A Model and Simulation Framework for Exploring Potential Impacts of Land Use Policies: the Brazilian Cerrado Case

Carolina G. Abreu	Cássio G. C. Coelho	Célia G. Ralha	BrunoMacchiavello
University of Brasília	University of Brasília	University of Brasília	University of Brasília
carolabreu@unb.br	cassio@cic.unb.br	ghedini@cic.unb.br	bruno@cic.unb.br

Abstract

Land use and cover change (LUCC) research is important to support insightful management of Earth's land use to avoid irreversible damage. However, LUCC is a complex process that relates the interaction between natural and social systems at different temporal and spatial scales. Nevertheless, the representation of different interaction patterns through agent-based modeling and multi-agent systems can contribute to decision support for sustainability that are essential to a better understanding of real environmental problems, including social, economic and physical aspects. Thus, this article presents the use of a Multi-agent System for Environmental Simulation (MASE) for exploring potential impacts of land use policies. MASE is a freeware multi-agent model system to simulate LUCC dynamics that is illustrated with the Brazilian Cerrado case. Considering the experimental results, we consider that MASE represents an interesting alternative for LUCC decision support.

1. Introduction

Land Use and Cover Change (LUCC) processes are amongst the most pervasive and important sources of recent alterations of the Earth's land surface [1]. It might be defined as a complex process caused by the interaction between natural and social systems at different temporal and spatial scales [2]. LUCC research aims to support insightful management of land resources in order to avoid irreversible damage [3].

Agricultural systems are a broader general type of LUCC problem, since they involve the consideration and inter-relationships of food, energy, fiber and other ecosystem services. There is a critical need to expand or intensify land use to meet increasing demand for agricultural production worldwide, while preserving ecosystem structure and function. Although public opinion strive for zero deforestation, there is still much debate around LUCC consequences. For some, economic benefits of current deforestation and the land uses that replace natural vegetation outweigh any environmental benefit of standing forests. Governments of different countries hope to enter into an agreement that would enable the effective formulation of actions and policy directions. To aim for environmental sustainability while ensuring or maintaining economic development is even more concrete in a regional scale. There is a real need for an understanding of how relative land use/cover policies affect general economic productivity and the outcomes for the environment.

Sustainability may be defined as meeting the needs of the present without compromising the ability of future generations to meet their own needs [4]. Recent researches reinforced the role of information technology on improving environmental sustainability in terms of information, representation, organization, innovative strategies and evaluation of systems that break new ground in environmental responsibility [5; 6]. Thus, policy makers and governmental planners in the LUCC sector start to rely on software, such as simulators, to do analyses of land resources and prepare the stakeholder dialogue on LUCC management decisions [7].

In this direction, two different agent based techniques that can contribute to scenario analysis and decision support for sustainability are agent-based modeling (ABM) [8; 9] and multi-agent system (MAS) [10; 11]. The agent representation of different interaction patterns is essential for a better understanding of real environmental problems, including social, economic and physical aspects.

MAS explicitly represents human decision-making processes by means of agents, represented as autonomous computer entities interacting directly with themselves and the environment, in order to achieve goals [12]. The use of MAS in LUCC can inform policy setting and decision-making processes

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on the use and management of land resources. The simulation results can represent the causal chains and feedbacks of LUCC, and thus be used as learning instruments for understanding the system dynamics and to explore future scenarios by testing the effect of land policies [13].

According to Gray et al. [14], software that integrates environmental modeling, stakeholder knowledge and decision making investigation is currently lacking. In order to address this critical issue, this paper presents a MAS to model and simulate LUCC dynamics. The Multi-agent System for Environmental Simulation (MASE) prototype effectively illustrates the environmental, economic and social dynamics while driven by regional management policies. MASE aims to assist analyzing LUCC dynamics using technical information to aid the decision making process. We performed a case study to explore the potential impacts of the recent changes in the Brazilian Forest Code and other regional land use policies in land use and cover of the Cerrado (Brazilian savanna). The results show how politics could influence the LUCC dynamics. We discuss how stakeholders and decision makers could use the framework and analyze different scenarios to support sustainability. Our approach is able to integrate stakeholder or expert knowledge, empirical and process-based spatial explicit models and national and regional policies datasets.

This paper is organized as follows: Section 2 recalls basic concepts on MAS, modeling, simulation and comparison framework to decision-making; while Section 3 explains MASE. Section 4 reports the LUCC study case and Section 5 discus the results and their implication to environmental management. Section 6 summarizes the findings and suggests future research issues.

2. Background

The MASE design framework draws upon three distinct but related theoretical and practical uses of MAS through the role of modeling and simulation. A comparison framework is also presented, highlighting, in particular, decision-making processes.

2.1. Multi-agent system

The MAS discipline is related to the distributed artificial intelligence area in Computer Science. A MAS is interested in the behavior and management of agents, which work together in groups or individually in an independent way [15]. An agent can be viewed as an entity that is situated in some environment, being capable of autonomous actions in this environment in order to meet its design objectives. In addition, an intelligent agent communicates with other agents in a distributed environment using a cooperative or competitive relationship approach [16].

Agents are autonomous entities. They are forced to coordinate their activities to avoid negative interactions exploiting synergic potentials. That is where the real potential of this technology becomes unleashed [17]. An important reason for growing success of multi-agent technology is its potential to cope with high complexity problems in dynamic and distributed environments due to their flexible and adaptive behavior [18]. MAS had been used to solve many problems with their features, mainly complex and real-life problems.

2.2. Modeling and Simulation

There are some clear differences between modeling and simulation. A model is intended to provide a precise and unambiguous description of a designated part of reality, written in a certain language, which can be formal or natural [19]. Environmental models are usually complex and might be addressed in a quantitative or qualitative approach. Quantitative models intend to replicate the behavior and interaction of key elements and processes of the natural systems under study. Qualitative or conceptual models aspire to undercover the causality chains and feedbacks among the elements.

The objectives of modeling in the environmental context are described by [14] as: (i) problem clarification and enhanced communication among scientists, managers, and other stakeholders; (ii) policy screening to eliminate options that are most likely incapable of doing much good, because of inadequate scale or type of impact; and (iii) identification of key knowledge gaps that make model predictions suspect.

Simulation tools use models for automated calculation and visualization of scenario outcomes [20]. Simulation is a central aspect of decision support for it provides information on the likely outcomes of alternatives from which policy makers and governmental planners can ground their decisions. Reynolds and Schmoldt [21] emphasize the visualization output of a simulation tool as the main feature to provide decision support. It could ultimately contribute to help stakeholders and decision makers arrive at reasoned and reasonable decisions about forest resource management.

Together, modeling and simulation have the potential to increase the intelligence and efficacy of environmental management. ABM and simulation has been proved particularly beneficial to decision-making [22].

2.3. Comparison framework to decision-making

Agarwal et al. [23] developed a detailed study of models and tools that involve human interactions and environment after analyzing tendencies and methodologies. As a result, they present a review and assessment of scale and complexity considering three dimensions: space, time and human decision-making. Space and time provide a common setting in which all biophysical and human processes operate. Most models also incorporate human processes, referred to as the human decision-making dimension. According to this study, the ultimate goal for modeling the dynamics between man and the environment involves high complexity in those three dimensions.

The modeling and simulation frameworks show a lot more convergence when comparing temporal and spatial dimensions of the models. The main characteristic that set them apart is how to incorporate decision-making in them. To discuss human decision-making, the authors parameterize the complexity of a model using an index with six levels, in order to represent the choices of how decisions are made and how these decisions influence the next step of the simulation (Table 1). The MASE system was designed to achieve the sixth level of human decision-making complexity, as described in the next sections.

3. MASE

MASE is a MAS for environmental simulation based on a hybrid modeling technique. MASE enables modeling and simulations of LUCC dynamics using a configurable user model and both top-down and bottom-up structures [13].

MASE was defined using a two-fold methodological approach in order to form a solid backbone based on: (i) the systematic and structured empirical characterization of the model [24]; and (ii) the conceptual structure definition according to the agent-based model documentation protocol - Overview, Design concepts and Details (ODD) [25]. For a complete description of MASE multi-agent model system for land-use change simulation, see [26].

Considering MAS methodologies, we adopted TROPOS [27], which allows incorporating system requirements to the ODD protocol for documenting MAS. The TROPOS diagrams are not included in this paper, since the development of MASE is not the focus, but the methodological aspects involved in the definition of the model that can be replicated in other LUCC simulation packages.

The empirical characterization and the conceptual structure of the model were defined by a group of ecologists from the University of Brasilia (UnB) and from the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA). The motivation behind this group was to forge the MASE system by its potential users: researches and land-use decision makers.

For the definition of MASE architecture, different classes and sub-classes of agents were defined (see Table 2). Each agent class is related to the definition of entities responsible for specific decision-making, execution of actions, perceiving the environment and the execution of the time-steps in the simulation. Six classes of agents were created at MASE prototype.

Table 1. Six levels of human decision-making complexity (Adapted from [23])

| Level	Description
1	No human decision-making (HDM) — only biophysical variables in the model
2	HDM assumed to be related determinately to population size, change, density
3	HDM as a probability function depending on socioeconomic and/or biophysical variables beyond population variables **without** feedback from the environment to the choice function
4	HDM as a probability function depending on socioeconomic and/or biophysical variables beyond population variables **with** feedback from the environment to the choice function
5	One type of agent whose decisions are modeled overtly in regard to choices made about variables that affect other processes and outcomes
6	Multiple types of agents whose decisions are modeled overtly in regard to choices made about variables that affect other processes and outcomes; the model might also be able to handle changes in the shape of domains as time steps are processed or interaction between decision-making agents at multiple human decision-making scales
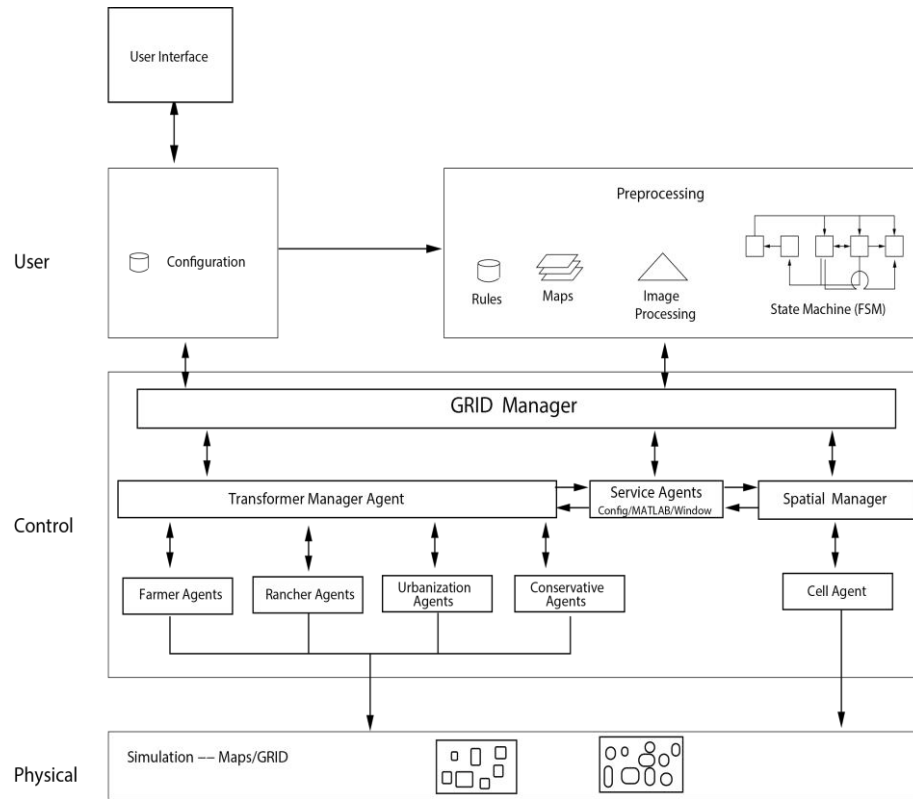
Figure 1. Three-layer MASE architecture (Adapted from [26])

The main actions performed by each of these classes are summarized as follows:

(i) GRID Manager (GRIDM): Promote interface parameterizations defined by users; Manage start, pause and end of agents; Receive agents state for the visualization; and Promote agents state visualization for the user.

(ii) Spatial Manager (SM): Set the instances of cells to simulate; Get orders from GRIDM and replicates to cells; Receive the states of cells and replicates to GRIDM.

(iii) Transformer Manager (TM): Set the instances of TA for simulation; Get orders from GRIDM and replicates for TA; Receive TA states and replicates to GRIDM (iv) Cell Agent (CA): Receive tasks from SM; Inform state to SM agent; Begin land/vegetation recovering or stop it; Signal whether or not TA occupies land.

(v) Transformer Agent (TA): Receive tasks from TM; Inform state to TM agent; Request position change to TM agent; Moving from one cell to another; Explore the cell; Identify if cell has exhausted its ability to be exploited.

(vi) Conservative Agent (CoA): Perceive the state of a cell; Receive tasks from TM; Receive messages; Wait on exploration; Recover the vegetation of a cell; Identify if a cell must be preserved.

All the classes can be expanded or new instances of these classes can be created, as the modeling of different behaviors of agents are found necessary. Linked to each class of agents there are images with the spatial domain to the native class, for example, the map of urban areas are associated with urban agents, forming a specific level of simulation.

One of the paramount definitions during a MAS project is the environment characterization. We have used the classical environment characteristics proposed by [28] and [16]. Although our approach deals with real environment (i.e., the geographical area over which the changes occur in coverage and use of land), the simulation grid by the agents perceptions is partially observable, stochastic, sequential, dynamic, continuous, multiagent and competitive, where several restrictions are necessary to be made in order to deal with computable model simulations. To the case study presented in Section 4, the environment has the following characteristics:

Table 2. MASE agent classes and types (Adapted from [26])

Agent Class	Type of Agent	Nº of instances
GRID Manager	Goal-based	1
Spatial Manager	Goal-based	1
Transformer Manager	Goal-based	1
Cell Agent	Reflexive agent with internal state	Set by the user
Transformer Agent	Reflexive agent with internal state	Set by the user
Conservative Agent	Reflexive agent with internal state	Set by the user

(i) Partially Observable: each agent has a restricted field of perception related to the grid cells neighborhood (i.e., adjacent cells).

(ii) Deterministic: the next state of the environment is determined by current state and the actions taken by the agent.

(iii) Episodic: time is not treated continuously. There are atomic time-steps that are considered for the simulation execution.

(iv) Static: the environment does not change while an agent is acting.

(v) Discrete: the possible transitions are defined by a finite-state machine (FSM);

(vi) Multi-agent: a set of agents with different roles and behaviors are used in the system.

(vii) Competitive: agents have interests that are competing, while the grid of resources is limited and has to be shared by agents.

Figure 1 presents the defined three-layer architecture for the MASE prototype system. The hierarchical arrangement of the agents into layers aims to organize the coordination of agents, cooperation and conflict resolution. For this reason, agents of higher levels have greater control over agents at lower levels. The user interface layer allows the configuration of the simulation model and presents the simulation results. All user-supplied configuration settings are translated into the Extensible Markup Language (XML) files and loaded into MASE, in order to start the action of agents, linking them to the other simulation layers. Through the user interface layer, user can configure which agents will be part of the simulation, adding behaviors to agents from a library available. User can also associate specific FSM to agents in order to define their behaviors. Moreover, additional rules as guidelines for global simulation are available at this

stage. The flexibility of configuration extends to the creation of the number of agents that compose each class, which interact in the space defined by the user simulation layer of each respective class.

The control layer uses the previously defined rules and settings to produce the simulation, where the logical simulation mechanisms are defined. At this layer, there is some layers overlapping, since the storage of the intermediate results is shared. The physical layer is responsible for loading the actual images and provides image attributes to agents in synchronized approach in order to guarantee threads safety and avoid image inconsistence.

As a spatially explicit model implementation, MASE can receive a set of input images defined by the user to simulate land changes. The space is represented through a grid in which each unit, or cell, is represented by a computational agent. It is a different concept from cellular automata, where each cell in the grid has a finite number of states and changes over time according to a fixed rule. The MAS allows each cell to know its own state and change according to the action of a TA and according to its perceptions of the simulation environment. As TAs may have different behaviors, neighbor cells might be under unique land use constraint at the same time step.

The development of MASE prototype was performed using the Java Agent Development Framework (JADE), version 4.0, a middleware for developing and executing applications based on intelligent agents, developed in Java [29]. For the image manipulations, we used the open source ImageJ Lybrary [30]. The agent interaction protocol used in MASE allows the simulations of cooperative and competitive agent relations. MASE is a free software developed in the UnB that aims to assist the decision making process by the use of environmental simulations. However, it is a prototype related to a running project. The software is available online for free download at: https://sourceforge.net/p/mase-unb.

4. Implications for land use policies: a study case in the Brazilian Cerrado

Recent alterations in the Brazilian Forestry Code has brought much debate in land use policies and its effects on the environment. Effective legal reserve requirements for rural properties are 80% in the Legal Amazon, but only 20% in all other regions, such as the Brazilian Cerrado biome.

Even though much of the attention of conservationists has focused on rainforests such as the Amazon and Atlantic forests, the Cerrado is

currently one the most threatened biomes of South America due to the rapid expansion of agriculture [31]. Soybeans and soy products are amongst the largest of Brazils export commodities, and the Cerrado support the largest cattle herd in the country [32]. The expansion of these activities is driven by a series of interconnected socioeconomic factors, often encouraged by government policy. Data from The Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) show a cumulative loss of 47.8% of the Cerrado natural vegetation cover (around three decades). Experts point out that there is a conservation effort far below the real needs of the biome. Only 2.2% of the territory occupied by the Cerrado is legally protected [32].

The LUCC of Brazilian Federal District Cerrado was chosen as a study case for its 68.11% of 5,789 km² of native vegetation cleared even when 90% of its area is protected by law in the form of protected areas of strict protection or sustainable use. The input of the simulation used two maps: the initial time (2002 − t0) and a subsequent time (2008 − t6). The maps were obtained by a semi-supervised classification technique of LANDSAT ETM satellite images performed by The Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) for the deforestation control of the Cerrado (Figure 2). This initial information is input into the MASE model. The yellow areas represents the anthropic used land, the green areas represents the native vegetation and the blue areas represent the watercourses.

The total area of study was divided into cells, in which every set of four cells represents one hectare, which is represented by a different CA. The physical state of the conservation of the cells is monitored and it can be influenced by six proximal variables defined by the user: (a) railway, (b) highway, (c) water course (river); (d) water body (lake); (e) street and (f) building. The input of the proximal variables is done in form of map layers that might affect the behavior of CAs and TAs.

In the simulation process, three different types of TAs represent the human factor over the land: farmers, ranchers and conservative agents. Each one has a predefined goal and behavior set by the user. The general political aspects are also taken as a compelling force in the simulation, translating the Federal District Spatial Plane (PDOT) onto an influence matrix for the agents who will change the use of the land.

Previous simulations [26] portrayed the business-as-usual scenario, where the agricultural farmers and ranchers behaviors were modelled based mainly on the expansion of the agricultural frontiers and up

scaling production. In this new study case, the effective legal requirements for rural properties, defined by the Brazilian Forestry Code, were specified as one of the agents 'beliefs'. The activity of each LUCC transformer agent was constrained by what is regulated by law. Each agent was forced to respect the 20% of legal reserve in rural properties. The conservative agents are responsible to assure the preservation and conservation of the land, according to the law. A constant natural regeneration of vegetation rate was also defined according to the specialists. The set of agent behaviors and model parameterization configured a more optimistic scenario, where the environmental policies were known and followed.
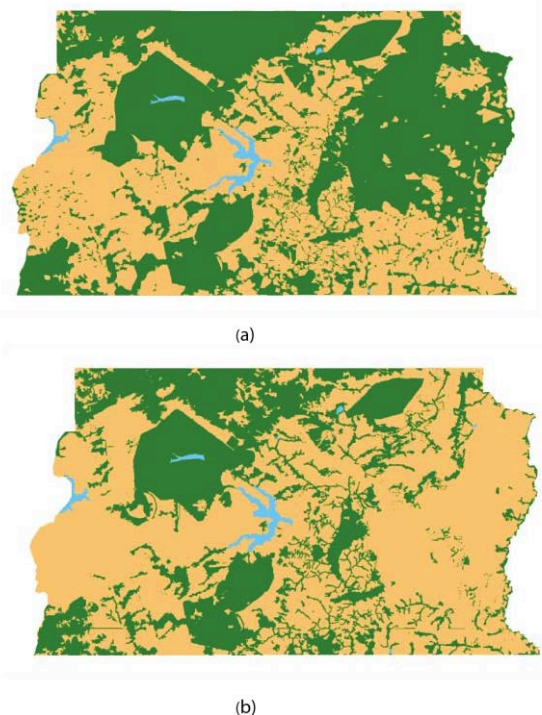

(a)

(b)

Figure 2. Land classification maps for the Brazilian Federal District, (a) 2002, (b)2008

5. Results and Discussion

The simulation results are illustrated in Figures 3-5. For each run of the simulation, the software was set with a variable number of agents, identified as Sim X: simulation with X transformation agents.

In order to compare quantitative and qualitative aspects of the multi-agent model proposed we applied two scientifically rigorous statistical techniques of map comparison to land change models. The first method, the RMSE is used to measure the differences

between values predicted by the model and the values actually observed.

From the Table 3 it can be observed that the best results are obtain with 90 agents. Moreover, all results indicate a small difference between the images. When comparing the RMSE value of the null model to our simulations, it can be seen that for 50 to 100 agents our results are significantly better.

The second method were developed by [33] to compare: (i) a reference map of initial time (2002), (ii) a reference map of subsequent time (2008), and (iii) a prediction map of the subsequent time (2008). According to the authors, the three-map comparison specify the amount of the predictions accuracy that is attributable to land persistence versus land change.

Table 3. RMSE results comparing the 2008 reference map and the predicted map.

Sim[1]	RMSE	Null model RMSE
10	2,1636	
20	2,1734	
30	2,1523	
40	2,1591	
50	1,9669	
60	2,044	2,0659
70	1,9837	
80	1,9714	
90	1,9443	
100	1,9515	

Sim X: simulation with X transformation agents.

According to the authors, the two most important components are quantity disagreement (i.e., net change) and location disagreement (i.e., swap change), which sum to the total disagreement. While the quantity disagreement derives from differences between the maps in terms of the number of pixels for each category, the location disagreement is the disagreement that could be resolved by rearranging the pixels spatially within one map. If the location disagreement can be resolved by swapping the pixels over small distances, then it budgets the error as "near" location disagreement, otherwise it budgets the error as "far" location disagreement. We adopted in this paper what [33] suggested for "near" location disagreement: the location disagreement that can be resolved by swapping within 64-row x 64-column clusters of pixels of the raw data (raster data).

Different applications can be summarized and compared using two statistics: the null model resolution and the figure of merit. Considering the figure of merit, the more accurate applications are the ones where the amount of observed net change in the

reference maps is larger [33]. The simulation results indicate the potential of the presented multi-agent model system. Considering the accuracy of the simulations using MASE, the application results were better than the null model (Figure 4), what examines both the behavior of the model and the dynamics of the landscape. The definition of this null model is a prediction of complete persistence, i.e. no change, between the initial and the subsequent time, therefore the accuracy of the null model is 100% minus the amount of observed change. Once again, MASE results were consistent and statistically better than other similar frameworks, reviewed and compared by Pontius [33]. The review of results show that 50% of the simulation frameworks are worse than the null model [33].
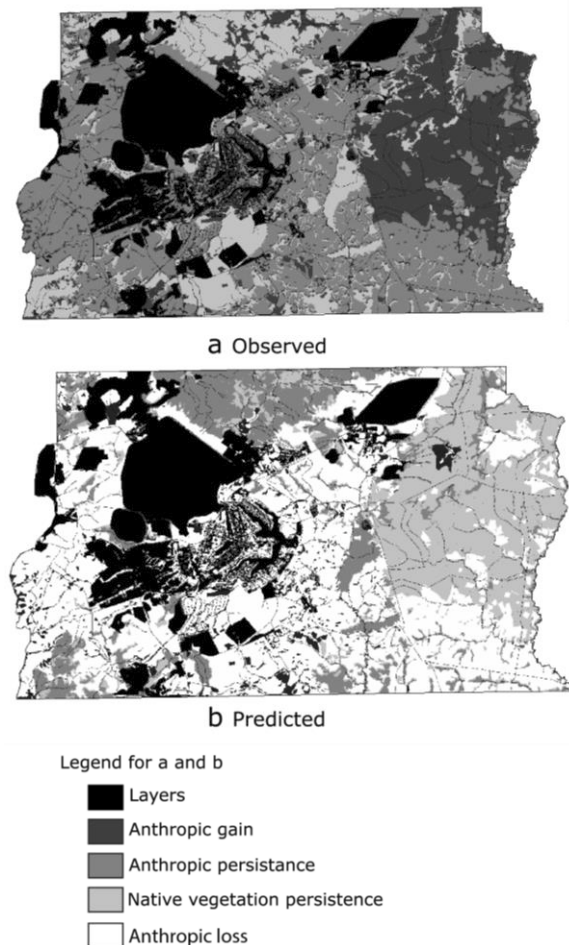

a Observed

b Predicted

Legend for a and b
- Layers
- Anthropic gain
- Anthropic persistance
- Native vegetation persistence
- Anthropic loss

Figure 3. MASE model predictions for the Brazilian Federal District, showing (a) Observed change 2002-2008, (b) Predicted change 2002-2008
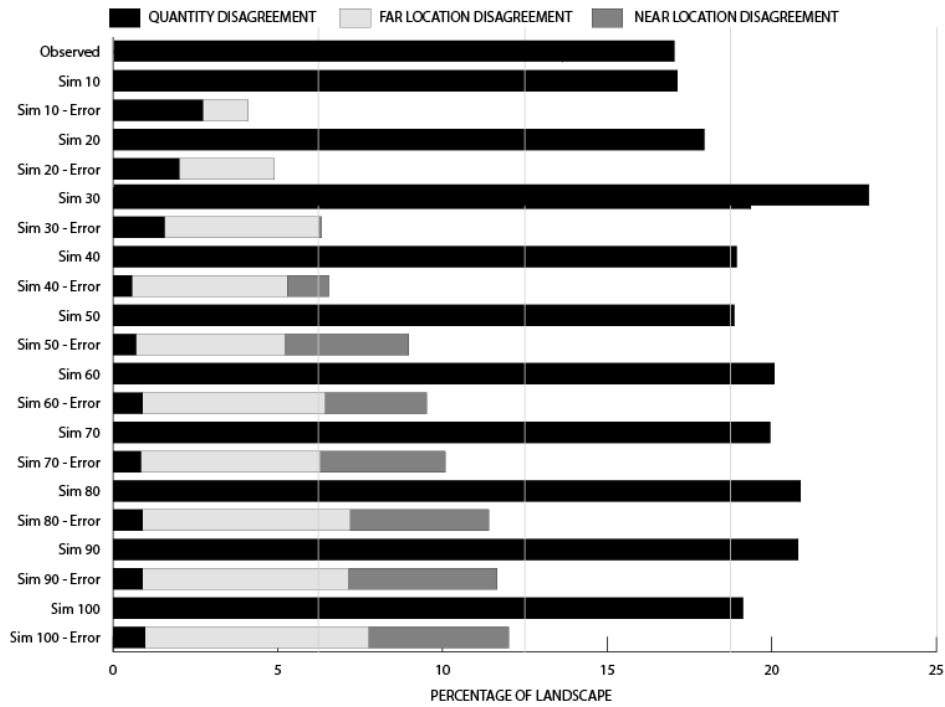
Figure 4. Observed change, predicted change, and predicted error for each of the 10 runs of the simulation with variable TAs. (According to the [33] methodology).
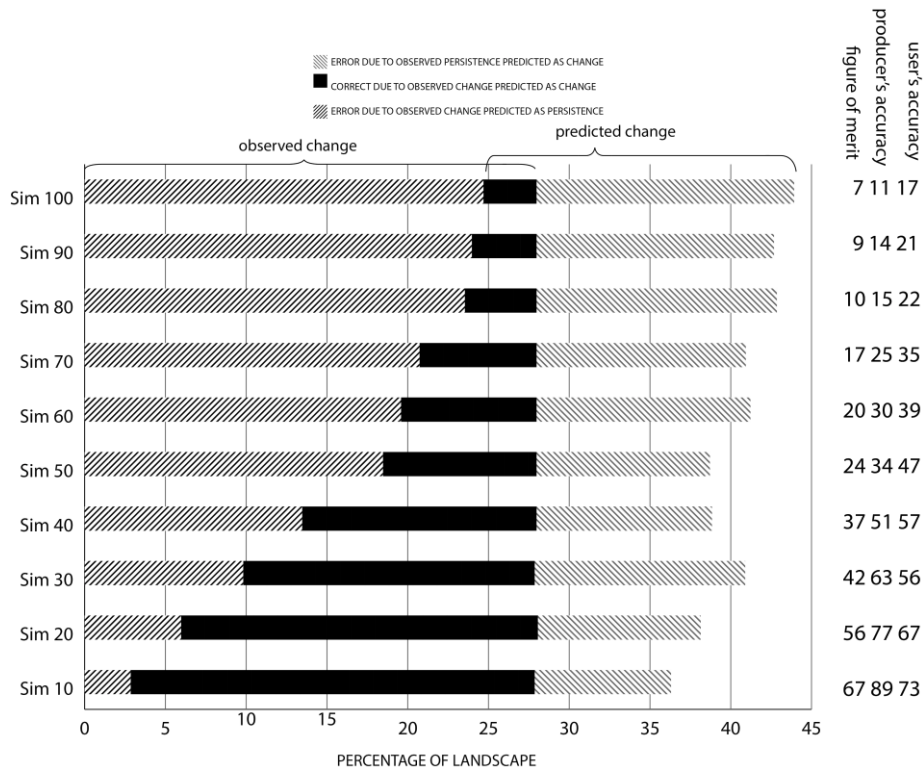

Figure 5. Sources of percent correct and percent error. According to the [33] methodology.

The figure of merit is a statistical measurement that derives from the information of the bars in Figure 5. The figure of merit is the ratio of the intersection of the observed change and predicted change to the union of the observed change and predicted change, which can range from 0% (no overlap between observed and predicted change) to 100% (perfect overlap between observed and predicted change, a perfect accurate prediction). Figures 3 and 5 show high error rate due to anthropic loss, or error due to observed change predicted as persistence. This means that natural vegetation would actually be preserved in the Forestry Code Regulation scenario. Specialist would argue if the 20% were enough to pressure the ecosystem services. A government planner would be able to see the impacts of LUCC policies in the simulation. It is even possible to extrapolate the results and investigate scenarios with different legal reserve limits to investigate the consequences of modifications in the Brazilian Forestry Code. The MASE framework allows the LUCC manager to configure variables and test new possibilities to the future. For this, it is possible to exploring potential impacts of land use policies and be a supporting tool for decision-making.

6. Conclusions

MASE system is a freeware multi-agent model system to simulate LUCC dynamics, using multiple agents to represent the interaction between different types of agents with autonomy. Considering the experimental results presented, we consider the multi-agent model system of MASE represents an interesting alternative for LUCC decision support. The model is done in a spatially explicit, integrated and multi-scale manner, being important for the projection of alternative pathways for conducting experiments that test human understanding of key processes in land-use changes.

The proposed strategy for modeling and simulation is a valid tool for the investigation of the consequences of environmental policies. To allow stakeholders and decision makers to investigate alternative scenarios in a MAS built with an individual based model is an alternative to raise awareness for environmental sustainability. The study case provides evidence that stating environmental policies does not imply an efficient environmental management. While considering the biophysical and economic aspect of land use and cover changes, a decision maker could benefit from our approach by stating environmental political issues in an explicit way.

The present study still has certain limitations. Regarding the system interface and usability, some improvements are needed to allow its use for a broader public. The system scope is restricted to LUCC and to allow general environmental modeling and simulation, some architectural changes are needed.

Future studies should revise the methodology to include the above-mentioned limitations, so that a friendly interface can be applied to any general environmental setting.

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