions on the automatons.

There is a disturbing agent that randomly generates events in the system, and that generates a positive or negative influence in the BDI reasoning, affecting directly in the decision-making process. The farmer agent is guided by a pyramid of priorities as shown in Fig. 2, this process is described in more detail in the Table 2. For example, in the case where the farmer agent has no energy to work and fulfill a goal related to making money by planting, it is necessary to execute the action of eating, the survival of the agent takes precedence over the productivity needs, this decision-making process will be explained in the next section in more detail.

The general process for the execution of the BDI model in the Farmer Agent is presented below, followed by a description of the beliefs and goals established in the model for reasoning and decision making.

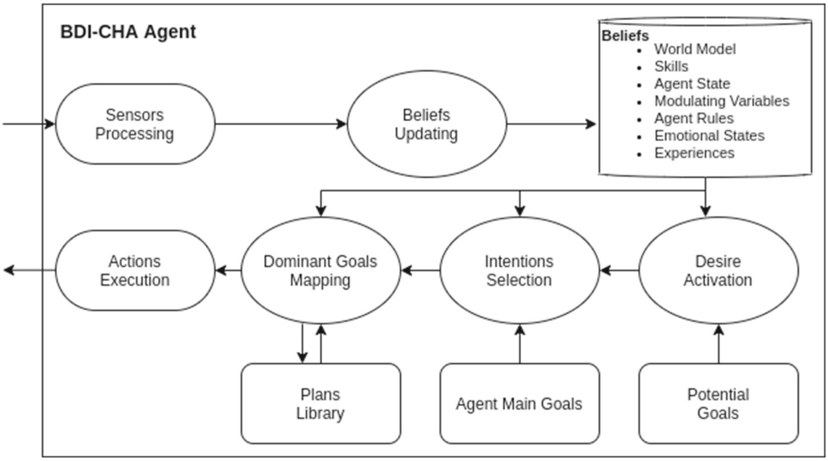



**Fig. 3.** BDI process

The overall goal execution flow process is based on the BDI-CHANS architecture and differs from a traditional BDI architecture in the proactivity with which beliefs, desires, and intentions are handled. To achieve this, agents include multiple threads running concurrently; there is also a series of internal events to update beliefs, evaluate goals, launch plans, or perform goal modification.

The Farmer Agent, represented in the Fig. 3, detects the conditions of its environment using different types of sensors, processes and shares the information with the process **Beliefs Update**, this process has the database of the Beliefs, composed by the model of the world, skills, the state of the agent, the modulating variables, the experiences and the rules of the agent itself. Once the Beliefs are updated, the **Desire Activation** process starts, in this process, the **Potential Goals** are analyzed and according to their activation function (consulting the Beliefs) the goal with the best valuation is activated, becoming a desire. Once the goals are activated, they go to the process of **Intention Selection**, in which the contribution is measured by evaluating the current state of the world (Beliefs) and the pyramid of priorities (explained in the decision-making model), concerning to **Agent Main Goals**. When the intent is selected, **Dominant Goals Mapping** selects an action or a set of these from the **Plans Library** to be executed or updated with an improvement for its next use.

**Table 2.** Farmer goals by BDI priority pyramid

| Goal type | Goal | Activation | Action triggered |
|---|---|---|---|
| Survival | Farmer agent must eat | No energy | The ability to feed is activated |
| | Farmer agent must work to earn money | Improve their conditions | Working in productive activity |
| Obligation | Farmer agent must pay bank obligations | Time to pay the debt | Check if you have money to pay, and pay |
| | Farmer agent must take care of his productive activities | Definition of productive activities | Technical knowledge and change to the desired activity |
| | Farmer agent must cultivate the soil | Crop demand | Learn about agriculture |
| | Farmer agent must work his livestock | Demand for livestock | Learn about livestock |
| | Farmer agent must work his mine | Mining demand | Lear about mining |
| | Farmer agent must take care of his Ecological service | Demand for ecosystem services | Learn about ecosystem services |
| | Farmer agent must consult the market price system, demand and supply of products | Pre-requisite of an economic activity to be performed | Negotiation of product purchase |
| Opportunity | Farmer agent must attend the trainings offered by the training entity | Being encouraged to be socially responsible Need to be trained to carry out an economic activity | Technical knowledge of ecosystem services |
| | Farmer agent must review the opportunity for assistance in the development of sustainable projects | Being encouraged to be socially responsible | High environmental and ecological awareness and technical expertise |
| | Farmer agent must partner with others to sell their products | There is a market for the product or activity | Sales and business persuasion skills are activated |
| Requirements | Farmer agent must apply for a loan in order to have money and develop his activity | The farmer needs to produce and has no money to invest | He asks for a loan from the bank |
| Needs | Farmer agent must sell his products | Offer the market | Negotiation and sale |

## 5 Decision-Making Model

The decision-making model in this simulation is an integration of the BDI architecture, presented before, with a Mamdani fuzzy logic inference system. The fuzzy rules are used to evaluate the agent state using the information registered in the believes. This evaluation process is achieved by using modulating variables and making decisions by applying fuzzy logic techniques as described below. The agent state is used to active and measure the contribution of the agent's goals. Then, the final action decisions are taking into account the goals according to the pyramid of priorities in which the base (or lowest priority) is the needs, moving up to the requirements, opportunities, obligations, with the highest priority being the survival of the agent itself.

### 5.1 Modulating Variables

A variable is considered to be a modulating variable when it is used to modify the value it contributes to an independent variable over a dependent one used to take decisions. In this case, they are used to quantify the status of the Farmer Agent in the decision-making process. The farmer's modulating variables are:

**Activity type** - the agent has the option to change his productive activity according to the influence of the received training, trying to maximize his investment and improving the quality of life of his family.

**Personal variables** - the agent can select the best way to use his property taking into account the environment and the implication of his decisions.

**Terrain-dependent variables** - the agent is influenced by its neighbors and by the basic needs satisfied by them.

**Opportunity** - the agent's opportunity goals are related to the development of productive activities that minimize environmental impact. This is achieved by improving the agent's knowledge, raising environmental awareness, or receiving an economic incentive for carrying out these actions.

**Need** - the need for training, sale of products, money for the development of their activity, and access to loans.

**Survival** - the agent must be attentive to his daily feeding and direct survival.

**Obligation** - the agent must pay bank obligations, carry out productive activities, take care of his family, check prices, available offers, and demand for market products.

**Requirements** - the agent must apply for loans from the bank to develop its activity if required.

These modulating variables define the values stored in the beliefs of the BDI Farmer agent and are necessary to determine the predominant goal at any instant of time. These variables are knowledge of the productive activity, level of proactivity, energy, emotional situation, well-being, and the amount of money available for basic needs or to develop productive activities.

The modulated variables change value as the simulation progresses and alter the beliefs of each agent as it interacts with other agents or its environment.

As beliefs change, intentions are also updated and prioritized differently, executing different actions according to the agent's internal decision-making process. This process was designed by applying fuzzy logic techniques as it is possible to apply reasoning in levels of uncertainty like humans, explained in the next section.

### 5.2 Decision Making with Fuzzy Logic

The decision-making process, used to evaluate the farmer goals, was implemented based on fuzzy logic inference. A set of simple fuzzy rules was generated, based on expert knowledge. The rules are if-then sentences, which approximate a fuzzy reasoning process that simulates the dynamics of each of the key decision variables of the farmer.

Figure 4 shows an example of two of the fuzzy variables, related to the six modulated variables of the Farmer Agent, that are used in the reasoning process. By applying four simple rules (see an example in Proposition 1), once the defuzzification process is done, the agent can calculate the level of productivity achieved in some commercial activity such as planting, selling or buying products.

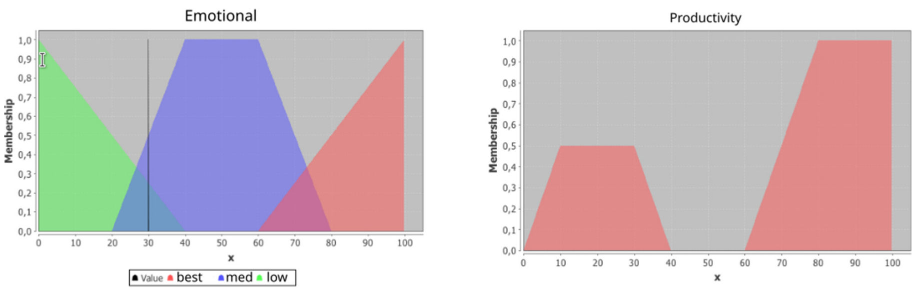



**Fig. 4.** SimSAC decision making: fuzzy

**Proposition 1.** *IF emotional IS best OR knowledge IS best OR money IS med OR energy IS best THEN production IS high.*

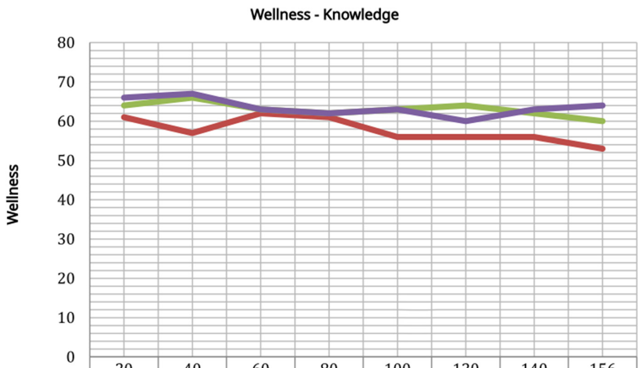
For example, a Farmer Agent might have 50% of his knowledge in agriculture, which may vary according to the occupation of activity, he has 50% of the money, money increases or decreases according to the sale, purchase, and welfare expenditure, 80% of energy, which may decrease in proportion to the day and the activities he performs, and 40% of welfare. Well-being is conditioned to the fulfillment or satisfaction of basic needs and increases depending on whether the farmer has more income. Emotional level 30%, calculated according to their level of work, well-being, and energy. If these are the values of the farmer's modulating variables at time $t$ of the simulation process, the productivity level is calculated using the fuzzy inference system; in this case, a result of 62.92% is obtained for the variable associated to the agent's productivity level.

This fuzzy oriented approach is very useful, as it allows to express in a very intuitive and understandable way, closer to the real world situation, the relations between the key variables associated to the farmer's decision process. A more detailed explanation of the fuzzy decision system is out of the scope of this paper.

## 6 Results

An experiment was designed in which 156 plots were created in the upper basin of the Rancheria River (using data from [11]) and one was assigned to each farmer. Then, the modulating variables of the farmer, such as knowledge, money, emotion, well-being, energy, and productivity, were configured. These variables change as the farmer interacts with other agents or with his context.

In the experiment was used as independent variable the number of agents, the dependent variable was the welfare of the Farmer Agent and the intervening variable, fixed for each experiment, was defined as the level of initial knowledge of the Farmer agent, using qualitative values low, medium, high. The simulation was run with the same number of agents for five periods (five years), with a factorial design, starting with 20 agents and increasing up to 156.




| | 20 | 40 | 60 | 80 | 100 | 120 | 140 | 156 |
|---|---|---|---|---|---|---|---|---|
| Low | 61 | 57 | 62 | 61 | 56 | 56 | 56 | 53 |
| Med | 64 | 66 | 63 | 62 | 63 | 64 | 62 | 60 |
| High | 66 | 67 | 63 | 62 | 63 | 60 | 63 | 64 |

**Fig. 5.** SimSAC results: wellness-knowledge

The results can be seen in Fig. 5. The simulation response shows characteristics of emergence and self-organization, with a very slight tendency towards welfare. Although it is clear, as expected, that agents who start with higher knowledge tend to retain a higher degree of welfare, and the more agents with low knowledge, the lower their welfare.

## 7 Conclusions

A recently addressed aspect in the CHANS literature consists of simulating the potential effect of the decision-making processes of agents that represent human individuals in order to model causality between humans beings actions and ecology systems sustainability. Therefore, for a given scenario of ecosystem services, biodiversity, and productivity, this approach can be very useful to predict both economic and environmental impacts.

Based on a project that was implemented in the Rancheria river basin, real data is used to verify in an experimental and controlled way how the BDI Farmer Agents exhibiting opportunity behavior to attend training can increase their level of knowledge, which therefore leads to an increase in their well-being. However, the evidence from the experiment pointed out that in the case of the BDI Farmer Agent, it is not necessarily enough to have excellent knowledge, but on the contrary, behavioral modulating variables such as emotions, money, productivity, and their energy, are fundamental in the generation of levels of well-being or others that can be combined in the CHANS simulator model, to obtain environmental prediction scenarios.

In this work, lines of action were shown that would allow us to understand from a more holistic point of view, the relationship between agent's decision-making processes and the nature of changes in terms of land use, consumption of ecosystem services, or productivity. Despite, it is not clear yet the effect that the community has on decision-making to an individual and collective level, BDI Farmer Agents can incorporate the social fabric concept and the effect of collective action on the decision-making of a unique agent. In this way, one of the most significant contributions of this work consists in highlighting the importance of CHANS research, incorporating the representation of decision-making process based on BDI architecture involving modulating variables of the internal state of the agent as knowledge of the productive activity, level of proactivity, energy, emotional level, well-being, and the amount of money available for basic needs or to develop productive activities. Future work will include a more complex model of the influence of the community in the agent's decisions by incorporating new interactions between farmers, modulating variables and rules that will modify the evaluation of the agent's goals.

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