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An Actor-Oriented and Architecture-Driven Approach for Spatially Explicit Agent-Based Modeling

Eric Fotsing[1], Severin Vianey Tuekam Kakeu[2*], Eric Desire Kameni[3], and Marcellin Julius Antonio Nkenlifack[1,2]

[1] Department of Computer Engineering, Fotso Victor University Institute of Technology, P.O. box 134, Bandjoun, Cameroon
[2] Department of Mathematics and Computer Science, URIFIA Laboratory, University of Dschang, P.O. box 67, Dschang, Cameroon
[3] Department of Computer and Educational Technology, Laboratory of Computer Science and Educational Technologies (LITE), Higher Teacher Training College, University of Yaoundé I, P.O. box 47, Yaoundé, Cameroon

efotsing@gmail.com, severinkakeu@gmail.com, ericokameni@gmail.com, marcellin.nkenlifack@gmail.com

Abstract. Nowadays, there is an increasing need to rapidly build more realistic models to solve environmental problems in an interdisciplinary context. In particular, agent-based and spatial modeling have proven to be useful for understanding land use and land cover change processes. Both approaches include simulation platforms often used in several research domains to develop models explaining and analyzing complex phenomena. Domain experts generally use an ad hoc approach for model development, which relies on a code-and-fix life cycle, going from a prototype model through progressive refinement. This adaptive approach does not capture systematically actors' knowledge and their interactions with the environment. The development and maintenance of resulting models become cumbersome and time-consuming. In this article, we propose an actor and architecture-driven approach that relies on relevant existing methods and satisfies the needs of spatially explicit agent-based modeling and implementation. We have designed an Agent Global Experiment framework incorporating a meta-model built from actor, agent architecture, and spatial concepts to produce an initial model from specifications provided by domain experts and system analysts. An engine is built as a tool to support model transformation. Domain knowledge including spatial specifications is summarized in a class diagram which is later transformed into the agent-based model. Finally, the XML file representing the model produced is used as input in the transformation process leading to code. This approach is illustrated on a hunting and population dynamic model to generate a running code for GAMA, an agent-based and spatially explicit simulation platform.
Keywords: Agent-Based Model, Methodology, Actor, Spatial Attribute, Metamodel, Model Specification, Land Use Modeling.

1 Introduction

Irrespective of the field of study, a model is an abstract representation of the reality observed, scaled down, and converted to a form that is easy to understand. It is also a spatio-temporal

* Corresponding author

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Additional information. Author ORCID iD: E. Fotsing – https://orcid.org/0000-0003-4863-2392, S. V. T. Kakeu – https://orcid.org/0000-0001-5348-7957, E. D. Kameni – https://orcid.org/0000-0001-9821-9470, and M. J. A. Nkenlifack – https://orcid.org/0000-0003-3322-4687.
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reference for our understanding of a system [1]. Agent-based models (ABM) and spatial models in Geographic Information System (GIS) have proven to be useful tools for land use change processes analysis as they provide a framework to build models and conduct simulations. On the one hand, GIS is a set of computer-based infrastructure, human resources, procedures, and standards for the management of geographical information to address a specific issue [2]. GIS-based models are composed of spatial entities including points, lines polygons, or pixels. On the other hand, ABM allows to define the behavior of agents in a common environment for solving complex problems. It is also used to model a distributed computing system with autonomous interacting agents that coordinate their actions to achieve their goal(s) jointly or competitively [3]. There are obvious similarities between agents and objects which usually prompt the designer of an ABM to rely on Unified Modeling Language formalism [4]. Both spatial and agent-based approaches include computer simulation platforms often used in several research fields (economics, ecology, sociology, geography, etc.) to develop models for explaining and analyzing complex phenomena [5], [6].

Several authors including [7]–[10] have proposed such models to understand the drivers of land use change and identify appropriate actions to maintain the target system. In interdisciplinary contexts and participatory modeling situations, there is an increasing need to rapidly build more realistic or effective models to solve environmental problems. A key idea to achieve this is to rely on field knowledge to mimic the attributes and behavior of the entities involved. Different research directions are investigated to increase the realism of the simulated environment. The first group of notable efforts oriented toward the integration of GIS and agent-based models can be seen in [11], [12]. Other efforts are oriented toward proposing appropriate agent architecture. In this regard, exploring the concepts of the actor paradigm to build effective and valid agent is a promising research pathway [13], [14]. In addition to computer and mathematical modeling (e.g. using ordinary differential equations [15]), agent design can rely on economic, social, and anthropological models [16].

The challenge of our research endeavor is to combine actor paradigm, agent architecture, and spatial concepts to develop effective models for addressing key environmental problems. The ad hoc approach is often used for model development, which relies on a code-and-fix life cycle, going from a prototype model through progressive refinement. However, this adaptive approach does not capture systematically actors' knowledge and their interactions with the environment. Technically, the development and maintenance of resulting models become cumbersome and time-consuming. From these facts, the actor paradigm appears to be a promising research focus in ABM as it links actor concepts to those of an agent and therefore improves the realism and validity of each model built. Moreover, to cope with a world evolving toward more applied artificial intelligence (AI), we need a more efficient and simple approach as close as possible to fields actors and appropriate for non-computer scientists that allows to capture the reality, data, and behavior shared within an interdisciplinary community and then, an efficient modeling technique to produce valid ABM simulations. In this article, we propose an actor-oriented and architecture-driven approach called Spatially Explicit Agent-based Modeling Approach (SEAMA) which relies on relevant existing methods and satisfies the need to design and build spatially explicit agent-based models that adequately mimic reality. We have designed an Agent Global Experiment (AGE) framework incorporating a meta-model built from actor, agent, and spatial concepts to produce an initial model from specifications provided by domain experts and system analysts.

This article is organized as follows. Section 2 deals with the state of the art on land use modeling with a focus on agent-based and spatial approaches. Section 3 presents the conceptual and theoretical framework undergirding the contribution made in this article. Section 4 describes our modeling approach with an emphasis on the meta-model and the transformation mechanism. Section 5 illustrates and discusses the application and validation of the methodology on a case study, while Section 6 is devoted to conclusion and prospects.

2 Agent-Based and Spatial Modeling for Social Side in Land Use

To justify and contextualize our contribution, this section formulates the land use change problem while highlighting and explaining associated concepts. It subsequently presents some major works in agent-based and spatial modeling addressing land use issues.

2.1 The Land Use Change Problem

Land use describes the economic and social functions of land or the purposes for which humans exploit it. The associated concept of land cover refers to the characteristics of the physical surface of the land (e.g. *built-up area*, *vegetation*, *bare soil*, *forest*) [17]. Land cover change is defined as the alteration process of land including, for instance, the loss of natural areas, particularly change from forest to urban area or transformation from agricultural to urban areas [18]. Land use change is a process in which human actors employ natural resources including forests, water, or agricultural land for their well-being. This process can lead to land cover changes including the modification or disappearance of biophysical entities at the land surface. Over the last decades, many research works have highlighted the complexity of land use/cover change. The magnitude of land use change varies with the time and geographical area being examined. The underlying processes are driven by a variety of forces that relate differently to one another in different spatial and temporal settings. In general, it is the human agency that brings about land changes and which is responsible for their magnitude and severity. Land use change is involved to a greater or lesser extent in most global environmental problems like urbanization, desertification, climate change, biodiversity loss, etc. The impacts of these changes are reaching threatening proportions with food security, health, and safety at stake [19]. W. de Groot [16] has proposed a methodological and interdisciplinary framework (Problem in Context also called PiC) for the explanation, analysis, and design of a solution to environmental problems. The land use change problem represented by PiC is the discrepancy between the chain of environmental effects of the underlying activities and the chain of associated environmental norms (Figure 1).

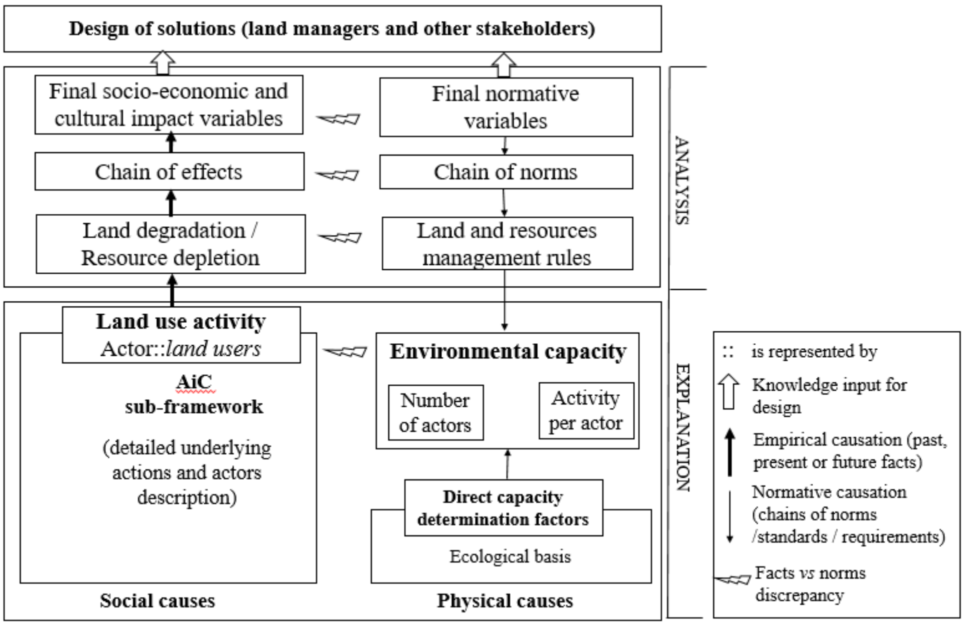

Figure 1. Land use problem representation in the PiC framework

Figure 1 allows the conceptualization of any activity behind a land use change problem in four directions. The social and physical causes on one side provide the problem explanation while the chains of environmental effects and norms provide the problem analysis, leading to the design of effective solutions. Actor-in-Context (AiC) sub-framework focuses on the social context of the activity by presenting all related actors, target groups/communities, and their policy options and generates interactions per group. Actors are all social entities (be it a farmer, a wood merchant, an authority, etc.) acting individually or collectively and carrying out or influencing the problematic activity. PiC allows to present the behavior of actors in several levels, and shows the links between actors, their activities, facts/norms, and the impacts of those ones on their environment. The example of the use of the framework is demonstrated in [9] to describe an environmental problem well detailed in [13].

2.2 Land Use Change Modeling Approaches

The study of land use change can target a very broad range of purposes including the description, explanation, prediction, impact assessment, prescription, and evaluation. A broad set of theories was developed, that allows us to explain the structure of the changes in the land use; why they occur, what are their causes, and what are the underlying mechanisms [17]. Each theory focuses on particular aspects of the subject with a different mode of theorizing including assumptions, type of land use and their determinants, the proposed mechanism of land use change, the reference spatial scale, and its temporal dimension. Existing theories can be grouped into the following three major categories of approaches that are applied to study the problems occurring in the land system:

- The urban and regional categories led by micro/macro-economic theoretical approaches,
- The sociological and political economics category in which behaviorist and institutionalist approaches are applied,
- The actor-environment category with natural and social sciences-based theories designed in human ecological and planning studies.

The three generic approaches usually adopted for the study of land use change, also called perspectives of understanding, include the narrative, the agent-based, and the systems approach. The narrative perspective provides an empirical and interpretative baseline by which to assess the validity and accuracy of the other visions. Both agent-based and systems approaches depend on explicit model development and empirical testing.

The literature on land use change suggests several model classification schemes depending on substantive, design, and methodological criteria. A well-known classification covering the majority of models of land use change distinguishes the following four main categories: statistical and econometric models (*e.g. linear regression* [20]), spatial interaction models (*e.g. Gravity* [21]) optimization models (*e.g. linear and dynamic programming* [21]) and integrated models (see [22] on the features of integration). However, there are several other modeling approaches including landscape ecology, Markov chain, and GIS-based approaches which do not fit in this classification and cannot constitute a separate category. The authors of [23] summarize the lessons learned from a collaborating cross-case comparison of 13 models as 9 challenges grouped under three major themes including mapping, modeling, and learning.

The difficulties faced in building truly dynamic models are not only technical but theoretical as well. The linkage between theories, models, and operational decision support tools for land use has not been strong over time in general. Whether and to what extent the use of models has improved decision-making on land issues is a question that cannot be answered satisfactorily. A central research requirement is that of producing coherent methodologies for integrating the various pieces of knowledge and building more realistic models to guide land use towards sustainable paths.

The development of effective land use simulation models should be based on an appropriate methodology taking into account actors and spatial aspects as highlighted from key challenges in the current review. The authors of [24] describe some of these challenges facing the development of spatial ABM as methodological and suggest potential solutions from an interdisciplinary perspective. The key issue in this case concerns the model efficiency and ease of use, cooperation of stakeholders in model design, and automatic model generation. Several agent-based methodologies and strategies are inspired by object-oriented software engineering methods. Methods such as ADELFE (Atelier de Développement de Logiciels à Fonctionnalité Emergente [25]) and INGENIAS (Engineering for Software Agents [26]) include steps and specific concepts of Unified Process (UP) [27]. PASSI (Process for Agent Societies Specification and Implementation [28]) and ASPECS (Agent-oriented Software Process for Engineering Complex Systems [29]) are methods following an incremental process like UP. A major drawback of most of these methods is the fact that they do not propose a process that goes all the way through to deployment, except for PASSI or INGENIAS, which cover the entire development cycle. Gaia (that has been the first complete methodology for the analysis and design of multiagent systems [3], [30]) only covers a part of the UP life cycle, namely, the requirements analysis and design. Prometheus and MaSE (Multi-agent Systems Engineering [29], [31]) also do not address all the parts of the UP cycle. Finally, Tropos is an agent-oriented software engineering methodology driven by requirements and focuses on the agent concept. In that methodology, the agent is a key concept and the development process is driven by requirement analysis where the agent and their dependencies are expressed in a meta-model as primitives [32]. Thus, agents' goals, beliefs, and capabilities are specified in detail, along with the interaction between them.

The challenge of coupling agents and spatial concepts in modeling is addressed by [11] that has identified four major alternative strategies to implement the conceptual linkages between GIS and ABM as presented in Figure 2.

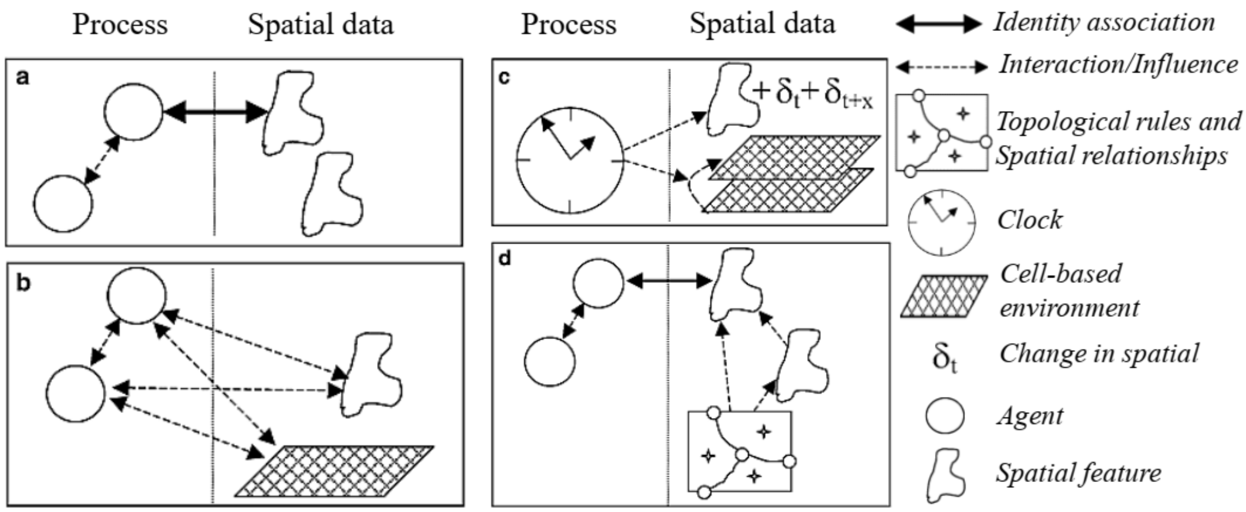

Figure 2. Relationships between agent and spatial entities (adapted from [11])

The loose coupling considers GIS and ABM as two different software entities where the identity relationships are built as in Figure 2.a; The intermediate or moderate coupling encapsulates techniques between loose and tight/close coupling [33]. For illustration, in Figure 2.c the processes can be directly implemented in the spatial side. The tight or close coupling is characterized by the simultaneous operation of systems allowing direct inter-system communication during the program execution [34]. Figure 2.b shows the agent-agent and agent-spatial entity interactions. Cooperative coupling is another broad approach that requires only the linking of existing systems, rather than building a new one. This approach is centered on neither ABM nor GIS but makes use of the functionality available in both environments to build an integrated system. An alternative to coupling is to integrate the required functionality of either the GIS or simulation/modeling system within the dominant system using its programming language to link both as in Figure 2.d [35]. Many simulation tools implement the last one and help us to produce a methodology for spatially explicit modeling. For instance, [36] proposes a model for simulating the spatial organization of hunting and animal population dynamics. The work in [12] highlights the effectiveness of coupling actor and spatial features in a model simulating urban development. The authors of [37] present the technical aspect of coupling using the GAMA platform to integrate the GIS data for simulation. The authors of [38] use an ABM-centric approach to integrate spatial data to simulate households and economic activities in an urban area.

In the same perspective, the authors of [8] present an integrated spatial model to simulate the competition between land use types taking into account a set of biophysical, socio-demographic and geo-economic driving factors. In their prospective conclusion, the coupling of agent- and GIS-based approaches is recommended as a solution to model the individual decision-making processes and their interaction with the spatial entities as early mentioned by [39]. In ABM research, individual decision-making is driven by agent architecture, a philosophic pattern well-argued, studied, and discussed early by [40] and followed by [41] that introduced Belief-Desire-Intention (BDI) which is a practical reasoning type of architecture. Several extensions of BDI were proposed later. The works [14] and [42] also provide details of modeling with BDI architecture and the subsequent implementation [43]. They highlight the usability aspect of the platform and its spatial components.

Following the methodological and actor-centric research line previously presented, recent work on agent-based modeling of land use is presented in [13] (initial version available in [44]). They address the issue of land use model validity using an actor-centric meta-modeling approach whereby actors in the field, domain experts and ICT specialists are involved in the participatory modeling activity and consequently the production of tools in context. The key idea is to design and maintain a certain consistency in the transformation from actor to agent during model building relying on associated concepts and technologies. At the requirement level, the observed system is described in pseudo-codes using the Object Role Modeling (ORM) language[†] to represent interactions between actors as early expressed in the AiC meta-model. However, the model and code transformation process is still cumbersome and time-consuming. Moreover, this initial study focuses only on the actors' field (multilevel analysis) and remains silent on the biophysical and environmental impact branches of the general PiC framework. In this article, we investigate a methodology for improving this approach in producing more realistic models through a deeper analysis of the actor options, motivations, and full expression of the spatial aspects from both actor reasoning and the biophysical environment.

3 Conceptual Framework

This section introduces and explains how the AiC framework, agent architecture concepts, and Model Driven Architecture (MDA) process are used to model the properties, activities, and interactions of actors and the subsequent model transformations.

3.1 Actor and Agent Modeling

Figure 3 provides a representation of the key concepts of AiC framework, and BDI architecture respectively, with actor and agent at the core. This prompts the designer to potential transformation rules linking the actor and the agent.

At the analytical and conceptual level, an AiC model depicts a given action performed by an actor in an environment and leading to land use changes or problems. This actor acts as it does as a result of a choice between alternative plans/actions depending on its options, motivations, and goals. The selected choice is also constrained by its resource capital. These detailed specifications represent the actor field which depends on any system, actor, or community (logging company, government, market, etc.) producing an influence on the actor's behavior.

[†] http://www.orm.net/

They represent the main building blocks of the actor's decision-making apparatus. Each causal linkage identified during problem analysis and explanation is relevant and therefore used to generate one or more potential plans to be executed by the actor, hence affecting their environment. This actor's faculty to combine selected options to form a plan represents a way to design a local solution hence participating in the whole solution. Then, Actor perceives the physical environment including both others actors and biophysical entities. The options and motivations toward a problematic action determine his structures and culture as well as influences from other actors represented in the actor's field. The resulting action impacts the physical environment through a chain of cause and effect relationship from this physical environment features to the final impacting variables.

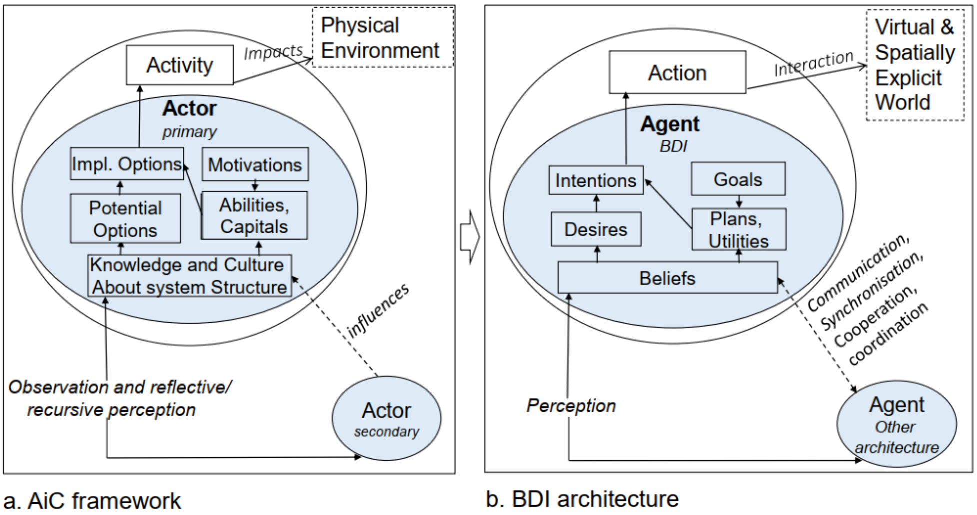

Figure 3. Representation of AiC framework and BDI architecture concepts

At the logical level, the agent concept is used to model and simulate the actor's abilities and reasoning pattern in a virtual environment. An agent is defined as a function *Ag* in a given environment *Env* = (E, e_0, τ) as follows. $Ag\colon R^E \rightarrow Ac$, where (Ac = a_1, a_2, a_3, ...). is a set of possible actions that the agent can perform, E is a set of states including the initial state e_0 and R^E is the set of possible runs. A run is a sequence (e_0, a_1, e_2, a_3, etc.) that carries the history of the system that the agent has witnessed to date. Depending on the system or problem to solve, agent architectures are classified into four categories including deductive reasoning, practical or goal-oriented reasoning, reactive behavior, and hybridization of the previous categories. In deductive reasoning, the system including agents states as the environment is represented as logical formulae and the agent decision-making program is logical theory. This means that the behavior is generated through logical deduction. In practical reasoning, also known as cognitive architecture, the agents are endowed with mental states such as belief, desire, intention, wish or hope and are increasingly used as a design pattern to talk about computer programs in agent-based simulations. The BDI architecture resulting from these trends consists of three components namely the belief, desire, and intention which lead the agent progressively from its world knowledge to the best choice of action to perform. Beliefs are the internal thought that an agent has about the environment. Desires are the set of what the agent wants to do. Intentions are the plans among options. In a purely reactive architecture, as defined in [45], there is no explicit representation and abstract reasoning. The agent reacts according to the perceptions of its environment, so decides what to do without any reference to its history. In this case, the decision function of the agent is defined as $Ag\colon E \rightarrow Ac$ going directly from environment states to actions. The hybrid type of agent architecture combines attributes of others to reach the kinds of capabilities that we might expect an intelligent agent to have (Be it reactivity, proactivity, or sociability). This is achieved through a decomposition of the agent behavior into separate subsystems and arrangement into a hierarchy of interacting layers (e.g., *InteRRaP*, *Touring*

Machines described in [29]). In other words, an agent uses its sensors to perceive the virtual spatially explicit world. It takes sensory input or percepts, transform them according to its decision-making apparatus, and produces actions as output that affect this virtual world through its actuators or effectors. The result of these actions is fed back to agent sensors in a usually ongoing, non-terminating interaction.

3.2 Model-Driven Transformation Process

The ultimate goal of the transformation is to produce a computerized version of actors mimicking adequately their decision-making mechanism in a virtual environment. In theory, any agent architectures presented in the last section could be used as a reference to build an agent model from AiC concepts. However, BDI is arguably the most popular and appears to be a simple and natural architecture when dealing with the agents representing human actors [46]. Its concepts are more similar to those of actor models and it offers a more straightforward description which makes models easy to understand and more expressive for formal knowledge representation and reasoning. As emphasized by many agent research works, the designing complex agents for socio/ecological systems is still an open research issue. BDI architecture has received particular attention as evidenced by a large number of extensions. The authors of [47] propose a BDI extension to include belief theory applied to agricultural land use where two main issues of the cognitive architectures are addressed, namely, the complexity and computation cost [14], [42]. Other extensions such as BOID[‡], EBDI[§], and BEN[**] deal with social aspects such as spatial abilities, obligation, emotion, cognition, personality and emotional contagion of human beings [48]–[50]. Table 1 summarizes the main correspondences between actor and agent concepts as depicted in Figure 3 and later used for the meta-model designed.

Table 1. Correspondences between concepts in actor and agent models

Actor-oriented model	Agent-based model	Description
Experience	Belief	What the entity knows about itself, others, and environment
Potential option	Desire	What the entity wants to do to modify its world
Implemented option	Intention	What the entity plans to do
Capital	Data	Resource of the entity
Object	Object	Situated geographic form
Property	Attribute	Characteristics of the entity
Motivation	Goal	What causes the choice of a plan
Interest	Utility	Importance of an action

In both actor-oriented and agent-based models, the environment is made up of agents/actors and objects representing land covers or land uses. These are represented in simulation platforms using the vector and raster layers coming from GIS software like QGIS or ArcGIS[††]. Several authors have demonstrated the power of spatial model and ABM integration in agent-based simulation platforms by examples (more details in [12], [36], [37], [42]). As in the traditional software development process, the major concerns in building an agent-based simulation model include cost reduction and quality of the end product referring mainly to the realism and validity of the generated model. MDA paradigm managed by Object Management Group (OMG) [51], provides a conceptual framework for building ABM at multiple levels of abstraction (depending on the representation of the reality observed, the tools used, the skill of modelers, etc.). This ensures that the model description is not solely tool-driven as this can affect the quality of the resulting model.

‡ https://www.researchgate.net/publication/220794078_The_BOID_Architecture_--_Conflicts_Between_Beliefs_Obligations_Intentions_and_Desires

§ https://www.researchgate.net/figure/EBDI-POMDP-agent-as-a-mediator-for-trading-Grid-resources_fig2_335611260

** https://www.jasss.org/23/4/12.html

†† https://gisgeography.com/qgis-arcgis-differences/

The MDA transformation process starts from a generic or Computation Independent Model (CIM) that represents the business process and requirements including actor models, data, messages, and resources to use. Then, the Platform Independent Model (PIM), including abstract models used for analysis and design steps, is created. Figure 3.b presents the main agent's concepts and shows the rationale of the agent's decision-making process. The agents use their sensors to perceive the world and produce as output the actions that affect it. The BDI agent processes from beliefs to action through goals, plans, desires and intentions. The result of these actions is fed back to agent sensors in a usually ongoing, non-terminating interaction. At the end of the MDA process, the final model code is generated from an existing Platform Specification Model (PSM).

4 Spatially Explicit Agent-based Modeling Approach

4.1 Methodology

The methodology proposed aims to address the complexity of the modeling situation. Thus, it helps to identify and ensure the full participation of the various actors involved in a typical land use modeling project at different levels to provide accurate information including IT, GIS specialist's specifications, and indigenous knowledge. Each step of the modeling workflow (Figure 4) is designed to be efficient to produce a model combining AiC, BDI, and spatial concepts.

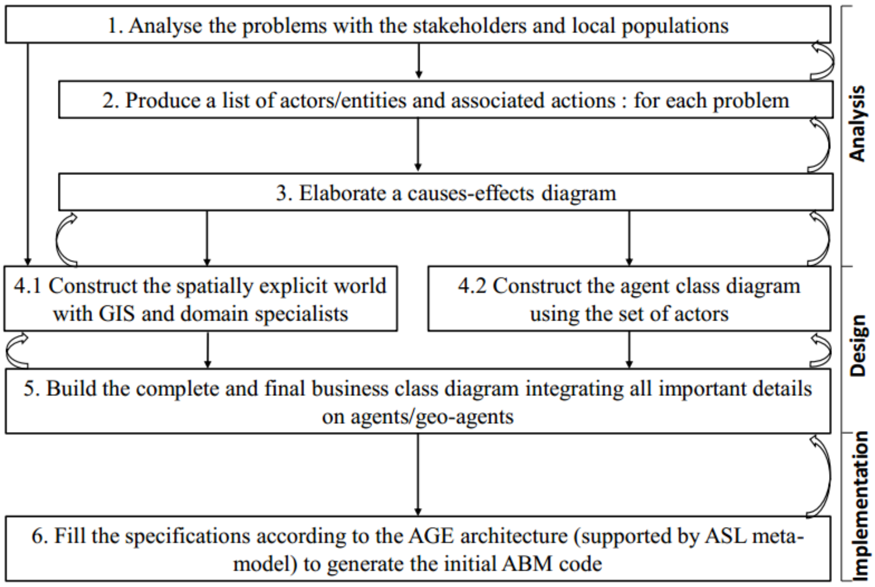

Figure 4. Workflow of spatially explicit agent-based modeling process

Based on modeling workflow steps represented in Figure 4, we describe the different phases of the methodology from analysis to implementation as follows:

- In the analysis phase (steps 1, 2, 3 in Figure 4), we define the problems in the context with the target community of practice in which the research is operated, the list of actors/entities, and their associated actions, liking actions or options to their consequences and leading either to a problematic action or final variables providing solutions to the land use problem (with the chain of environmental effects from PiC and the actor field from AiC). The correlation matrix indicates the different relations.
- In the design phase (steps 4.1, 4.2, and 5 in Figure 4), we construct the spatially explicit world with domain experts and GIS specialists to represent the physical environment (directly from the analysis phase with PiC). Using the previous correlation matrix, a class

diagram is also designed to represent the social context using the causes-effects diagram as a starting point.

- In the implementation phase (step 6 in Figure 4), we specify the agent model in a dedicated tool to produce an initial code for a spatially explicit agent simulation platform. We note that in step 6, the test and evaluation of the resulting generated model code are done by the modeler. If there is a problem or missing elements (agents, spatial entities, some behavior), the current model can be refined in step 5 and specified in 6 with all updates.

4.2 Meta-Model for Spatially Explicit Agent-Based Modeling

In the process of setting up the agent-based model specification language (ASL) we first define all the concepts for representing agents and their physical environment in the model. We also build minimal grammar for a new Domain Specific Language (DSL). We finally use a generator engine (called ASL2GAML) to facilitate model-to-model transformations up to the generation of an initial code that can further be customized with detailed information obtained from actors. To build a spatially explicit agent-based model in a simulation platform, the modeler will need to specify all the attributes of these components with the header block containing meta-data useful for the model copyrights (authors' names, model description, target domain, etc.), include Beliefs in the agent component of AGE framework according to the hierarchical representation of different concepts used. Operationally, AGE fixes the base of agent code development following several blocks to provide and get the whole code to run in an agent-based simulation platform. The ASL meta-model presented in Figure 5 is a PIM built with Eclipse platform [52] using AGE concepts (Agent and Global and Environment) to transform the specifications provided into an XML(Extended Markup Language) model taken as input for code generation.

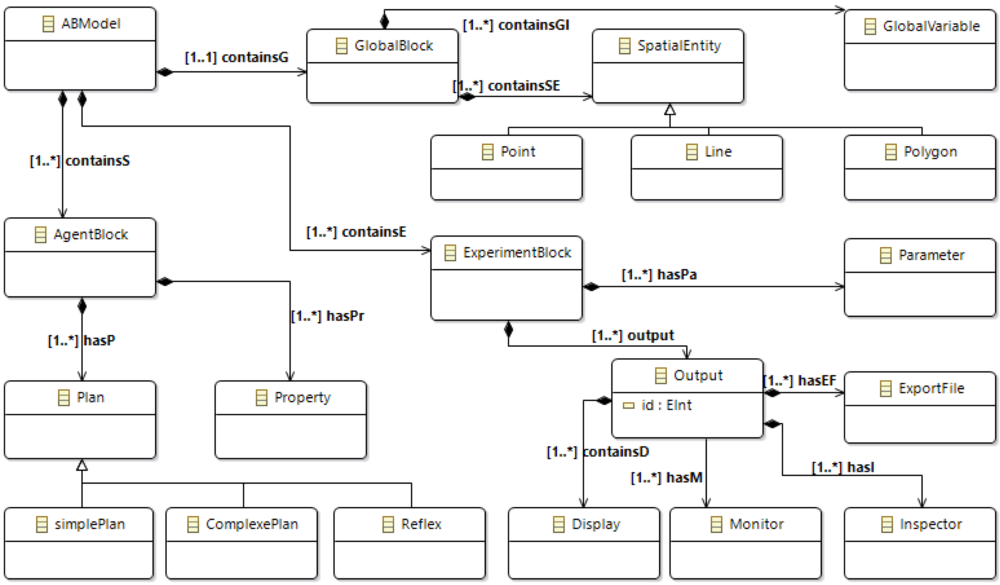

Figure 5. Class diagram of ASL meta-model

We defined and built a minimal grammar G for the new Domain Specific Language (DSL) which is represented by the following algebraic expression. G = (V_N, V_T , P, S) where:

- V_N is the set GlobalBlock, AgentBlock, ExperimentBlock, Action, SimplePlan, ComplexPlan, Output, Display, and Reflex of non-terminals which are variables denoting strings:

  V_N = {*GlobalBlock, SpecieBlock, ExperimentBlock, Action, SimpleAction, ComplexAction, Output, Display, Reflex*}

- V_T is a set of tokens, known as terminal symbols from which the strings are formed with identifiers and terminal symbols like INT, BOOLEAN, STRING, etc.
- S represents the starting symbol or axiom from which the production begins and is represented as follows: Axiom = {*ABModel*}
- P represents a set of not detailed production rules that specifies how terminals and non-terminals are combined to form strings. Hence, a spatially explicit ABM composed of Global variables, Agents (depicting a real-life actor), and Experiment Blocks is represented by the following rulers (1):

$$P = \begin{cases} ABModel \rightarrow GlobalBlock\ SpecieBlock\ ExperimentBlock \\ GlobalBlock \rightarrow GlobalVariable\ SpatialEntity \\ SpecieBlock\ \rightarrow Property\ Plan \\ ExperimentBlock \rightarrow Parameter\ Output \end{cases} \qquad (1)$$

The DSL is described in Xtext using an EBNF style grammar [53]. To improve the quality of the final model, some constraints are subsequently specified in the grammar file using OCL (Object Constraint Language [4]). Finally, a parser allows the production of an ASL editor with syntax highlighting, code folding, content assistance, and integrated error markers.

4.3 Transformation Rules from Actors to Agents

Concerning the implementation level, Figure 6 summarizes the ASL2GAML's transformation process, from the model specifications to the platform specific code.

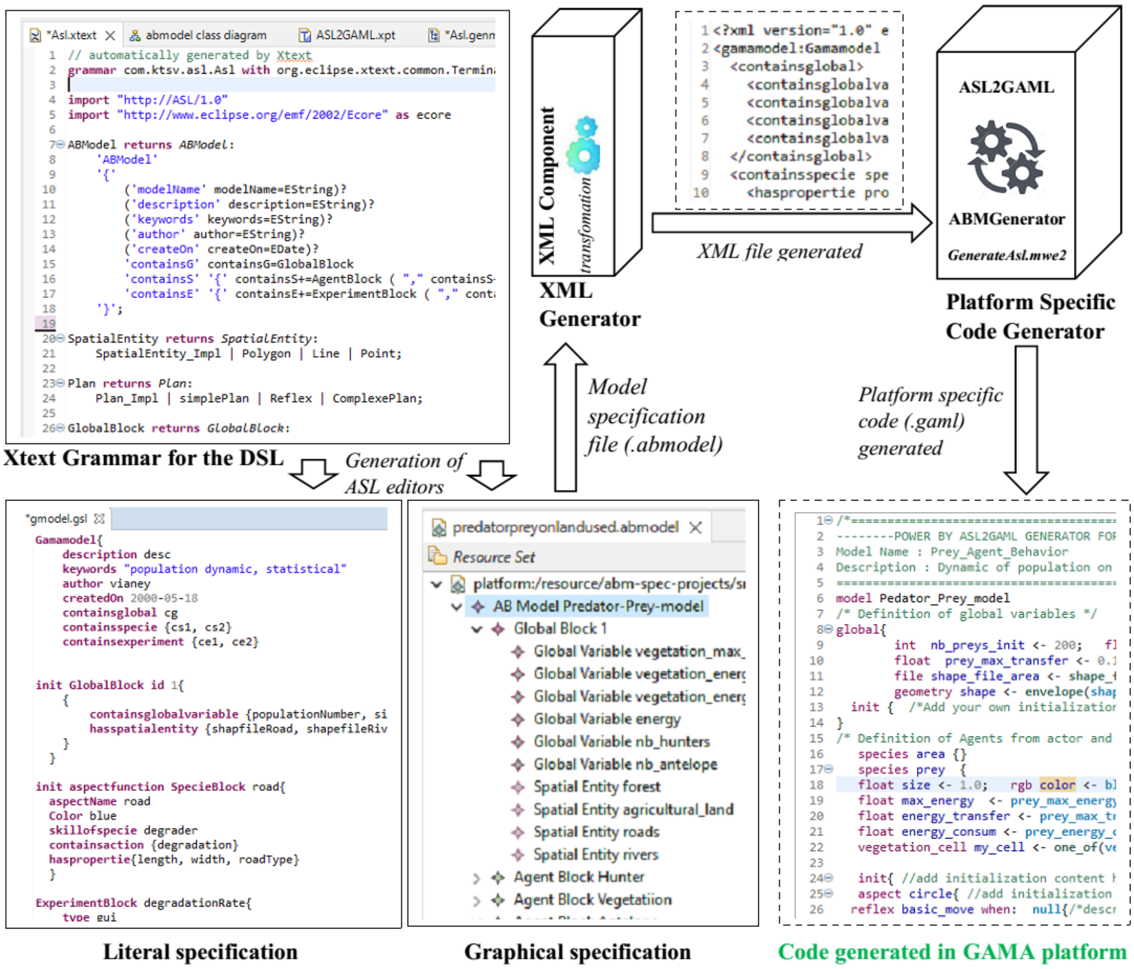

Figure 6. An illustration of the ABM transformation process

In Figure 6, the Xtext grammar for DSL, XML generator, platform specific code generator, literal specification, graphical specification, and code generator in GAMA platform are represented:

- The Xtext grammar allows to produce the literal and graphic user interfaces.
- Model is specified according to the data got from the field.
- The data model is transformed into an XML model.
- The generator engine (ASL2GAML) designed with formal rules transforms the XML model into GAML code for the simulation tool.

Considering the social, biophysical and environmental impact branches of the PiC framework the following rules are applied :

1. Each *actor* becomes an *agent* and its properties become the agent's variables/attributes.
2. Its personality including *options, abilities, and experiences* becomes the *desires* with a simple name driven by *plans* to implement and supported by beliefs. So, a plan is used to give more details on the actor's option better than desire.
3. Each object of society becomes a spatial entity that can be identified during the simulation depending on the relevance of doing so.
4. Each association denotes an ability, a desire, or a request of agent X towards agent Y and thus defines an interaction between the future agents during simulation.

5 Illustration of SEAMA Approach on a Modeling Case Study

The approach introduced in this article is illustrated in a case study of modeling and simulation of hunting and animal population dynamics [36]. This model is useful for understanding the organization of hunting activities between local actors and the impact of hunting on the dynamics of land use. In this section, we highlight the relevance of the approach in terms of model expression during the design and subsequent transformations from domain analysis to code generation through CIM, PIM, and PSM.

5.1 Domain analysis for CIM

In this model, human hunters are key actors triggering the dynamics of land use changes through their activities with consequences on land cover and biodiversity. Hunting takes place 6 months/year in a spatially explicit environment according to temporal shifting rules (*e.g. every year, each hunter changes the location of his trap*). Over the years, hunting camps were created and further increased land transformations from the forest into other land uses. A simulation platform is used to develop a model based on the antelope's life history and the inhabitant's behavior. It developed an artificial landscape similar to that of a hunting area representing the village. Thus, data have been digitalized with a GIS and set in the raster format and integrated into the simulation process. Figure 7 illustrates the problem analysis of land use chosen as globally presented in Figure 1. The actor side is constituted of hunters, conservation agencies, and blue duikers. Physical side is represented by roads, rivers, subdivisions, forests, and vegetation or agricultural land.

5.2 Entities, Variables, and Behaviors of PIM

At the conceptual level, the list of agents includes Conservation Agency (CA), Hunter and the mammal species (antelope or blue duiker). Other objects considered to build the environment are spatial entities representing subdivisions, roads, rivers, forests and agricultural lands where vegetation can grow. These geographical entities can become the geo-agents in simulation according to the model orientation. Table 2 gives detailed knowledge of the actor's properties, behavior, and important variables for modeling. Table 3 summarizes the relationships (0 or 1 and the nature) between the entities.

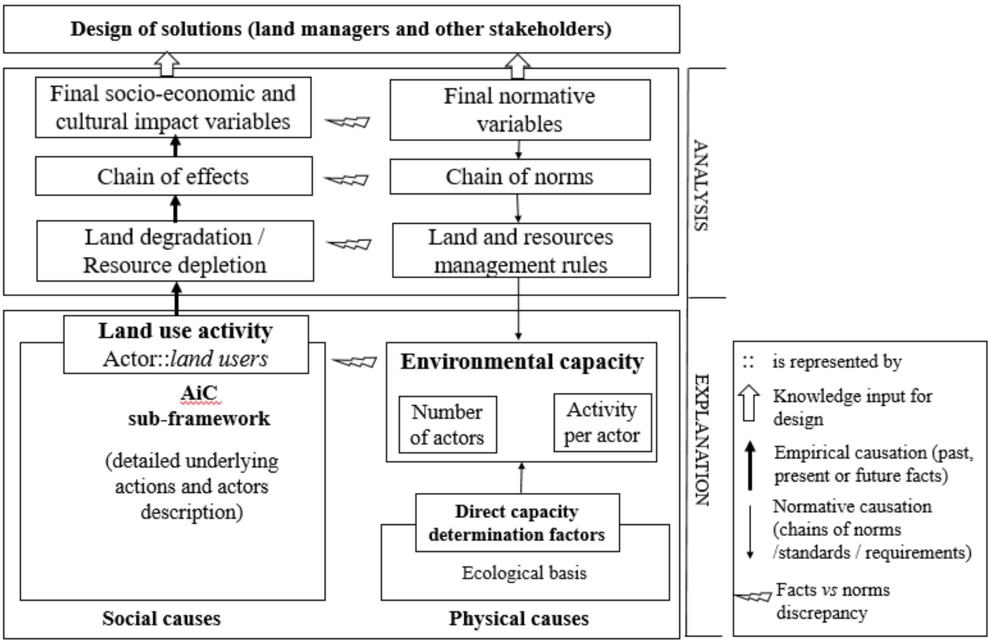

Figure 7. Problem analysis of the sustainability of hunting activity

Table 2. Actor's description and parameters of the hunting model case study

Elements	Details
Hunters	• Action: *hunting*; • Motivation: *make money to survive, reduce poverty*; • Goal: *catch blue duiker*; • Properties: *size, color, ethnic group, speed*; • Abilities: *move, pursue, catch, stop hunting, die, change strategy*.
Conservation Agencies	• Action: *make formulate rulers prohibit the abusive hunting*; • Motivation: *the disappearing of biodiversity affecting the live chain*; • Properties: *name and type*; • Goal: *sustainable management of our environment*; • Abilities: *move, pursue hunters, stop hunting, inform hunters.*
Antelopes	• Action: *grow*; • Properties: *age, sex, gestation length, size, color, max energy*; • Goal: *survive*; • Abilities: *eat, escape, panic, conceive, reproduce.*
Data used for spatially explicit world	• Features: *roads, rivers, subdivisions, forest, agricultural land*; • Source: *Global Forest Watch database in land use/cover section*; • GIS tool: *Quantum GIS 3.10.*
Global and output variables	• In actor/agent level: *number of hunters and antelopes, vegetation energy to consume or transfer, probability to catch antelope, etc*. • In physical level: *names of geo-entities and their characteristics*.

Table 3. Correlation matrix of the entities involved in the model

Relation	Antelope	Hunter	Forest	Vegetation	CA
Antelope	0	1 (hunting)	1 (feed)	1 (feed)	1 (is protected)
Hunter	1 (hunting)	0	1 (use)	0	1 (control)
Forest	1 (feed)	1 (use)	0	0	0
Vegetation	0	0	0	0	0
CA	1 (protection)	1 (control)	0	0	0

At the conceptual level, the resulting model is represented as a class diagram (Figure 8) showing the social as well as the physical context. The social part includes actors and their relationships while the physical part includes the environment and its geographic entities.

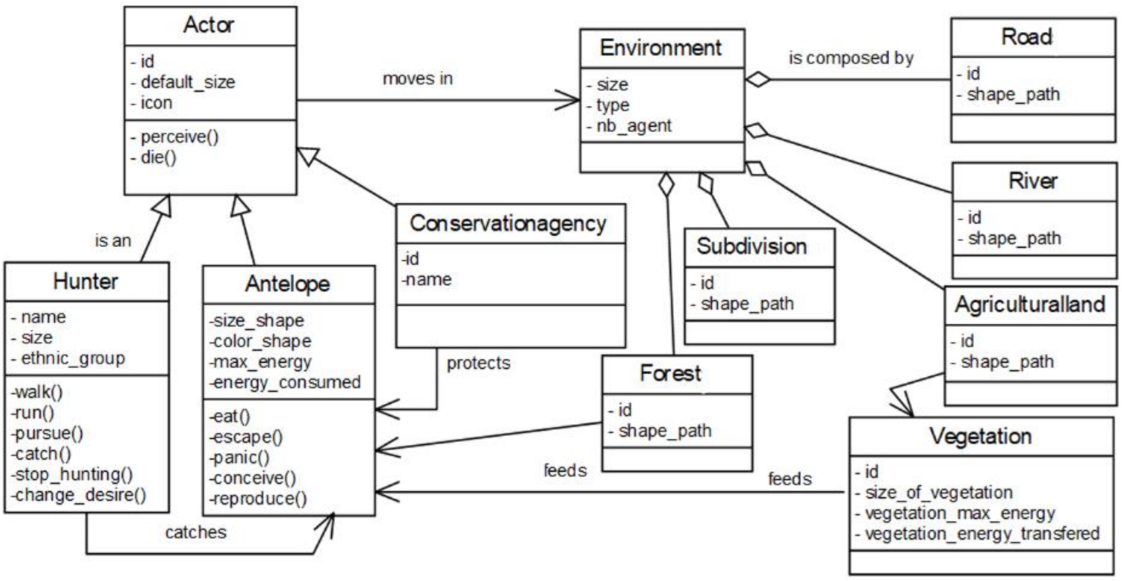

Figure 8. Class diagram of the model portraying actors' behavior and environment attributes

5.3 From PIM to PSM

By referring to the actor-environment class diagram, we use the graphic editor to specify each block of the AGE following actor-agent rules defined in Section 4.3. Technically, in the Eclipse platform, using the new plug-in, we created the new *abmodel* project as presented in Figure 9.

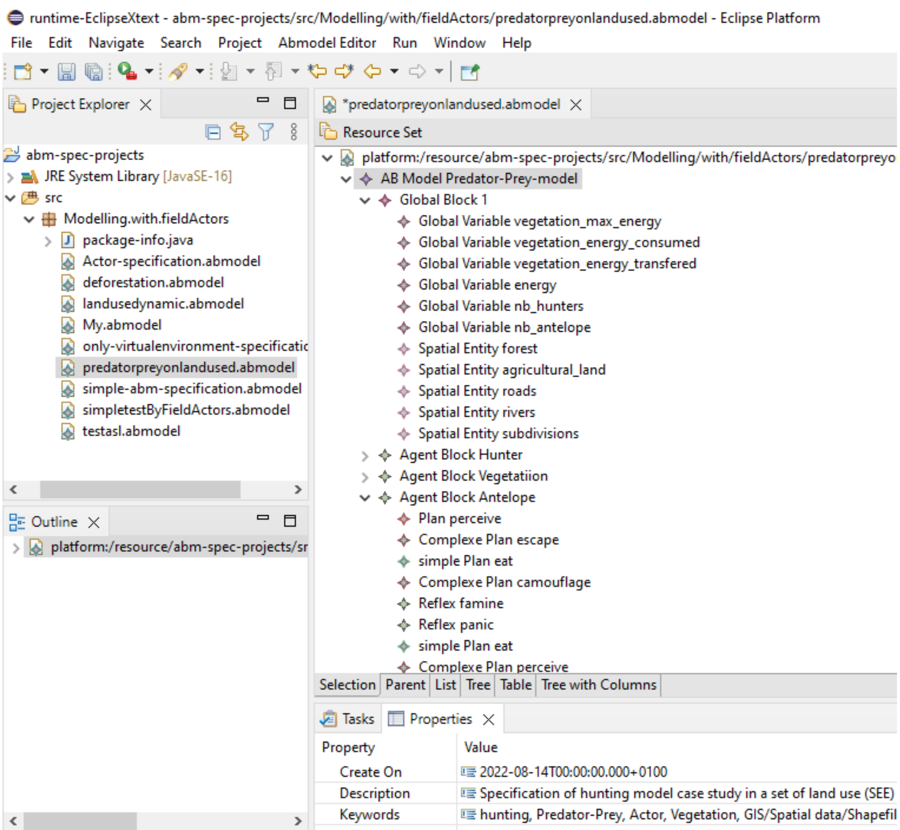

Figure 9. Specifications in the graphic editor

In Figure 9, the list of AGE projects is available on the left. The current project edited, at right, shows the specification process of the case study model.

The initial and base model code automatically generated is presented in Figure 10.

```
HuntingModelASL2GAML.gaml

/*======================================================================================
--------POWER BY ASL2GAML GENERATOR FOR GAMA SIMULATION PLATFORM-------
Model Name : Predatorprey model Kewords: hunting,Predator-Prey, Vegetation,GIS/Spatial data
Description : Specification of hunting model case study in a set of land use (SEE)
=======================================================================================
*/
model Hunting_model_from_asl
/* Definition of global variables according to AGE Framework*/
global{
    float vegetation_max_energy<-100.0; float vegetation_energy_consumed<-0.0
    float  energy; float vegetation_energy_transfered<-2.0;
        int nb_hunters <- 6; int nb_antelope <- 300; int<-reproduction;
    file shape_roads <- shape_file("D:/Worspace-QGIS data4ABM/roads.shp");
    file shape_rivers <- shape_file("D:/Worspace-QGIS data4ABM/rivers.shp");
    file shape_agri_land <- shape_file("D:/Worspace-QGIS data4ABM/agri_land.shp");
    file shape_forest <- shape_file("D:/Worspace-QGIS data4ABM/forest.shp");
    file shape_sudivisions <- shape_file("D:/Worspace-QGIS data4ABM/subdivisions.shp");
    image_file shape_icon<-image_file("D:/antelope.png");
    geometry shape <- envelope(shape_sudivisions);
  init {  /*Add your own initialization code here*/ create area from: shape_sudivisions;  }
}
/* Definition of Agents according to AGE*/
   species antelope  {
   float size <- 1.0;   rgb color <- blue; int<- age; string<-sex; float<-max_energy;
   float max_energy  <- vegetation_max_energy; int <- gestation_length;
   float energy_transfer <- vegetation_energy_transfered; bool<-made;
   float energy_consum <- vegetation_energy_consumed;
   vegetation_cell my_cell <- one_of(shape_forest);

   init{ //add initialization content here}
   aspect circle{ /*add initialization content here*/}
  reflex basic_move when:  null{/*describes the reflex behavior here*/}
  reflex eat when:  my_cell.food > 0{/*describes the reflex behavior here*/}
  reflex die when:  energy <= 0{/*describes the reflex behavior here*/}
  reflex conceive when:  energy <= 0{/*describes the reflex behavior here*/}
  reflex reproduce when:  energy <= 0{/*describes the reflex behavior here*/}
 }
species vegetation_cell  {  //...
   init{ //add initialization content here}
 }}}
species hunter skills: [moving]{    //
    geometry shape<-circle(0.1); rvb color<-red; float speed<-0.05;
    reflex catch when:{} reflex die when:{} reflex change_strategy when:{}
    reflex move when: {} reflex pursue when: {} //other...
}
species antelope skills: [moving]{  //
    geometry shape<-circle(0.1); float speed<-0.05; //1.0
    rgb color<-#red;
    reflex hunting{} reflex panic when: {} reflex famine when: {} //other...
    reflex eat when: {} reflex perceive when: {} //other...
}}
/* Definition of experiments according to AGE*/
  parameter number of antelope: var: nb_antelope;
  parameter number of reproduction: var: reproduction:;
  parameter vegetation max energy: var: vegetation_max_energy:;
  parameter vegetation energy consumption: var: vegetation_energy_consumed;
  output {
      display standard {
        species rivers aspect: geom;    species agri_land aspect: geom;
        species roads aspect: geom; species subdivision aspect: geom;
        species roads forest: geom; circle hunter line: #red
}}
```

Figure 10. GAML code generated from ASL2GAML

The code is constituted by:

- The header represents the meta-data corresponding to the case study model dedicated to the hunting simulation. That generated code is constituted by three main blocks according to the AGE framework.

- All agents (a hunter, CA, and an antelope) become the *species* blocks in the GAML context (lines 22–49) or *turtles* in NetLogo context.
- All variables (energy, number of agents, geographic entities) denoted by *global* and concerning the simulation process and virtual environment specified are observed in the *global* block at the beginning (lines 9–19).
- All parameters (variation of the number of antelopes, energies, etc.) concerning the simulation outputs in the *experiment* block are observed at the end (lines 52–60).
- Some outputs of variables are defined in standard displays. Those outputs allow us to observe the land uses defined in a virtual environment during the simulation process.

The result of running the generated code is presented in Figure 11 where:

- We observe a representation of the virtual spatial explicit world and agents generated from the initial code produced.
- That world includes agents (6 hunters in red icons and 300 antelopes in grey icons) and spatial entities (the roads in red lines, the rivers in blue lines, the hamlets in blue shapes, the forests in green shapes).

This knowledge can be specified by a domain expert or IT specialist or jointly and imported into the GAMA platform for simulation. But, it remains to complete the skeleton generated with AGE policy, based on the actor’s behavior.

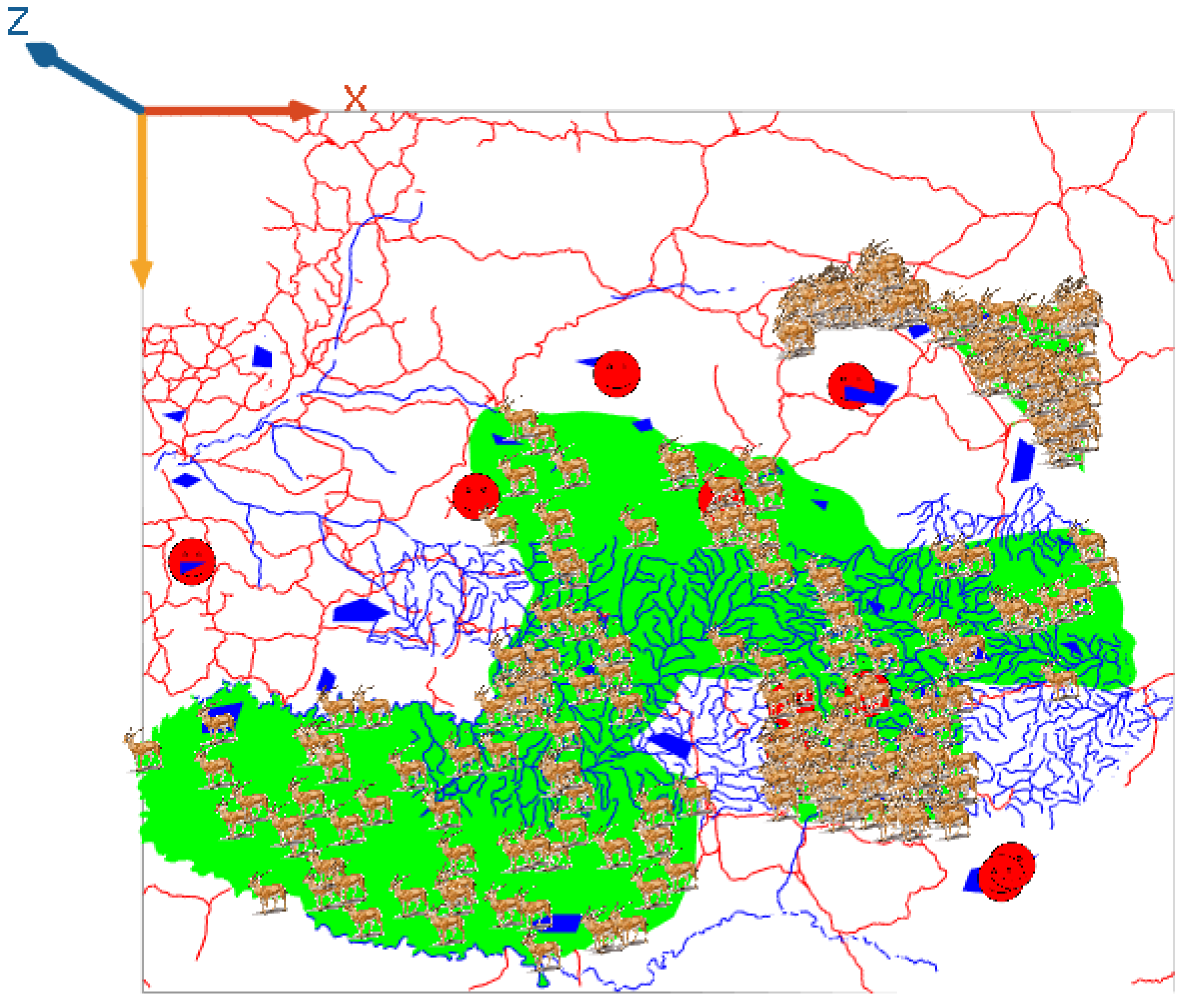

Figure 11. A resulting map from the model code execution displaying agents and geographic entities

This environment and the associated code can be easily produced and a domain expert involved in a modeling project can reuse or customize it later to build a new model. This result meets the requirements of a community of practice where people are working together to share knowledge related to some domain concepts. In addition to the quality attributes provided by the MDA process and automatic code generation and editor tools with error detection, this approach includes the spatial and social aspects (actors) in the modeling process to improve the expressiveness and validity of the final models. However, the transformation process of the AGE producing the GAML code is still in a preliminary state.

5.4 Validation

The validation of our approach was performed on a model case study, with the GAMA platform, using the metamodel to produce simulations in a participatory modeling context in Gribé village (Eastern Cameroon). All information concerning actors, their behavior and the environment were specified jointly with various stakeholders on the field including workers of the conservation agency who provided statistics of hunters and hunted animals; hunters who provided information on blue duikers (small antelopes) and researchers who provided GIS data/information. Specifications of the hunting model were elaborated according to AGE framework in ASL tool. In order to model actor reasoning, the approach experimented with two agent architectures to assess the validity of our approach: a simple BDI and an extension of BDI called SBDI designed and published in [48]. This architecture allows the integration of spatial knowledge and reasoning in the decision-making process of an agent. Before the generation of the initial model code, a total of 20 hunters were divided into two groups of agents according to these two architectures. 2000 antelopes were randomly distributed in the environment composed of spatial entities including a set of 35 subdivisions containing 6 forest stands, and 10 villages, crossed by roads and rivers. It also includes 4 land uses imported into the simulation tool. Each layer representing one land use type was described and organized in geometric and attribute information files. The simulation was carried out in order to assess the relevance of the model in terms of agents behavior and performances (number of captures) plotted in Figure 12.

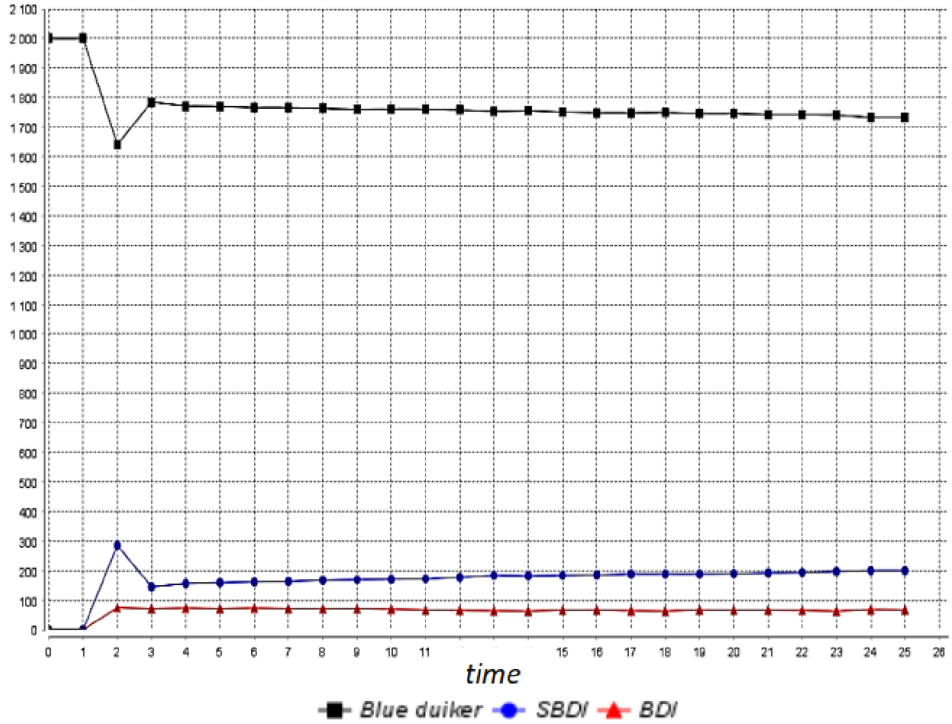

Figure 12. The result of spatially explicit simulation: hunter's performance during the hunting activity for 24 cycles (6 months)

BDI and SBDI agents mimicked adequately the actual hunter's behavior and blue duiker dynamics. The comparison of their performances also demonstrates that the integration of a cognitive dimension into the agent processes strongly improves the model's realism and validity. The description of the approach used to integrate spatial knowledge in agents representing human actors is out of the scope of this article. The validation exercise on a case study discussed above highlights the operational aspect of our methodology on specific agent architectures. The proposed methodology is currently under user validation and their comments and inputs are gathered to be used for further improvements.

5.5 Discussion

In this article, an agent-based modeling approach, called SEAMA is introduced and supported by the ASL framework based on Belief-Desire-Intention architecture. A metamodel is built from this one to support the generation aspect of ABM and implementation. The approach is designed to handle many situations encountered in participatory modeling where the ABM paradigm is adopted and also where the hierarchical or non-hierarchical multi-level systems with spatial and temporal dynamics, actors, and behavior are taken into account in land use situations. Moreover, SEAMA relies on general ABM methodologies published in the literature [24], [41], [54]. This approach has been well described, and the transformation processes have been demonstrated and also applied to a modeling case study for user validation. The initial modeling problem created by the ad hoc models is solved by this approach. Moreover, the actor and spatial aspects are integrated into the metamodeling process allowing to capture of the environment and actor's specification through agent architecture according to the AGE framework proposed. Finally we have compared our approach with existing metamodeling approaches according to five criteria with four taken in [13]: generating instances, editing metamodels (or models), user intervention, error detection; and spatial dimension in ABM. Table 4 summarizes the main similarities and differences.

Table 4. Comparing our approach with others from the literature

Approach/ Tools	**Criteria of positioning or comparison**										
	Generating instances			**Editing meta (models)**		**User intervention**		**Error detection**		**SE ABM for land use**	
	Auto	**Man**	**No**	**Yes**	**No**	**Edited**	**Param**	**Auto**	**Man**	**Actor**	**Spatial**
IRM4MLS/ SIMILAR [54]		*		*		*			*		
GEAMAS [55]			*	*		*		*			
SPARK [56]			*	*	*		*		*		
NMDC/ TiC [13]	*			*		*		*		*	
SEAMA/ TiC	*			*		*		*		*	*
Auto: Automaic. Man: Manual. Param: Parameter. SE: Spatially Explicit											

In addition to presenting identical properties with the existing approaches, our approach allows us to specify the actor and environment properties and generate an instance of a spatially explicit model that we wish to develop for land use simulation. The experimentation of our approach on a land use case study clearly reveals that SEAMA respects the diversity of situations related to the actor's behavior and environment at the same time in a generative process. Comparing this approach with the approach of Natural Model-based Design [57] we can see that our approach takes into account the driving concepts such as Belief, Desire, and Intention more clearly and combines them with the agent's spatial interaction to represent the process. According to [58] our transformation generates about 43% of the GAML code (see Figure 10), these results are encouraging compared those obtained with Natural Model-based Design [57] approach.

6 Conclusion

In this research, we have addressed the issue of effective participatory modeling and simulation of land use by combining agent-based and spatially explicit approaches. The main problems identified in existing methods are related to the lack of domain knowledge from ICT analysts, low productivity of domain experts, and low rate of model re-usability which translate into questionable model validity, higher costs, and longer development time. In the proposed SEAMA approach, the system analyst describes actor behaviors and spatial features using information, knowledge, and perceptions obtained from the various stakeholders in a community of practice. These specifications are used in the AGE framework designed to automatically generate an initial model code. The pilot experimentation of this methodology is implemented in the eclipse development platform and illustrated with a hunting model case study. The validation exercise carried out reveals it to be more efficient than other approaches, especially, easier to carry out for domain experts and less cumbersome in terms of the number of model-to-model transformations in the whole life cycle. As a consequence, SEAMA improves the model validity and reduces considerably the time allocated to model implementation. The next steps of this research are to enrich the ASL to capture more spatial and agent specifications and improve the transformation rules for more meaningful generated codes. Another work foreseen to improve model validity could be to integrate spatial knowledge and reasoning in the agent decision-making mechanisms. Finally, an appropriate formal testing and evaluation scenario should be elaborated for each category of stakeholders as such validating the model with all stakeholders.

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