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Integrating cognitive models of human decision-making in agent-based models: an application to land use planning under climate change in the Mekong river delta

Chi Quang Truong

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Pierre and Marie Curie University

Can Tho University

Doctoral School EDITE de Paris

UMMISCO/IRD

INTEGRATING COGNITIVE MODELS OF HUMAN
DECISION-MAKING IN AGENT-BASED MODELS: AN
APPLICATION TO LAND USE PLANNING UNDER
CLIMATE CHANGE IN THE MEKONG RIVER DELTA

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Doctoral thesis of Informatics - Complex Systems Modeling

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RÉSUMÉ

Titre de la thèse en français : Intégration de modèles cognitifs de la prise de décision humaine dans les modèles à base d'agent : application à la planification de l'utilisation du sol dans le Delta du Mékong en tenant compte du changement climatique.

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Au Vietnam, l'aménagement du territoire agricole est une étape importante de la planification gouvernementale. Les plans sont établis chaque dix ans sous l'égide de l'Organisation des Nations unies pour l'alimentation et l'agriculture (FAO), et définissent en même temps deux principaux objectifs : les types de culture qui doivent être développés en priorité par les agriculteurs ; et les investissements en infrastructure à réaliser par les autorités. Dans ce contexte, la précision de la planification est déterminante pour déterminer quelles politiques publiques seront les plus appropriées. Cependant, concernant la dernière période de planification (de 2000 à 2010) la comparaison entre ce que prévoyait le plan en 2010 et les cartes réelles d'occupation du sol la même année témoignent de profondes différences.

La raison principale de ce décalage entre planification et réalité n'est pas très claire, mais nous faisons l'hypothèse dans ce travail qu'elle est liée à la complexité de la prise de décision individuelle des agriculteurs. Les agriculteurs sont en effet ceux qui, en dernier ressort, décident de l'usage final des parcelles agricoles. Et leurs comportements individuels sont influencés par un ensemble de facteurs externes comme la planification, bien entendu, mais aussi l'usage actuel des parcelles, certains facteurs socio-économiques et les changements qui s'opèrent dans leur environnement immédiat (changement climatique, montée et salinisation des eaux, etc.). En conséquence, ces comportements ne peuvent pas être, encore, facilement représentés par les modèles prédictifs utilisés en planification (quand ceux-ci les représentent). De nombreuses tentatives ont été faites, en particulier à l'aide d'approches à base d'agents, pour modéliser plus finement les comportements des agriculteurs et être ainsi capable de mieux planifier. Cependant, ces approches ont été limitées par des choix de conception erronés ou par la puissance de calcul disponible. La représentation des

processus de prise de décisions reste ainsi encore très simple dans la plupart des modèles de planification agraire.

L'objectif initial de cette thèse est d'apporter une solution à ce problème en proposant, premièrement, une approche cognitive basée sur le paradigme appelé Belief-Desire-Intention (BDI) pour représenter les processus de prise de décision des acteurs humains, et deuxièmement, une validation de cette approche dans le contexte d'un modèle complet de changement d'usage des sols dans lequel la plupart des facteurs cités ci-dessus sont également simulés. Le résultat de ce travail est une approche générique qui a été validée sur un modèle intégrant le changement d'usage des sols d'une région située dans le Delta du Mékong au Vietnam. Nos contributions principales sont les suivantes :

Intégration d'une architecture BDI au sein d'une plateforme de modélisation à base d'agents (GAMA) ;

Conception d'un cadre générique baptisé « Multi-Agent Based Land-Use Change » (MAB-LUC) permettant de modéliser et de simuler les changements d'usage des sols en prenant en compte les décisions des agriculteurs ;

Proposition d'une solution permettant d'intégrer et d'évaluer les facteurs socio-économiques et environnementaux dans le cadre de la planification agraire et d'intégrer MAB-LUC dans le processus existant proposé par la FAO.

Ce travail, au-delà du cas d'étude concernant le Delta du Mékong, a enfin été conçu de façon générique afin que la méthodologie utilisée puisse être généralisée à la modélisation de systèmes socio-écologiques où les facteurs humains doivent être représentés avec précision.

Mots clés : Aménagement du territoire, Modélisation à base d'agent, BDI, Modélisation avec agents cognitifs, Décision humaine, MAB-LUC, Modélisation des changements d'usage des sols, Modélisation de systèmes socio-environnementaux.

ABSTRACT

In Vietnam, land-use planning (LUP) is an important part of national public policies. Decennial plans stipulate both how the land should be used by individuals, making the implicit assumption that they will follow it, and which investments need to be undertaken by authorities to support this use. A good accuracy of these plans is therefore essential to establish correct public policies. However, as it has been the case for the period from 2000 to 2010, the actual land-use, which can be assessed by remote sensing technology or assessment surveys, has been constantly at odds with the proposed plans, sometimes by an important margin.

The main reason behind this discrepancy lies in the complexity of the decision-making of farmers, who are the ones who ultimately decide how they will make use of their parcels. The decision-making is an individual behavior, influenced by external factors like institutional policies, land-cover and environmental changes, economic conditions or social dynamics. Therefore, it cannot be easily represented in the predictive land-use models. Several attempts which use agent-based modeling approaches (ABM) have been made in the literature to simulate the decision-making of farmers. However, these approaches have been systematically limited by design choice or by available computational capabilities. Therefore, the represented decision-making processes are still very simple.

The initial goal of this thesis has been then to address this problem by proposing, on one hand, a cognitive approach based on the Belief-Desire-Intention (BDI) paradigm to represent the decision-making processes of human actors in agent-based models and, on the second hand, a validation of this approach in a complete land-use change model in which most of the factors cited above have also been simulated.

The outcome of this work is a generic approach, which has been validated in a complex integrated land-use change model of a small region of the Vietnamese Mekong Delta. Our main contributions have been:

The integration of the BDI architecture within an agent-based modeling platform (GAMA);

The design of the Multi-Agent Based Land-Use Change (MAB-LUC) integrated model that can take into account the farmers' decision-making in the land-use change processes;

The proposal of a solution to assess the socio-economic and environmental factors in land-use planning and to integrate the MAB-LUC model into the land-use planning process of.

I conclude by showing that this work, designed in a generic fashion, can be reused and generalized for the modeling of complex socio-ecological systems where individual human factors need to be represented accurately.

Keywords: Agent-based Modeling, BDI, Cognitive modeling, Human Decision-making, MAB-LUC, Land-use Change modeling, Land-use Planning, Socio-environmental Modeling.

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The GAMA platform is an open source platform developed collaboratively by many researchers. One part in Chapter 4 of my thesis is the result of this collaborative work. Thus, I am extremely thankful to the GAMA developers, especially the BDI plug-in developers: Assoc. Prof. Philippe Caillou from LRI, University Paris Sud; Mr. Mathieu Bourgais from IDEES and Assoc. Prof. Carole Adam from the University of Grenoble for their works in implementing the plug-in and for giving me a great chance to participate in this work.

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LIST OF ACRONYMS

Abbreviation	Description
ABM	Agent-Based Modeling
ADP	Absolute Deviation Percentage
AHP	Analytic Hierarchy Process
BDI	Belief – Desire – Intention
CA	Cellular Automata
DARD	Department of Agriculture and Rural Development
DONRE	Department of Natural Resources and Environment of the Socialist Republic of Vietnam
FAO	Food and Agriculture Organization
GAMA	GIS & Agent-based Modeling Architecture modeling platform
GAML	GAMA language
GIS	Geographic Information Systems
LS	Land suitability
LUC	Land-Use Change
LUCC	Land-use and land cover change
LUP	Land-Use Planning
MAB-LUC	Multi-Agent Based model for Land-Use Change
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MONRE	Ministry of Natural Resources and Environment of the Socialist Republic of Vietnam
PRS	Procedural Reasoning Systems
RCT	Rational Choice Theory
SLR	Sea Level Rise
TBR	Theory of Bounded Rationality
TPB	Theory of Planned Behavior
UML	Unified Modeling Language
VGSO	Vietnamese General Statistics Office

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CHAPTER 1 INTRODUCTION

This chapter presents the context of this thesis. In particular, I introduce the Land-Use Planning (LUP) domain and show its important role in the socio-economic development of Vietnam. I also introduce the main difficulties in LUP that are due to the fact that the planned land-use solutions are not performed as expected. These challenges lead to the objective of my thesis in which I have investigated and proposed a new way to support planners in building land-use plans.

1.1 Agricultural Land-Use Planning in Vietnam

Agriculture and aquaculture are the main economic activities of Vietnamese people (46.3% of population - (VGSO, 2015)). Thus, Land-Use Planning (LUP) in agriculture (including aquaculture) is an important part of the national public policies that define the socio-economic development orientations. The land-use plans are built based on the Vietnamese government objectives in terms of socio-economic development for the next 10 years for the three main administrative levels in Vietnam (province or municipality¹, district and commune). After 5 years, the land-use is reviewed and compared with the plan; the plan is then updated in consequence.

The design of these land-use plans by the Vietnamese government is driven by general rules defined in the Law on Land (VNA, 2003, 2013) and by more precise guides from the Ministry of Natural Resources and Environment of Vietnam (MONRE, 2009b, 2014). These official rules provide only the general guidelines and requirements for the plans. Concerning the technical aspects of the plans, planners apply the process guide from the Food and Agriculture Organization (FAO) for land-use planning support (FAO, 1993). The LUP process of FAO is composed of 10 successive steps (cf. Figure 1). Most of them (steps number 1, 3, 5, 6, 7) require planners' decision-making.

¹ The five main municipalities (Ha Noi, Ho Chi Minh City, Hai Phong, Da Nang and Can Tho) have the same administrative level as the provinces.

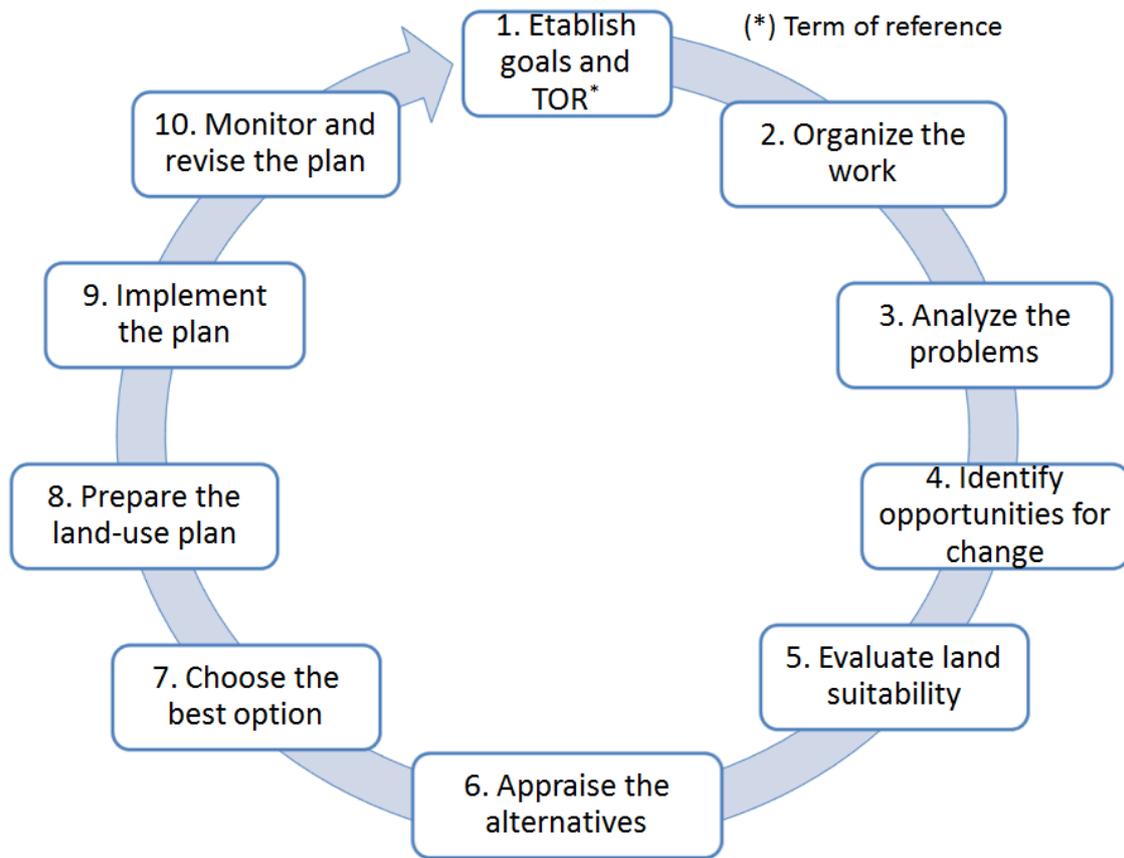


Figure 1. *The main steps of the Land-Use Planning process (Source: (FAO, 1993))*

Steps 5 and 6 are the most important ones in the FAO process. Step 5 consists in assessing the suitability of the land according to its planned land-use type. The main analysis criteria focus on natural conditions such as the soil type, the water quality and the level of floods. The results of the 5th step show which land-use types are suitable for each land unit. These land suitability results are not enough to determine the land-use plans because the produced alternatives do not take into account social, economic and environmental factors. This appraisal is done in the 6th step: the FAO guideline shows which activity should be installed on each land unit and the activity is assessed from an environmental point of view. The economic assessment takes into account both the investment of the government and the income of farmers.

FAO provides also a specific guideline for land evaluation (FAO, 1981) in order to support the land suitability evaluation in the 5th step. Many studies have simply applied the guidelines of FAO for land evaluation (Kauzeni, Kikula, Mohamed, Lyimo, & Dalal-Clayton, 1993; Kutter, Nachtergaele, & Verheye, 1997) or modified the land suitability assessment by using a Multi-Criteria Decision Analysis (Kalogirou, 2002; Chandio, Matori, Yusof, Talpur, & Aminu, 2014; Vu et al., 2014). These studies mainly concentrate on the 5th step of the LUP process.

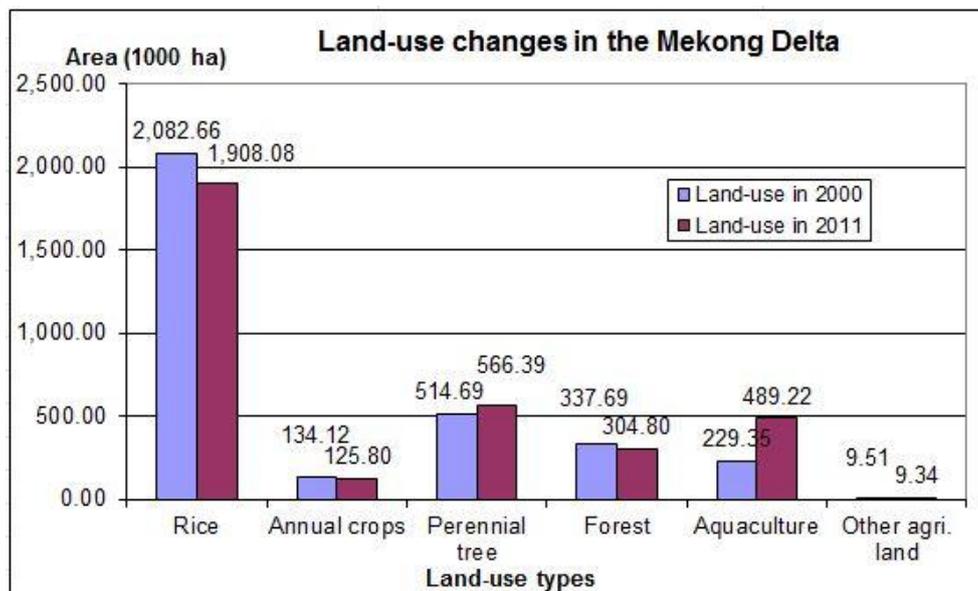
Other studies in the literature have concerned the 6th step. Trung et al. (2006) proposed to take into account the socio-economic and environmental factors which mainly focus on the gross income, investment costs and labor's day requirement. Tri et al., (2013) optimized the capital, labors and incomes in the elicitation of potential scenarios. Following the same approach, Gowing et al., (2006) assessed social and environmental factors. In this study, the assessment of the social factor concerns the change of cropping of farmers and their strategy to adapt to the change of salinity of water. These studies only focus on a subpart of Step 6 of the LUP process. They enrich the plan assessment but they do not take into account the social aspects of farmers behaviors, which happen to strongly impact land-use plans.

In summary, none of the previous studies have proposed a dynamic appraisal of the socio-economic and environmental factors, whereas it is mandatory to understand and predict land use changes for an efficient planning. Why it is mandatory will be better understood by reading the next section, which analyses the issues of recent land-use plans for the area of the Mekong Delta, Vietnam.

1.2 Analyzis of the recent land-use plans issues in the Mekong Delta

The region of the Vietnamese Mekong Delta (VMD), which is composed of 13 provinces including a municipality and is home of approximately 18 million of inhabitants, was by far the most productive region of Vietnam in agriculture and aquaculture in 2014. In terms of rice production, for instance, 47% of the cultivated areas in Vietnam were situated in the VMD, and they outputted 54% of the total production; in terms of aquaculture, 2/3 of the Vietnamese production originated from the VMD. According to (Young, Wailes, Cramer, & Khiem, 2002), these performances, which have roughly tripled in the last 30 years in all sectors, have fueled the boom of the Vietnamese exports of agricultural products (especially rice, shrimps and fruits). This spectacular rise is due to a number of factors: a better economic environment (thanks to reforms more favorable to the private sector), the adoption of modern techniques (fertilizers, mechanical harvesting and progresses in aquaculture), yield improvements, improved irrigation and drainage, among others.

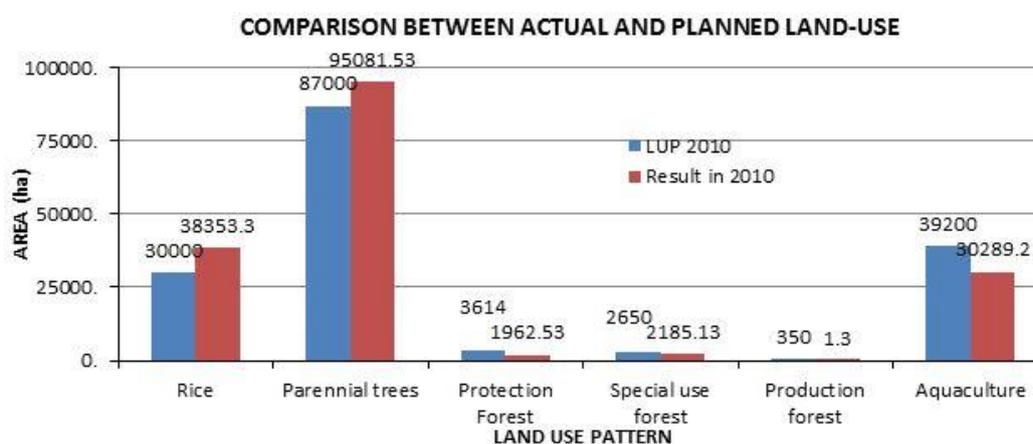
Regarding the statistical data on land-use of the Mekong Delta during the period 2000-2011 (**Figure 2**), it is easy to see that it has had a trend to shift from rice to shrimps. The surface dedicated to rice crops has strongly decreased (more than 170,000 ha) while the one dedicated to shrimp aquaculture has doubled from 229,350ha to 489,220ha. Young et al. (2002) showed that in early 2000 the market price of rice was near or below the production cost, which explains that a majority of farmers have shifted their land-use away from rice.



(Source: Vietnamese General Statistics Office (VGSO, 2000) and Ministry of Natural Resources and Environment of Vietnam (MONRE, 2012))

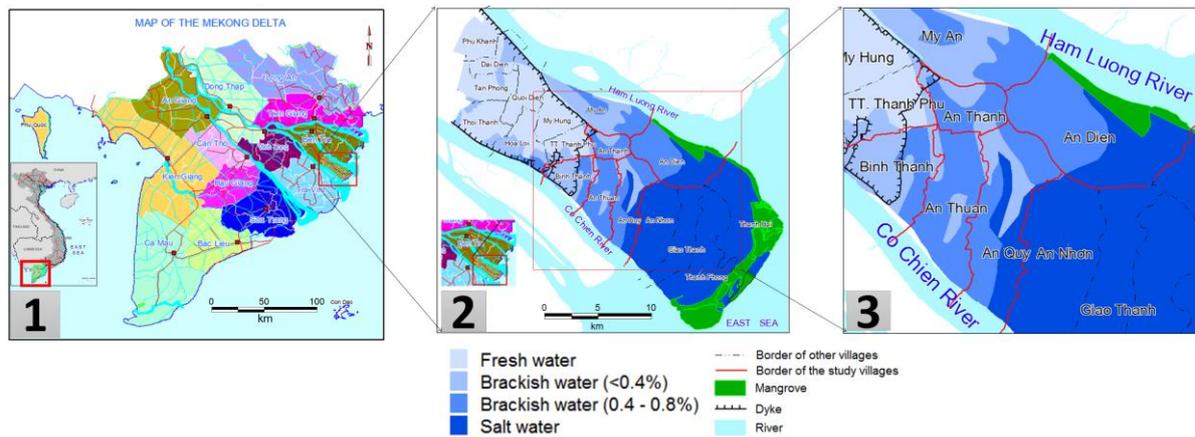
Figure 2. Land-use area in the Mekong Delta in 2000 and in 2011.

This trend of land-use changes can also be observed at the province level. For example, the land-use plan of Ben Tre province (Figure 3) predicted an increase of the aquaculture area in 2010. However, the comparison of the plan with the observed land-use in 2011 shows that a total cultivated area of 175,824ha was planned, where in fact it reached 179,671ha. These values (which gather all kinds of agricultural activities) do not seem so significant at the macro-level, but profound divergences can be unveiled when studying the situation in more detail, in particular the deviation of the cultivated area for each activity. For example, the rice area increased to 38,000ha but was planned to be only 30,000ha (+ 27%); the surface devoted to aquaculture, which was supposed to reach 39,200ha, only reached 30,289ha (-23%); finally the forest area, which was expected to cover 350ha (PCBT, 2011), remained at 1.30ha.



(Source: PCBT, 2011)

Figure 3. Comparison between the planned and the actual land-use of Ben Tre province



(Source: Combination of data from the Land resource department, Can Tho University, Vietnam (Vo, Q. M. and Le, Q. T., 2006) and the Department of Environmental and Natural resources of Ben Tre province, Vietnam (PCBT, 2011))

Figure 4. Maps of the five villages of Thanh Phu district in the Mekong Delta.

To understand these shifts, let us consider more specifically five villages situated in the middle of Thanh Phu district in Ben Tre province (**Figure 4**). They have been chosen because they exhibit a huge variety of land-use while remaining geographically close enough to allow considering that the farmers living in these villages share common "cultural traits" and traditions. Figure 5 shows the results of a spatial comparison I conducted on these 5 villages in order to evaluate the shift of land-use between, on one hand, the two projections for the year 2010 of the plans produced in 2000 and 2005 and, on the other hand, the actual land-use map in 2010 (PCBT, 2011). Changes are measured using the Fuzzy Kappa indicator (Visser & de Nijs, 2006), a variant of the Kappa indicator (J. Cohen, 1960) that provides a fuzzy distance measure close to how humans compare maps. The darkness of the areas in maps 4 and 5 in Figure 5 is proportional to the land-use difference. We can observe that, although the average shift for the whole province is not huge, the local changes show a complete change of productions on the whole territory. The plan published in 2000 is completely different to the land-use in 2010 (almost all parcels have changed) and the rectified plan published in 2005, although it corrects some errors, completely misses the shifts in two villages and along the canals.

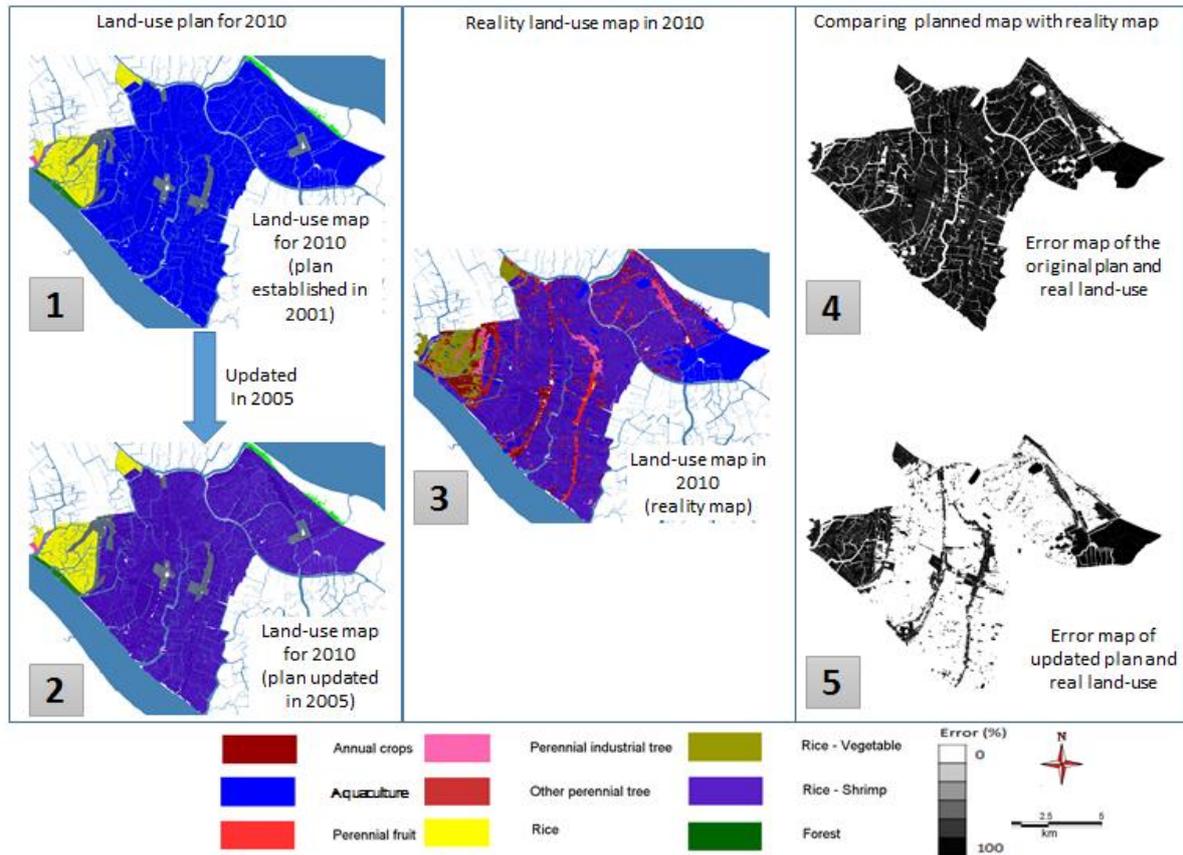


Figure 5. Comparison of planned land-use map and actual land-use map in 2010 for five villages of Thanh Phu district, Ben Tre province. (1) Land-use planning map 2010 (planned in 2001), (2) Land-use planning map 2010 (modified in 2005), (3) Land-use map in 2010, (4) Fuzzy Kappa map between 1 and 3, (5) Fuzzy Kappa map between 2 and 3.

Note that the environmental conditions have almost not been changed during these years. We can see that, even in this favorable situation, land-use planning does not give a good result. This error can be explained by the human factors involved in land-use change. In order to better understand this factor, we conducted an interview with 25 farmers in Binh Thanh village of Thanh Phu district, Ben Tre province. The interviewees were selected among the farmers who have changed their land-use at least once until 2014 (some of them have changed their land-use many times). The goal of these interviews was to identify the reasons why these farmers decided to change. Figure 6 shows seven reasons that have been expressed. The five main ones are: following neighbors (nearly a third), seeking high benefit (a quarter), because of the suitability of parcels (21.43%), to follow tradition (12.5%) and finally because of price drops (7%)

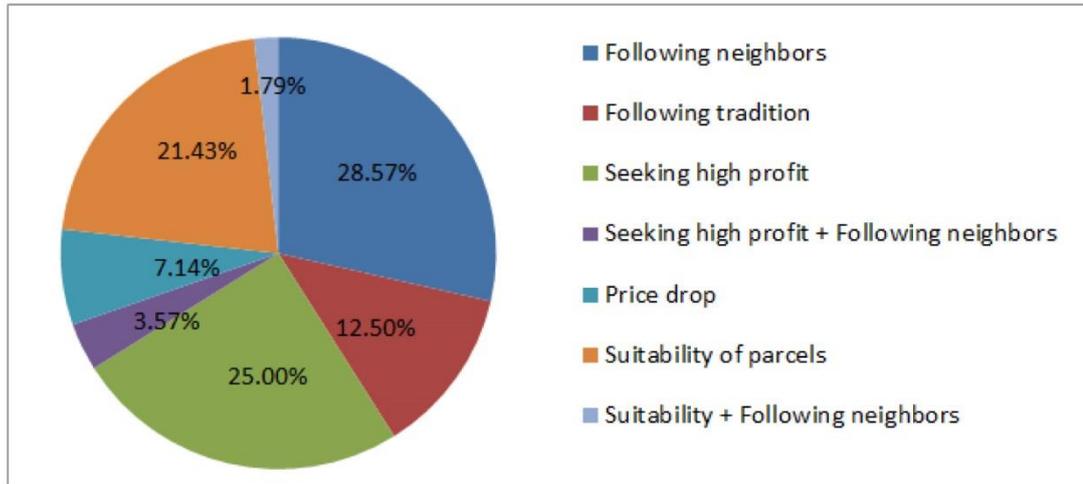


Figure 6. *Farmers' choices for land-use change*

To conclude, the analysis of the predicted land-use plans of Thanh Phu district highlights a lack of efficient tools and methods in existing planning decision-support systems, especially ones able to take human factors into account. I argue that this lack is the main reason for the discrepancy in terms of land-use between the predicted plan and the actual world, because farmers have the ultimate choice on how they use their parcels.

1.3 Research questions

The example presented above on a particular case study raises a more global question related to the support of building a land-use plan where human being's decisions play a key role in the evolution of the territory. The main question of this thesis can thus be expressed as follows: how to build a land-use plan taking into account individual human decisions in the context of land-use change?

To answer this question, I propose an integrated model that combines quantitative and qualitative data and that can represent the complexity of farmers' behaviors (and decision-making process) in order to build and test realistic scenarios of land-use changes.

1.4 Objectives of the current research

Derived directly from this research question, my thesis has four objectives:

The first one focuses on the integration, within an agent-based simulation platform, of an architecture able to better represent human decision-making processes. This architecture is generic and has been tested on the modeling of the farmers' decision-making process concerning their parcel land-use.

The second objective concentrates on the design and implementation of an agent-based model of land-use change, integrating quantitative and qualitative data. It contains agents representing human beings in order to take into account the complexity of the farmers' decision-making process within a rich and complex environment.

The third objective is to simulate the land-use change in the Mekong Delta (more specifically in the Ben Tre province) and to validate the capacities of the proposed model with real data.

Finally, simulations with various scenarios have been carried out to illustrate the genericity of the architecture and of the model. This aims at showing its applicability for land-use change planning in supporting the 6th step of the land-use planning process of FAO.

1.5 Contribution of the thesis

The main contribution of this thesis is a generic framework integrating human decision-making in socio-environmental modeling. The framework is based on the use of the classical BDI (Belief – Desire - Intention, Bratman, 1987) paradigm to define the cognitive architecture of socio-environmental actors. The framework is integrated into an agent-based platform (GAMA², Grignard et al., 2013). The platform provides modelers with a dedicated modeling language (GAML) easing the development of any kind of agent-based models even by non-computer scientists. We have extended the platform and provided extensions in the GAML language to allow the design, implementation and integration into a socio-environmental model of cognitive agents based on a BDI architecture.

A strength of this work is to be grounded on a concrete and important application. The second contribution is thus an application-oriented approach. This work is able to provide, on a part of the Ben Tre province, a model reproducing the land-use change which was validated with actual data. However, the approach is fully generic and can be applied on other case studies.

The framework and the implemented model promise to be a helpful tool for planners and people in the environment field.

² GAMA website: <http://gama-platform.org>

1.6 Structure of the thesis

The next chapters of this thesis are organized as follows:

In chapter 2, I propose a brief state of the art of existing land-use change models. I show that human behaviors and decision-making processes are not really well taken into account in these models and how this restricts their relevance. I then explore some basic theories of human behavior modelling that could be used for this purpose in a land-use change model. In particular, I take a closer look at the BDI architecture that fulfils most of my requirements.

In chapter 3, I show that a complex architecture like BDI is actually required to represent the farmers' behaviors. To this purpose, I introduce a modular agent-based model of land-use change, in which these behaviors can be represented using different architectures (Markov-based or multi-criteria selection). This presentation allows me to also introduce the different components of the model and the data sources I have used throughout the thesis, including the results of surveys conducted with farmers.

One of the problems a modeler might face is that BDI is not commonly used to simulate socio-environmental systems. Therefore, beside simple or ad-hoc solutions, few existing implementations in GAMA can simultaneously support the representation of complex data (with thousands of agents) and the modeling of complex behaviors. Chapter 4 describes how I have integrated a BDI architecture into the GAMA simulation platform in order to benefit from its spatial explicit/multi-modeling/multi-scale underpinnings.

In chapter 5, I validate the relevance of the BDI architecture in representing the farmers' behaviors in land-use change models. A real dataset (taken from a coastal district of the Mekong Delta) is used to calibrate the different sub-models and to validate their outputs. The comparison of my 3 implemented behavioral models (Markov-based decision, multi-criteria decision-making and BDI-based decision) shows that the BDI architecture allows to produce more realistic outcomes.

One of the main difficulties of the FAO land-use planning process (see Figure 1) is to be able to assess the future impacts of alternative options or land-use policies, which corresponds to the 6th step of the process. Based on the results obtained in Chapter 5, I explore in Chapter 6 how our model could be used to perform this assessment and show two examples of this use: the first one tests various economic policies regarding the access of farmers to credit, the second takes into account the construction of infrastructures such as salt water sluice gates to change the environmental conditions.

As a conclusion, I examine in Chapter 7 two different aspects of my contributions. On one hand, I show how our model can be integrated in the current land-use planning processes used in Vietnam, but also the possible limits of this integration, in particular regarding the uncertainty of the data sources. On the other hand, I show how our model and its sub-models, which have been tested against one dataset so far, can be generalized to other case studies, bringing modelers more flexibility in building land-use models and more accuracy in representing human behaviors.

CHAPTER 2 STATE OF THE ART

In this chapter, I present a brief literature review of the existing land-use change models to investigate how the human behaviors and decision-making processes are taken into account in these models. Then, I explore some basic theories of human behavior modeling that can be used to improve land-use change models. In particular, I take a closer look at the BDI architecture that fulfills most of my requirements. Finally, I show which simulation platform is the most appropriate one to my study.

2.1 Land-use and land-cover change models

The objective of this section is to explore the existing modeling approaches that deal with Land-Use and land Cover Change (LUCC). Among them, the most popular ones are based on the use of spatial analyses using Geographical Information System (GIS) data, Markov Chain, Cellular Automata or Multi-Agent systems.

LUCC models have a long history in the spatial modeling domain (Dawn C. Parker, Berger, & Manson, 2002). We propose to classify these models in two, not exclusive, categories: descriptive models on one hand and explicative models on the other.

2.1.1 Descriptive and explicative models

The primary concern of Descriptive models is not to represent realistic mechanisms but to faithfully reproduce global-level dynamics of land-use changes. These models usually rely on a discretization of the space into identified spatial units that are often named “parcels” or “patches”. The evolution of these patches over time is driven by the aggregated influence of several global-level factors. The evolution rules can be written using various formalisms, *e.g.* equations in mathematical models (Serneels & Lambin, 2001), transition rules in Cellular Automata models (Zhao & Peng, 2012; Subedi, Subedi, & Thapa, 2013), transition functions or matrices in Markov Chain (Kemeny & Snell, 1983), and so on. Individual decisions are usually not taken into account in these models.

Conversely, the second category of models, the explicative ones, are focusing on representing realistic dynamics of land-use change based on a more detailed and faithful representation of the possible factors. Rather than producing very accurate results, these kinds of models allow the modeler to find out the causes behind land-use changes. Therefore, these

are more explicitly targeting decision-support system in which, for example, “What-if” experiments (Trickett & Trafton, 2007) can be investigated.

In this second category, some of the recent models rely on the agent-based approach. An Agent-Based Model (ABM) is built by identifying in a reference system the entities, their activities and interactions with other entities, the environment and its global dynamics. The joint execution of agent activities and global dynamics generate the studied phenomenon (Drogoul et al., 2002). ABM tools can now be used to design large-scale, data-driven, individual-based models that can become valuable Decision-Support System (Bonabeau, 2002; Sánchez-Marroño et al., 2013) for LUCC and Land-Use Planning (Villamor, van Noordwijk, Troitzsch, & Vleka, 2012). They can also make valuable simulations for larger scales of geographic data (D. C. Parker, Manson, Janssen, Hoffman, & P, 2003; Valbuena, Verburg, Bregt, & Ligtenberg, 2010; Mena, Walsh, Frizzelle, Xiaozheng, & Malanson, 2011; Bakker, Alam, van Dijk, & Rounsevell, 2015). Nevertheless, these models use simple human behavioral models whereas some recent research works have proposed architectures to represent the stakeholders’ behaviors in more sophisticated ways. For example, (Taillandier & Therond, 2011) have proposed an approach based on the belief theory and on a multi-criteria decision-making process in yearly cropping plan decision-making.

2.1.2 Bridging the gap: toward hybrid models

These two categories of LUCC models have remained for a long time somehow separated, firstly because they had different objectives and secondly because they relied on different modeling paradigms. However, their objectives are in fact quite convergent: explaining and predicting large-scale area changes in land-use and especially their variability over time. The fact that human activities are not taken into account casts doubt on the ability of the first category of models to produce realistic predictive models; conversely, the "environment" of the human agents cannot be considered solely as a product of their activity. Especially in countries (like Vietnam) that are threatened by climate change, land-cover changes as well as other stressors (economy, innovations) need to be taken into account and the first category of models can become essential in that respect, in conjunction, of course, with models of the second category. These reasons have led to the emergence of a new type of models, known in the literature as "hybrid models" (Parrott, 2011), which basically combine different sub-models into one to produce richer insights, at the price, however, of an increased complexity: a complexity in the design of these combinations of models and a complexity in their exploration.

LUDAS (Le, Park, Vlek, & Cremers, 2008), built in NetLogo, or Aporia (Murray-Rust, Robinson, Guillem, Karali, & Rounsevell, 2014), built on top of the Repast Symphony platform (Michael J. North, Collier, & Vos, 2006), are two good examples of this trend, and underline both the potentialities of this new modeling approach, but also its drawbacks, which are summarized in the four following issues.

Lack of genericity. Until now, despite the similarity between the objects, processes or actors that can be found across different LUCC case studies, a model developed for one case study usually remains specific to it. In particular, no real effort has been made to generalize and share methodological outcomes (architectures, sub-models, patterns) because they rely on assumptions that cannot be easily translated to other contexts; Aporia (Murray-Rust et al., 2014), for instance, is dedicated to European farmers and their environment, while LUDAS (Le et al., 2008) remains restricted to highlands and mountainous areas in Vietnam.

Lack of flexibility. With the notable exception of Aporia (which partially supports the change of sub-models), most of the existing hybrid LUCC models are designed as a static composition of carefully chosen (or written) sub-models. This does not allow considering sub-models as possible parameters of experiments, something that can be necessary to explore different configurations or scenarios. In our case, given the variety of identified factors, explaining LUCC in the Mekong Delta with an integrated model requires that we explore several causes, some of them represented not only by parameters but by entire sub-models or specific combinations of them. The underlying software architecture thus needs to provide a high degree of modularity and flexibility, in order to easily add, remove or change sub-models, and also to change their way of interacting, exchanging data and contributing to the overall outcome.

Lack of "necessary complexity". Despite their goal, most of the hybrid LUCC models (Zhao & Peng, 2012; Subedi et al., 2013) tend to not treat the different dynamics equally: some are well represented whereas others remain superficial. When the environmental factors are represented with great details, the behavior of stakeholders remains simple (e.g. Lambin and Geist, 2007). Conversely, when their behavior is modeled using advanced mechanisms, like the BDI architecture (Taillandier & Therond, 2011), the environment lacks a proper representation. Of course, simple models have many advantages, e.g. being easier to understand and more tractable from a simulation point of view, but a “necessary complexity” is, sometimes, necessary to provide LUCC models their heuristic power in terms of decision-support (Edmonds & Moss, 2005).

Lack of representation of high-resolution spatial data. Most of the existing LUCC models lack genericity, flexibility and the necessary complexity. In addition, almost all these models are built on raster data with a low resolution. Each cell in a raster model represents a large area that contains many parcels with several land-use types inside. The uncertainty of these data could thus produce very uncertain prediction results at a higher resolution. Transforming small-scale models into large-scale models requires taking into account human decisions to get accurate simulation results.

The limitations of existing models are quite clear for socio-environmental system modelers. Even in the socio-ecological modeling design, Ostrom (2009) and then McGinnis and Ostrom (2014) have presented a general framework with the purpose of analyzing the sustainability of socio-ecological systems (SES). Developing and integrating complex interactions into real complex SES are still challenging with the current SES framework. Thus, integrating cognitive agents to represent social actors could be a very important step to improve these models (Singh, Padgham, & Logan, 2016). However, cognitive agents' architectures are quite difficult to understand and to implement, even for computer scientists. In the two next sections, I provide some details about the decision-making process of farmers concerning land-use change, which highlights the needs to improve the cognitive agent architecture for farmers in my model and gives some clues to choose the most appropriate architecture among all the existing ones.

2.2 Decision-making of farmers concerning land-use change

To analyze the impact of human decisions on land-use change, I first describe the main activities of farmers in the coastal regions of Vietnam (see Figure 6, Section 1.2, Chapter 1 for the description of the case study) as an example that illustrates the necessity to integrate human decision-making behaviors into LUCC models.

First of all, what I call a *farmer* represents a human being who performs all the necessary activities to raise living organisms or raw materials for food on a parcel. In his/her parcel, he/she can choose one among a few popular land-use types (in this particular area): rice, rice + other crops, fruit, vegetable, aquaculture, and rice + aquaculture.

As analyzed in Chapter 1, people in the coastal area tend to shift from rice cultivation to aquaculture (or rice + aquaculture). The higher income of these new land-use types is the main motivation of this change. As far as rice production is concerned, it demands a low capital but it gives the lowest income whereas aquaculture activities give the highest income

but demand a large capital investment. Indeed, the income of rice production in the Summer-Autumn season of 2006 is 246USD/ha (832 VND³/kg) (Thanh, 2010) while the income of rice-shrimp farming in 1997 is 317USD/ha with an estimated cost of 455USD/ha (Brennan, 2003).

Given a land-use plan, authorities try to make land-use changes fit their plan by indirectly influencing the environment through the building of irrigational infrastructure (dikes, sluice gates, fresh water canals, etc.). However, at the end, farmers remain the final decision-makers. Before changing their land-use, farmers have to take into account the constraints of the environmental conditions (such as soil, salinity...), economic conditions (price and cost of products, investment for a new type...), and cultivation techniques. Some factors such as the financial capital can prevent a farmer changing his production and make him wait many years to have enough money to be able to change.

Considering the environmental factors (including soil properties, water salinity and temperatures), some farmers follow their own knowledge to decide whether their parcels are suitable for a new land-use type. Some others follow their neighbors by watching their land-use and their changes or by asking information about their experience. Farmers can also exchange cultivation techniques.

Environmental conditions are not the only constraints in the farmers' decision-making; they also have to take into account economic conditions. Although aquaculture activities give a high income, they also demand a large capital investment. Most of the farmers do not have enough money for this investment. Farmers should thus take into account their capital (and the ways to increase it if needed) and also the cost and price of the production. The money for investments can come from a loan from a bank located in each district (in the form of mortgagee) with a limited budget of disbursements each year. Beside loans from official banks, there is also a black market for loans (which are often easier to get). Official loan interest rates are always lower than black market ones. However, black market offers more flexibility (with of course much more risk). This flexibility could lead the farmers to have many objectives at the same time.

³ 1USD ~ 16,000VND, in 2006- <http://www.xe.com/currencycharts/?from=USD&to=VND&view=10Y>

Looking at the activities of farmers, I argue that it is important to model farmers as the main decision-making actor in a land-use change model. Thus, in the next section, I will analyze the human decision-making theories and also the cognitive agent architectures that could be used to represent farmers.

2.3 Brief introduction to decision-making in socio-ecological systems

The previous section showed the importance to integrate human decision-making processes in LUCC models. For this purpose, in this section, I propose an overview of the decision-making approaches used in socio-ecological models. I start this overview with a brief introduction to the Markov chain and the Multi-criteria decision-making (MCDM) approaches that are the most popular ones for designing agents in land-use models. Then, I review the cognitive decision-making approaches that are commonly used to represent humans in agent-based modeling.

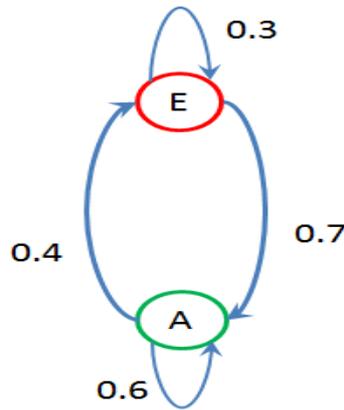
2.3.1 Decision-making approaches for reactive agents

Reactive decision-making processes have been modeled with a huge variety of approaches, even in ecological or environmental modeling. In this section, I introduce the Markov theory and MCDM for representing the decision-making process when they are integrated in existing LUCC models and LUP process.

2.3.1.1 The Markov chain approach

A Markov process (Kemeny and Snell, 1983) is a random process where the decision for the next state only depends on the current state and on a probability distribution. The decision is totally independent of the sequence of events that preceded it. As an example, in Figure 7, a system can be in two states A and E. If the system is in state A, the probability to stay in state A is 0.6, and the one to move to state E is 0.4. These probabilities are not dependent at all on the states in which the systems was before moving to A.

Markov chains combined with Cellular Automata (Gutowitz, 1991) is an appropriate method for predicting and distributing spatial phenomena. A Cellular Automaton consists of a grid of cells, each cell having a value and a set of neighbor cells. The functionality of each cell is based on some fixed rules (a mathematical equation or a Markov chain). This method is mostly applied at the macro level for land use change models with the definition of a global transition probability matrix between the different land-use types. The LUCC models cited in Section 2.2.1 are good examples of use of this method.



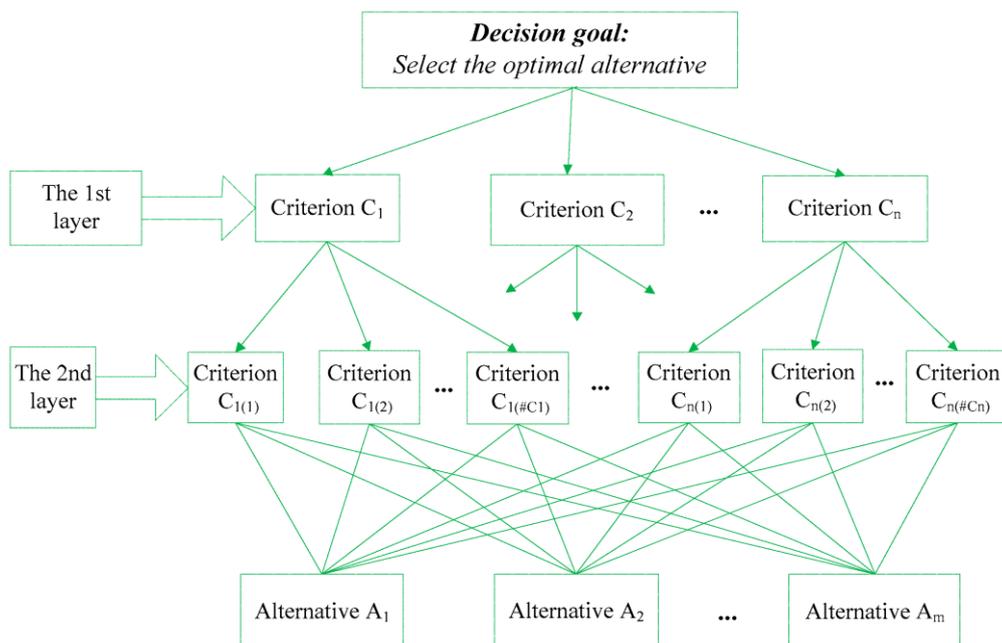
(Source: https://en.wikipedia.org/wiki/Markov_chain)

Figure 7. A simple two-state of Markov chain

Jeffers (1988) pointed out that Markov chain is a convenient method in ecological modeling when it does not require deep insight into the mechanisms of dynamic change. However, Markov models need significant data to build the probability distributions. In addition, they are not appropriate when the number of possible states is high or when sudden and unexpected changes can happen.

2.3.1.2 Multi-criteria decision analysis

Multi-criteria decision making (MCDM, Zionts, 1979) is a way of facing complex problems through an analysis to define criteria and then aggregate them for decision makers (Department for Communities and Local Government, 2009). Figure 8 illustrates the hierarchical multiple criteria decision making that includes the main criteria and the alternatives, each main criterion has the sub-criteria (Zhang, Xu, & Liu, 2016).



(Source: Zhang, Xu, & Liu, 2016)

Figure 8. A hierarchical multiple criteria decision-making

Following this approach, many different methods have been developed to support the personal decision process of decision makers. Each of them has its own advantages and drawbacks as pointed out by Velasquez and Hester (2013) and Aruldoss et al. (2013). From a general point of view, MCDM approaches are easy to be used for modelers and do not need a huge amount of data.

The general MCDM approach has been applied in various domains (economics, environment, socio-ecology). In land-use change and land-use planning applications, the MCDM approach has mostly been used for land-use evaluation and land-use allocation. For example, some works have proposed to apply the Goal Programming method to optimize the land-use allocation based on several criteria concerning social, economic and environmental aspects (Nhantumbo, Dent, Kowero, & Oglethorpe, 2000; Trung, Tri, van Mensvoort, & Bregt, 2006). Another MCDM method that was often applied in LUCC and LUP is the Analytic Hierarchy Process (AHP), It was used in the selection of land-use (Akinci, Özalp, & Turgut, 2013; Bagheri, Sulaiman, & Vaghefi, 2012; Elaalem, Comber, & Fisher, 2010; Nyeko, 2012; I. Santé & Crecente, 2005) and in spatial allocation of land-use planning (Ma & Zhao, 2015; Riveira & Maseda, 2006).

However, the biggest issue is the need to precisely define the preferences for the evaluation process. It is sometimes difficult to determine the weight of the criteria and this could lead to inconsistencies between the judgment and rank criteria.

The reactive decision-making architectures provided by MCDM approaches are well known and extensively used in existing decision support models. These approaches are close to human decision-making in many aspects. However, they are not well adapted to represent the knowledge required in some decisions and the necessity to plan actions in the long-term. I then present in the next section some approaches which are solely dedicated to human decision-making modeling.

2.3.2 Decision-making approaches for cognitive agents

After having presented popular decision-making approaches in land-use planning, I introduce in this section decision-making theories dedicated more specifically to human beings' decision-making. These theories are widely used in psychology, socio-economy and medicine for analyzing human behaviors, e.g. to simulate behaviors of customers, patients (Jager & Edmonds, 2015). Although the decision-making process of real humans is complex

and difficult to reproduce, the simulation of complex human behaviors are needed for representing the human actors embedded in socio-ecological systems. In this section, I focus on the theories related to socio-ecological modeling.

2.3.2.1 Rational choice theory

The rational choice theory (RCT) is a micro-economic theory. It first makes the assumption that complex social phenomena can be explained in terms of elementary individual actions (Scott, 2000) and considers that individuals are rational actors. Rational individuals choose among different alternatives the one that is likely to give them the greatest satisfaction (Carling 1992). Their decisions are based on a cost-benefit analysis on the available information. Note that the “rational” in these cases means that the decisions are “goal-oriented”. In the continuity of this theory, Simon (1972) has proposed the Theory of Bounded Rationality (TBR). The TBR is based on the idea that individuals make rational decision according to their cognitive limitations on both knowledge and computational capacity (Grüne-Yanoff, 2010).

There are several limitations to this theory: individuals are not able to evaluate all possible outcomes to choose the best behaviors; the limitation of rationality does not permit the actors to choose the best possible decisions.

2.3.2.2 Theory of Planned Behaviors

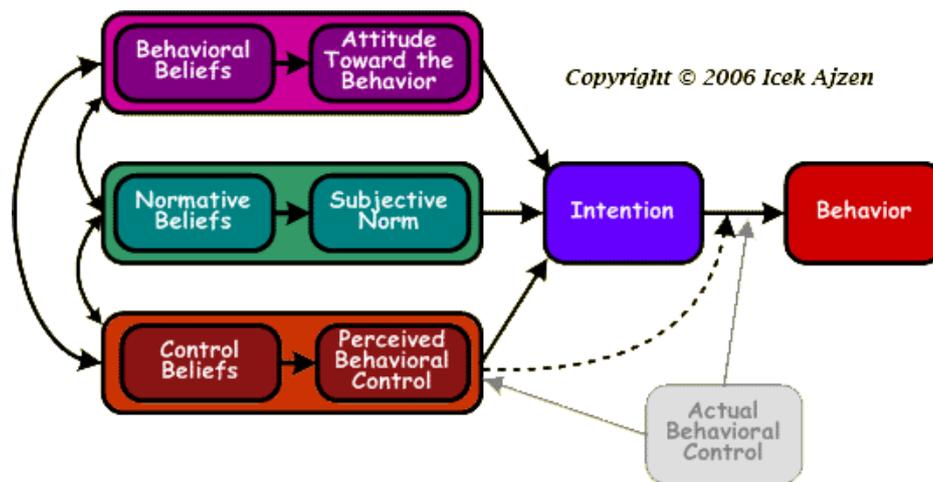
The Theory of Planned Behaviors (TPB, Ajzen (1991, 2004)) is an improvement of the Theory of Reasoned Action of Fishbein and Ajzen (1975). TPB is a model coming from social psychology. It is based on the assumptions that the behaviors of individuals are determined by their intentions and that the intentions are influenced by three states: the individual attitudes, the subjective norms and the perceived behavior control (Figure 9).

Attitude toward the behavior refers to the degree to which a person has a favorable or unfavorable evaluation of the behavior of interest. This state is evaluated based on the outcomes of a behavior.

Subjective norms refer to the beliefs about whether most people approve or disapprove the behavior. It relates to a person's beliefs about whether peers and people of importance think he or she should engage in the behavior.

Perceived behavioral control refers to a person's perception of the ease or difficulty of performing the behavior of interest. The perceived behavioral control varies across situations

and actions, which results in a person having various perceptions of behavioral control depending on the situation.



(Source : Ajzen, 2006)

Figure 9. Theory of planned behavior

Although TPB is known to provide a relevant theory of human behavior, Ajzen (2004) has analyzed several challenges in predicting the behaviors. The main limitation comes from the fact that intention determinants are limited to attitudes, subjective norms, and perceived behavioral control whereas there are many other factors that influence the behavior (Godin & Kok, 1996).

The study of human decision-making process is a very fruitful research field and has been of interest to researchers from many disciplines (psychology, economics, sociology, etc.). Simple to very complex theories have been proposed, but as illustrated by (Gutnik, Hakimzada, Yoskowitz, & Patel, 2006), no theory, once implemented, can accurately predict or reproduce human decision-making.

My purpose is, nevertheless and despite this, to integrate some model of human decision-making processes into an implemented agent-based model of land use change. To this purpose, I focus in the next section on the operational decision-making theories and on the various agent-based architectures able to embed them.

2.4 Agent architectures embedding decision-making processes

In the previous section, I have presented some existing theories usually proposed in socio-ecological models. However, none of them has a corresponding operational computer architecture. In this section, I focus only on human decision-making theories for socio-ecological models that have an implemented decision-making agent architecture.

2.4.1 Cognitive agent architectures

Balke and Gilbert (2014) have proposed a review of 14 agent architectures that could be used for modeling humans in socio-ecological systems. The authors propose to classify them in terms of complexity, from the What-If rules-based architectures to the most complex cognitive ones inspired by psychology and neurology (cf. Table 1). In particular, they associate architectures to the previously presented Bounded Rationality Theory and Theory of Planned Behavior.

Table 1. *Classification of cognitive agent architectures*

Decision theory	Agent architectures⁴
What – If	Production Rules System
Bounded rationality	BDI, eBDI, BOID, BRIDGE, Conumat
Theory of Planned Behaviors	BDI, eBDI, BOID, BRIDGE, EMIL-A
Emotional	eBDI, BRIDGE, PECS, SOAR
Social norms	Del. Norm. Agents, EMIL-A, NoA,
Psychology and Neurology	MHP, CLARION, ACT-R/PM, SOAR

One of the criteria to measure the success of an agent architecture is its reusability and adaptability for new case studies. Among the number of different agent architectures that have been proposed in the literature, some authors (C. Adam, Gaudou, Hickmott, & Scerri, 2011; Klügl & Bazzan, 2012; Norling, 2004; Singh et al., 2016) have pointed out that the BDI is widely used in many different applications. In addition, it has been extended to take into account more concepts such as emotions or norms. At last, as shown in Table 1, these architectures can be used to implement various Decision theories (Bounded rationality, Theory of Planned Behaviors ...). The next section proposes a more detailed presentation of these architectures.

2.4.2 BDI architectures

The BDI (Belief-Desire-Intention) theory comes from the philosophical work of Bratman (1987) about practical reasoning and have been formalized in modal logic by (P. R. Cohen & Levesque, 1990) and (A.S. Rao & Georgeff, 1991). Wooldridge (2000) defined later a BDI agent architecture. The basic idea of the BDI approach is to separate the reasoning components leading to action into three separate components:

- **BELIEFS:** they represent the subjective knowledge that the agent has about its environment which includes also other agents. They can come from the perception of the environment, the communication with other agents or they can be produced by any kind of reasoning process. It is a subjective representation of the world and can thus be false or inaccurate.
- **DESIRES:** they represent the goals that the agent wants to reach. Desires and goals are often used with the same meaning.
- **INTENTIONS:** an intention is often described in a philosophical point of view as one desire chosen by the agent and to which the agent has committed itself to achieve. In

⁴ The agent architectures are reviewed by Balke and Gilbert (2014)

BDI architectures, intentions store the actions that the agent is going to do. In most of the implementations, the intentions are represented by the plans chosen to achieve it. A plan is chosen based on the beliefs and the desires of the agent.

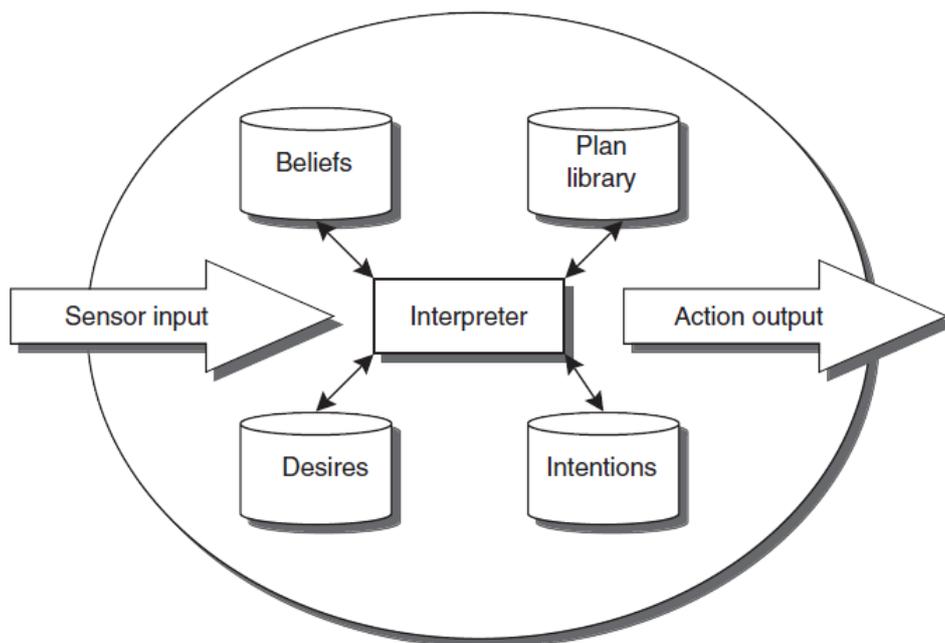
Most of the BDI architectures contain the three main components that are beliefs, desires and intention bases, but they differ depending on the authors and on the application. Next, I present some pure open source BDI platforms.

2.4.2.1 BDI in the Procedural Reasoning System

Georgeff and Lansky (1986) propose the Procedural Reasoning System (PRS) as the first agent architecture to explicitly illustrate the belief–desire–intention paradigm. Besides that, the PRS has also proved to be one of the most durable approaches to develop agents (Bordini, Hübner, & Wooldridge, 2007).

Figure 10 illustrates the PRS system. In addition to beliefs, desires and intentions, a PRS agent has a library of pre-compiled plans. Each of these plans is manually constructed in advance by the programmer. Each plan has a goal (the post-condition of the plan), a context (the pre-condition of the plan) and a body (the actions of the agent).

In simulation, the goal to be achieved is pushed onto an intention stack. Then, the agent selects among its plan library the plans that have the goal on the top of the intention stack as their post-condition.



(Source : Bordini et al., 2007)

Figure 10. *The Procedural Reasoning System*

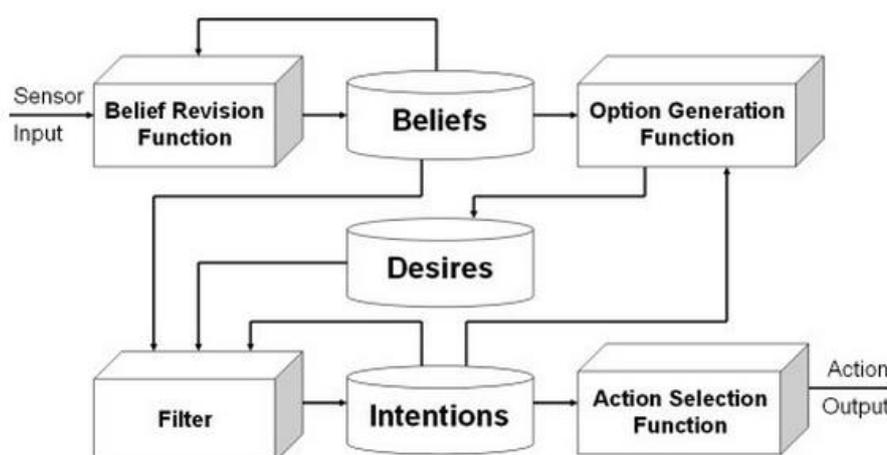
2.4.2.2 BDI architecture in JASON

Jason is a multi-agent system platform using the Jason agent programming language, an extended version of the AgentSpeak language, introduced by Rao (1996).

As proposed by Bordini and Hübner (2005), the BDI architecture in Jason is based on the PRS and the AgentSpeak language. AgentSpeak is an agent-oriented programming language based on logic programming. It is inspired by the work on the BDI architecture of Rao and Georgeff (1991) and BDI logics (A. Rao & Georgeff, 1998). An AgentSpeak agent is defined by a set of beliefs with an initial belief state, a plan library, a set of events and a set of intentions. Intentions are courses of actions that an agent has committed for handling certain events. In Jason, each intention is a stack of partially instantiated plans.

2.4.2.3 BDI for JADE

BDI4JADE (Nunes, 2014) is a BDI architecture for the JADE agent-based framework. This architecture is based on the Procedural Reasoning Systems (PRS) (Georgeff and Lansky, 1986) and dMARS (the Australian Artificial Intelligence Institute's distributed Multi-Agent Reasoning, D'Inverno et al., 2004). Figure 11 shows the structure of the BDI architecture of BDI4JADE. In this architecture, a belief revision function receives input information from the environment to update the beliefs base. Based on the beliefs and the current intention, the desires are determined by the Option Generation Function. The beliefs and desires are then used to determine which intention will be selected from the intentions base through a filter function. From the intention, a suitable action is selected and performed.



(source: BDI4JADE website⁵)

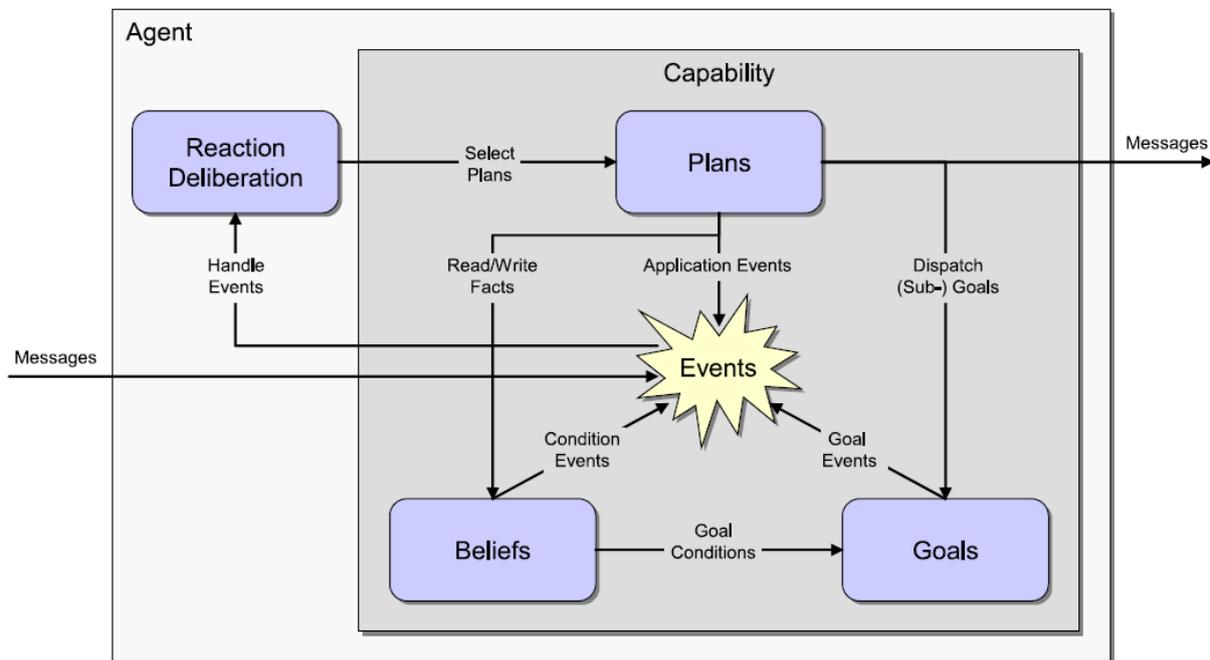
Figure 11. The BDI4JADE architecture

⁵ http://www.inf.ufrgs.br/prosoft/bdi4jade/?page_id=31

2.4.2.4 BDI in JADEX

Pokahr et al. (2005) presented the BDI architecture named Jadex for the construction of intelligent agents.

Figure 12 shows an overview of the Jadex abstract architecture where an agent is designed in two parts, the reaction deliberation mechanism and the capacity of the agent. The reaction and deliberation mechanism is the global component of an agent, which receives the events from the goal event component and select plans from the plans library. The capacity is a reusable module that contains all of the others components.



(Source : Pokahr et al., 2005)

Figure 12. *Jadex abstract architecture*

BELIEFS: In the Jadex architecture, beliefs are represented by arbitrary objects that are stored as facts or sets of facts. Changes of beliefs may directly lead to goals being created or dropped.

GOALS: Goals are represented as explicit objects contained in a goal base. A goal consists of three states: *option*, *active*, and *suspended*. A goal state is set to *option* when it is adopted, it is also added to the goal base of an agent as a top-level goal. A goal deliberation process decides which goals will become *active* and which are just *option*. When the context of a goal becomes invalid, its state is set to *suspended* until the context is valid again.

PLANS: Plans in the Jadex architecture are similar to the ones in other BDI systems. Plans represent the behaviors of an agent. Each plan is composed of a head and a body part.

The plan head specifies the conditions for it to become selected. The plan body provides the actions with a procedural language.

2.4.2.5 Conclusion on BDI architectures

Many agents' architectures have been proposed in the literature. However, not all of them are adapted to the simulation of socio-ecological systems and more particularly to the simulation of farmer behaviors. The next section aims at discussing about the architectures and the simulation platforms that are the most adapted to our application context.

2.5 BDI architectures and platforms to simulate farmer behaviors

2.5.1 Agent architectures for representing farmer behaviors

As pointed out in the previous sections, many architectures have been proposed to represent the behaviors of human beings. The choice of an appropriate agent architecture depends on the purpose of the studies and the specific research questions.

In the context of this work, I argue that the BDI architectures are particularly well fitted to model the behaviors of farmers:

- Agents have desires: farmers have not only one but many goals in their social activities; their priorities can change overtime, they can be postponed or canceled. When simulating the farmers who live in a complex social environment combined with economic behaviors, the desires base of the BDI agents appears to be an ideal solution.
- Agents have beliefs: these attributes of the agent could permit the modeler to represent his knowledge for a long period. Based on these attributes, the agent could “remember” past experiences and use them to analyze his goals and compute, update and choose the appropriate plan to perform the most precise actions. The human knowledge, and in particular its memory, is complex.
- Agents have plans: This part is very important to simulate the human behaviors and particularly to represent the farmers. The survey data for the case study on the reasons leading farmers to change their land-use shows that they do not change suddenly. This is due to many constraints to change from one land-use type to another one. The suitability of the land is only a technical constraint. The biggest constraint is that the farmer has to “think” about the capital to choose and implement the new land use type as well as the price and cost of the products for the next years.

Many land-use change models have been built, but there are very few models including cognitive agents. Most of the time, the model of the farmer behaviors remains simple and uses heuristic rules (decision tree, satisficing) or optimization (linear programming, genetic algorithms and neural networks) (Villamor et al., 2012). Concerning the integration of cognitive models, some authors, like Norling (2004) and Singh et al. (2016)) argue that one of the most important limitations is their usability by non-programmers. To deal with this issue, we argue that there is a need to integrate an easy to use BDI architecture into an agent-based modeling and simulation platform. The next sections deal with the integration of the BDI architecture inside ABM platforms.

2.5.2 BDI architecture in existing ABM platforms

A goal of this work is to create a land-use change model that is generic enough to be reused and distributed and that the land-use planners, who are not computer scientists, could continue to develop. Consequently, I chose to develop my model using an ABM modeling and simulation platform, and in particular one that could support the development of complex agents based on a BDI architecture.

Kravari and Bassiliades (2015) have listed the main characteristics and features of the popular ABM platforms. Adam and Gaudou (2016) have continued by classifying these platforms into 3 groups with relation to their BDI support. The first group is composed of the full native BDI platforms (frameworks) such as Agent Factory (Russell, Jordan, O'Hare, & Collier, 2011) , AgentBuilder (AgentBuilder, 2016), INGENIAS Development Kit (Gomez-Sanz, Fuentes, Pavón, & García-Magariño, 2008), Jack (Winikoff, 2005), Jadex (Braubach & Pokahr, 2013) and Jason (Bordini et al., 2007). The second group includes the platforms fully supporting BDI agents by coupling (with Jadex or Jason), such as AgentScape (Oey, Splunter, Ogston, Warnier, & Brazier, 2010), JADE (Bellifemine, Caire, & Greenwood, 2007), EMERALD (Kravari, Kontopoulos, & Bassiliades, 2010), JAMES II (Himmelspach & Uhrmacher, 2007), MadKit (Gutknecht & Ferber, 2000) and SeSAM (Klügl, 2009). The third group provides a limited support to BDI architecture platform and includes Netlogo (Tisue & Wilensky, 2004), GAMA (Grignard et al., 2013) , Repast Symphony (M. J. North, Howe, Collier, & Vos, 2007) and Mason (Luke, Cioffi-Revilla, Panait, Sullivan, & Balan, 2005).

Regarding platforms of the first group, we can notice that most of them are commercial products (AgentBuilder, Jack) or are BDI native frameworks that require to be coupled with another agent-based platform in order to be able to deal with multi-purpose

models. Most of the platforms included in the second group require deep programming skills (in particular in Java) to be used and are thus not easy to use for non-computer scientists.

Finally, platforms from the third group appear to be a better choice. In addition, they are often generic and are well adopted by a user community. Among them, NetLogo and GAMA have, from my point of view, the great advantage to provide a dedicated modeling language that eases the development of models by providing high-level primitives dedicated to agent-based modeling. As I am mainly interested in socio-ecological system models, the chosen platform has to support geospatial data, to be able to import and integrate GIS data into agent-based models and to provide necessary spatial operators.

Looking back to the two modeling and simulation platforms, Netlogo and GAMA, NetLogo is widely used for both education and research projects. An extension of NetLogo proposed by Sakellariou et al. (2008) allows modelers to use a basic BDI architecture. GAMA aims at developing large-scale spatial explicit agent-based model and strongly support GIS data (Kravari & Bassiliades, 2015). In addition, it provides graphical tools to support model building (Taillandier, 2014), making it very easy to be used by non-computer scientists.

Concerning the development of BDI agents with GAMA, different pieces of works have been done. Thus, some researchers have developed models that use specific BDI architectures (Van-Minh, Benoit, Patrick, & Duc-An, 2013; Taillandier, Therond, & Gaudou, 2012). In particular, (Taillandier et al., 2012) proposed a simple BDI architecture based on multi-criteria decision making that has been applied to simulate the farmer decision-making process for their cropping plan. Another important work was the development of a dedicated extension called *simpleBDI* (Caillou, Gaudou, Grignard, Truong, & Taillandier, 2015) that allows to define basic BDI agents. With this extension, a modeler was able to define beliefs, desires and plans for the agents. However, the reasoning engine was very limited and the manipulation of beliefs, desires and intentions was very complex and required to write many lines of code.

As the GAMA platform fits perfectly most of my criteria, I chose to use it for the work in this thesis. The challenge was then to enrich and improve the *simpleBDI* extension in order to facilitate its use and make it able to manage more complex reasoning and to use it to model the farmer behaviors.

Note that the first part of the work concerning the enrichment of the *simpleBDI* architecture has been carried out in the context of the ANR ACTEUR project (ACTEUR,

2016), with the collaboration of researchers from different research teams (UMR IDEES, TAO TEAM, UMR IRIT, UMR LIG, UMI UMMISCO).

2.6 Conclusion

To conclude, this chapter highlights the fact that many land-use change models have been built but that only a few of them integrate cognitive agents with realistic decision-making processes. Thus, I have looked for the most popular theories of decision-making process, including the non-cognitive decision-making process that ecological models widely use, and the cognitive decision-making theories. After that, the existing agent architectures have also been reviewed. Finally, I have argued that the BDI architectures and the GAMA simulation platform were the most adapted to model socio-environmental systems and more particularly land-use change processes.

CHAPTER 3 THE BASIC MULTI-AGENT BASED MODEL OF LAND-USE CHANGE (MAB-LUC)

After having analyzed the limitations of the existing LUCC models in Section 2.2, I will demonstrate that a complex architecture like BDI is really required to represent the farmers' behaviors. To this purpose, I first introduce a modular agent-based model of land-use change, in which these behaviors can be represented using different architectures (Markov-based or multi-criteria decision-making). This presentation also allows me to introduce the different components of the model and the data sources used throughout the thesis, including the results of the surveys conducted with farmers. I conclude that "simple" behavioral models may have some difficulties to accurately represent the farmers' behaviors and that the BDI architecture might be a better solution.

The results of the chapter have been partly published in two papers (Drogoul, Huynh, & Truong, 2016) and (Truong et al., 2016).

3.1 Basic integrated model for the land-use change

Land-use change is a term that defines the human (farmer in the context of agricultural land) modification of earth's terrestrial surface for agricultural or non-agricultural activities.

During the year, farmers can choose a farming plan that can contain several land-uses at different times in the year. If farmers can change their land-use several times a year, they tend to repeat the same combination of land-uses for the next years if they keep the same farming system. Thus, in the statistics, the combination of land-uses that a farmer has taken in a year on his parcel is considered as one land-use type. For example, the land-use type rice + aquaculture means that the farmer will do one season of rice and one (or two) season(s) of aquaculture. Then, in modeling land-use change, I consider the land-use type of a parcel as a yearly process.

In order to overcome the limitations of the previous works (cited in section 2.2.2) and to provide an effective way to simulate human decision-making, I propose an integrated model for land-use change modeling named MAB-LUC (Multi-Agent Based model of Land-Use Change). MAB-LUC aims at providing a generic, reusable and flexible model of land-use change. The integrated model not only contains the basic components of popular land-use change models (Nhantumbo et al., 2000; Trung et al., 2006), (Akıncı et al., 2013; Bagheri et

al., 2012; Elaalem et al., 2010; Nyeko, 2012; I. Santé & Crecente, 2005) but integrates also decision making approaches for modeling human decision-making.

In this section, I focus on the definition of the basic conceptual model of the MAB-LUC and how its modularity was ensured by the use of a hybrid solution.

3.1.1 The conceptual model of the MAB-LUC

Farmers are the main actors in land-use planning processes. They decide their land-use type under the influence of factors of different natures: social, economic and environmental (cited in Section 2.3). The UML class diagram of MAB-LUC is proposed in Figure 13. In this diagram, we decompose the influencing factors into different groups (highlighted by different colors).

The first group (highlighted in orange) contains the classes linked to economic factors: the *Market_Price* and the *Credit_source* classes. The *Market_Price* class provides the average price and cost in a year of the farming products. Besides that, the *Credit_source* is in charge of managing the investment credit of farmers.

The second group (highlighted in light blue) is composed of classes related to the environmental factors. These classes include the soil type, the soil salinity, the hydrological system, the sluices and the regions that are protected by dykes. Besides these classes, two important classes are *Land_unit* and *Land_suitability*. The *Land_unit* class contains the characteristics of the soils, their salinity, flooding times and the flooding depth. These classes are used for land evaluation (with the guide of FAO, 1983). The *Land_suitability* class stores the suitability of each land unit for each land-use type.

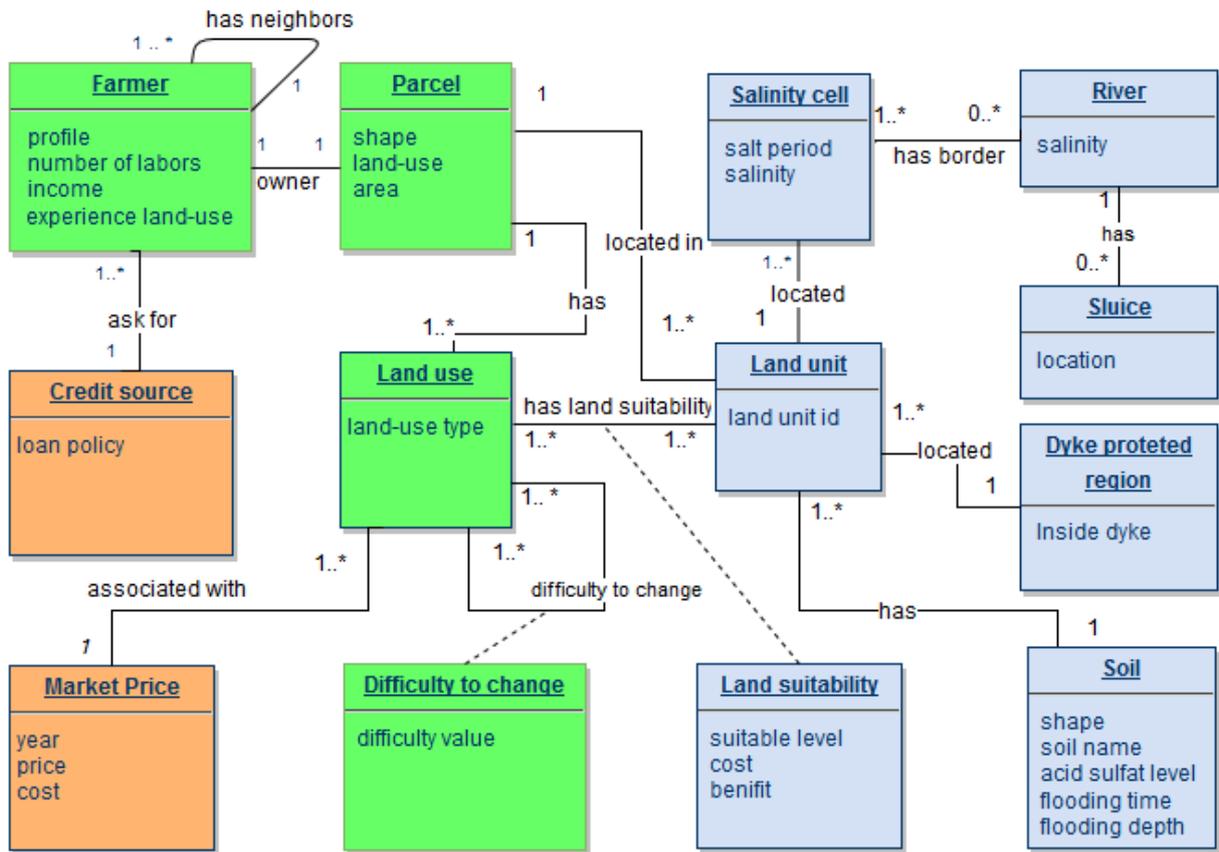


Figure 13. UML class diagram of the conceptual model of the MAB-LUC

The third group of classes (highlighted in green) concerns human factors. The *Farmer* class represents the farmers, which own their parcels. For the sake of simplification, we assume that each farmer owns a unique parcel and that a parcel has only one land-use type each year. As the social relations of farmers with their neighbors play an important role in their land-use decisions, we integrated a neighborhood relation between farmers in the conceptual model.

As it can be observed, the different classes are well separated, which allows for a certain modularity of the model. The next section focuses on this modular aspect of the integrated model.

3.1.2 Modularity of the MAB-LUC

The factors influencing the land-use change are numerous and heterogeneous. In most of the cases, these factors can be expressed as the result of complex calculations. Thus, it would be difficult to design, maintain, adapt and run experiments with a single model integrating all these factors.

In order to ensure the genericity and flexibility of the integrated model, I propose to split it into various components, *i.e.* sub-models. Each of them is related to a specific set of factors such as economic and environmental factors, farmers' decision and farmers' social network influence. This approach allows the modeler to freely and dynamically add, remove or substitute sub-models. Besides that, it simplifies the development of the integrated model as each sub-model can be independently implemented, tested and integrated into the model.

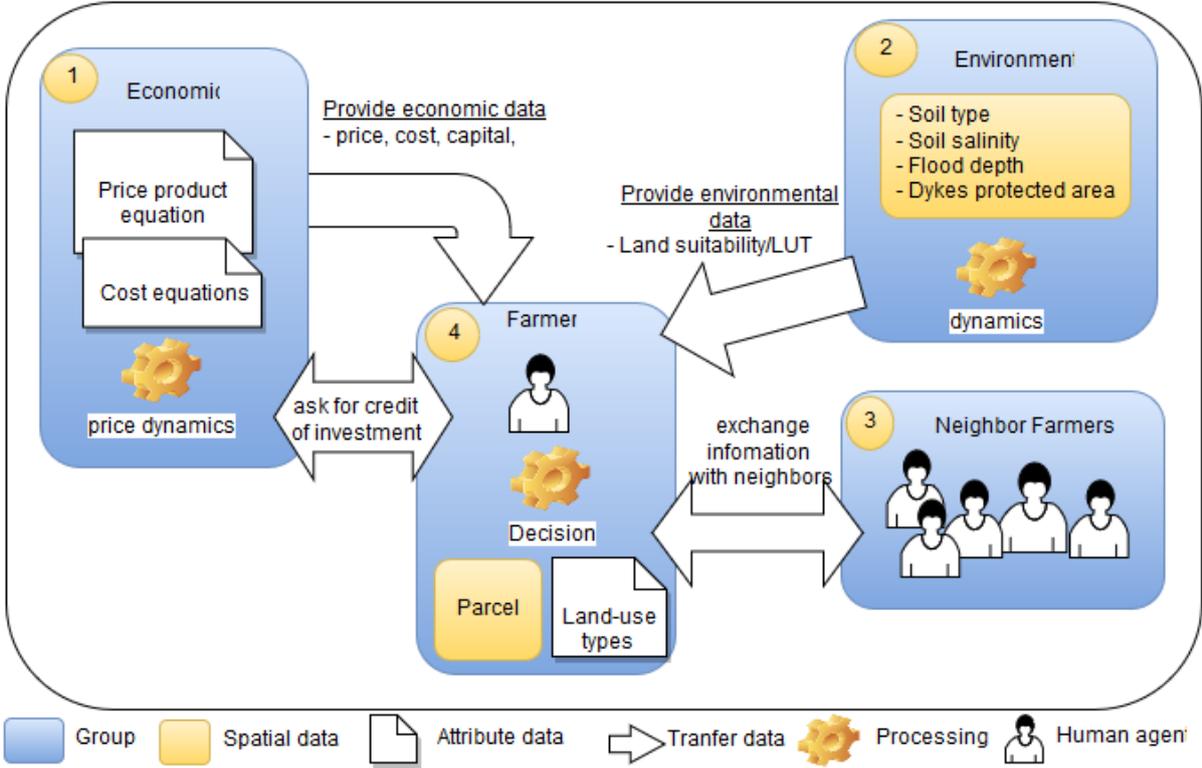


Figure 14. Conceptual view of the MAB-LUC

Figure 14 shows an example where the MAB-LUC is split into four sub-models influencing the land-use change: (1) the economic sub-model ; (2) the environmental sub-model; (3) the sub-model of farmers' social influence; (4) the farmer sub-model.

In the economic sub-model, among all the possible economic factors, I chose only the cost and price of products and the capital that can be provided by banks. The latter factor is particularly important for farmers as it will set the financial constraints on their future development. Data provided from this sub-model are the average price and cost of the products, the capital needed to install a particular land-use type or the total workdays requested to implement a particular land-use type during a year. These pieces of information are directly used by farmers to take their decisions.

The second sub-model is related to environmental factors. These factors are focused on soil and water properties. The value of these factors could come from the soil and water

salinity maps. These data are dynamic and evolve according to different temporalities: the soil properties change slowly while the water salinity changes faster. In my model, these two factors will be used to evaluate the land suitability for a given land-use type and thus will have an impact on the land-use selection of farmers.

The farmer sub-model is composed of farmers and parcels. As a simplification, we consider that each farmer cultivates a unique parcel. Parcel objects are impacted by the decision of farmers. Parcels have spatial relations with soil and water factors. Farmers receive the economic and environmental data from the two first sub-models and can take into account their neighbors' decision to choose a land-use for their parcels.

At last, the sub-model of farmers' social influence contains all the social factors. Decisions of the people in the community in which a farmer is living can have a strong effect on the farmer decisions. This community is represented through a social network.

In my integrated model, I consider farmers as the main human actors and the ones who take decisions in terms of land-use change. They can have complex strategies to interpret the socio-economic and environmental factors in their decision. They can also exchange information with their neighbors.

The use of sub-models provides flexibility to the integrated model: according to his/her need, a modeler can easily replace a simple sub-model by a very complex one. If modelers want to keep the system simple, they can take only the core of the model composed of the farmers, the land-use map, and use static data for the economic (price, cost, labors and so on) and environmental (land suitability for each land-use type, difficulty of transitions among the land-use types) factors. If modelers want to make their model richer, they can simply add economic and social sub-models that feed data to the farmer sub-model. In addition, the model is modular: for each sub-model, various implementations can be provided from very simple ones (*e.g.* a random decision-making for farmers) to complex ones (*e.g.* multi-criteria decision-making process for farmers).

In the next section, I will define our integrated model through its sub-models.

3.2 Definition of the MAB-LUC

As discussed in Section 3.1, I propose a framework in which the factors affecting land-use changes are well separated in four sub-models. In this section, I detail the four sub-models: (1) Economic sub-model; (2) Environmental sub-model; (3) Sub-model of farmers' social influence; (4) Farmer sub-model. For the farmer sub-model (decision-making process),

we show that it is possible to replace one model by another by presenting 3 models based on different decision-making processes.

3.2.1 Economic Sub-model

3.2.1.1 Overview

Ahnström et al. (2009) point out that economic factors, such as the selling price of products in the market, costs of production (the production costs) and expected benefits (benefits = income - cost of production), are the most important factors influencing the decision of farmers. Farmers usually tend to produce products that are supposed to provide them with the highest income in the future. In my model, farmers then need a forecast of these factors to make their decision.

The chosen solution to implement this sub-model is to use global mathematical equations for the whole region that are used to predict the economic values of the different products. Data concerning the market prices and product costs in the past years are used to build these equations. We select the popular products for each land-use type, thus, the price and cost of product are represented for land-use types. Each year, this sub-model provides the farmer sub-model with the prices and costs of the different products.

3.2.1.2 Model design

The main idea of the economic forecasting model is presented Figure 15. In this sub-model, the main component is a set of mathematical equations. From historical economic data, I have inferred evolution equations that will be used to compute and export a simulated price and cost for each product.

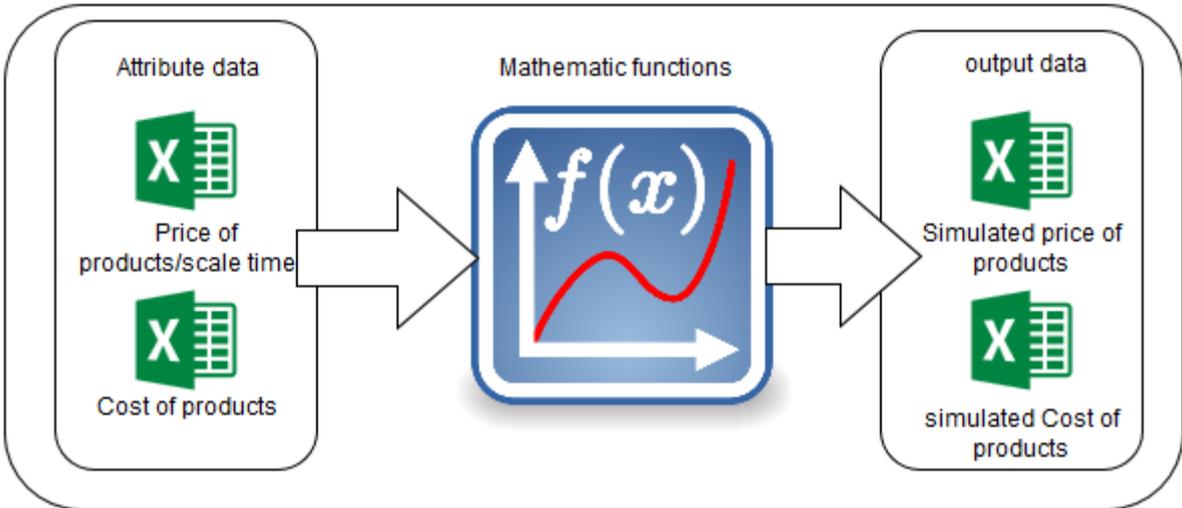


Figure 15. *Mathematical models for simulating the price and cost of products.*

The UML class of this sub-model is shown in Figure 16 where the yearly price and production cost of the products (related to the land-use) are stored in the price and cost variables. The dynamics of the model are performed with 2 functions (providePrice() and provideCost()) that simply get the price and cost of land-uses from mathematical equations and update the Price and Cost of each land-use type.

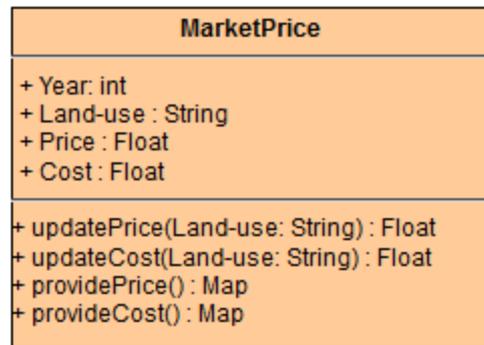
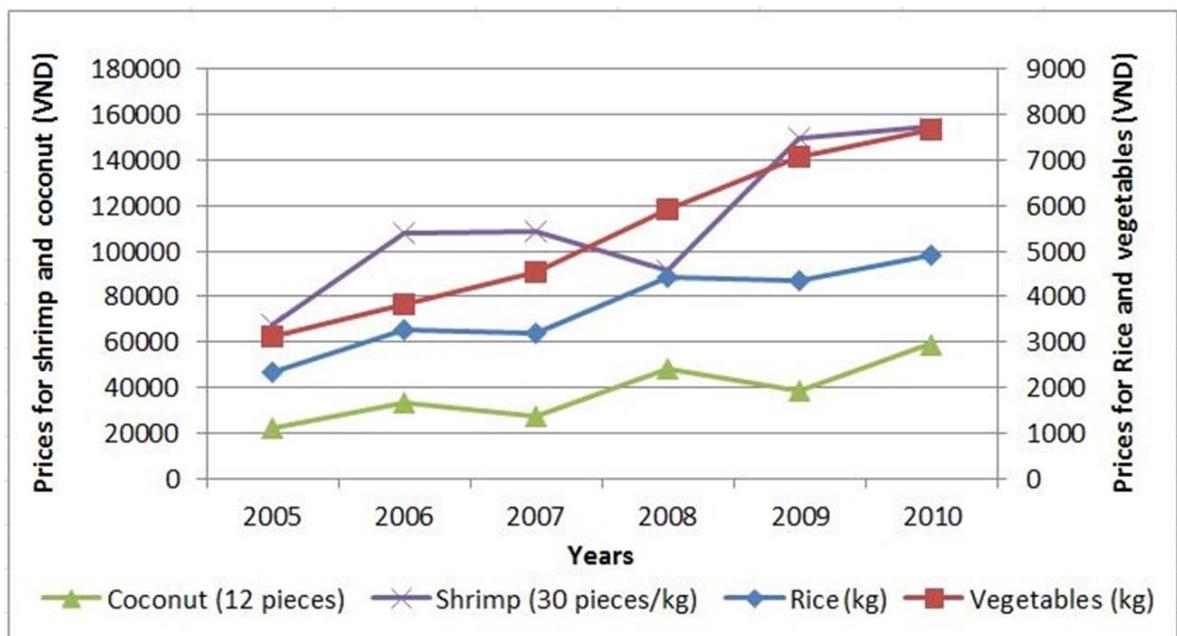


Figure 16. UML diagram of market price economic models

3.2.1.3 Details

In order to induce evolution equations for my sub-model, I have collected data on the evolution of the prices of the four main products (rice, vegetables, shrimp or coconut) in Ben Tre and An Giang provinces from 2005 to 2010 from regional sources (**Figure 17**) and computed the average value for each year.



(Source: Combined from various sources (DARD, 2015a,b; VASEP, 2015; VFA, 2015) (1USD ≈ 21,840VND)).

Figure 17. Market prices of the most popular products in the Mekong Delta from 2005 to 2010.

The historical cost of productions within the corresponding period was not easy to obtain. I then used the costs in 2010 (evaluated in Nguyen *et al.*, 2014) and extrapolated them from 2005 to 2010 using the CPI (Consumer Price Index) from 2005 to 2010 (see Table 2, source: VGSO, 2010a).

Table 2. CPI of Vietnam from 2005 to 2010

	2005	2006	2007	2008	2009	2010
CPI (%)	8.4	6.8	12.53	19.89	6.52	11.75

(Source: VGSO, 2010a)

Benefit by one square meter of each type of production is computed by Equation (1). The benefit of a production p in the year y is calculated by subtracting its cost from its selling price multiplied by the yield of production. The cost of production in the year y is computed according to the cost of production in 2010 and to the evolution of prices given by the CPI.

$$\text{Benefit}(p, y) = \text{price}(p, y) * \text{yield}(p) - \text{cost}(p, y) \quad (1)$$

where: $\text{Cost}(p, y) = \text{Cost}(p, 2010) * \text{CPI}(y) / \text{CPI}(2010)$

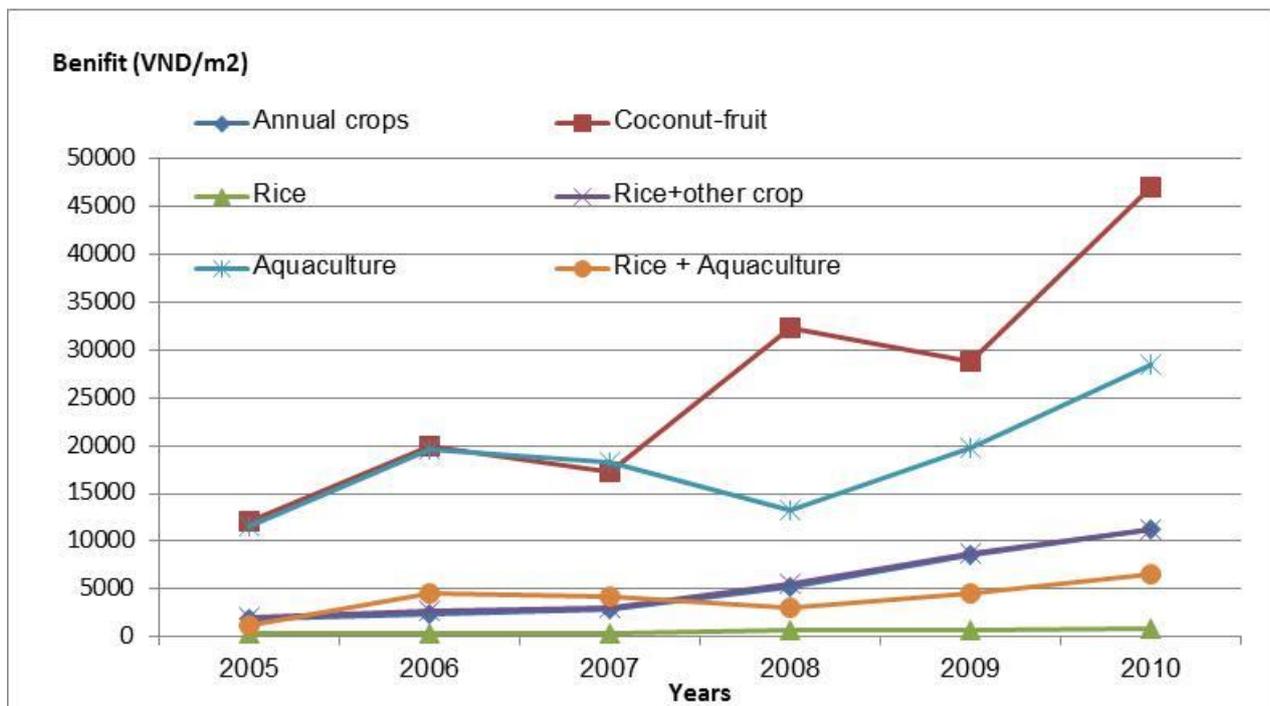


Figure 18. Benefit of different land-use types in the Mekong Delta from 2005 to 2010

Based on these computed data, the equations for the benefit of each product have been generated using a linear regression analysis (Equations 2 to 7). This method was already used in some previous studies (Allen, 1994; Brennan *et al.*, 2000; Brennan, 2003) to estimate the price of agricultural products. Regarding the data on the benefits of aquaculture and rice+aquaculture, they do not fit a linear regression ($R^2 = 0.5$ and 0.54). However, collected

data are very few for a regression analysis, thus, these equations are mainly used for short time dynamics. In the equations of benefit, x represents the time in year (*i.e.* from 2 to 7 corresponding to 2005 and 2010). The benefits are expressed in the Vietnamese currency, Dongs, per square meter (VND/m²).

$$\textit{benefit_vegetable} = 1962.7x - 1511.3 \quad (R^2= 0.91) \quad (2)$$

$$\textit{benefit_cononut_fruit} = 6207.8x + 4529 \quad (R^2= 0.81) \quad (3)$$

$$\textit{benefit_rice} = 110.55x + 190.22 \quad (R^2= 0.73) \quad (4)$$

$$\textit{benefit_rice_other} = 1912.8x - 1171.4 \quad (R^2= 0.92) \quad (5)$$

$$\textit{benefit_aqua} = (2022.4x + 11101) \quad (R^2= 0.5) \quad (6)$$

$$\textit{benefit_rice_aqua} = (606.22x + 1724.8) \quad (R^2= 0.54) \quad (7)$$

3.2.2 Environmental sub-model

3.2.2.1 Overview

Besides economic factors, when farmers decide which type of production to choose, they need of course to take into account the suitability of their parcel for each land-use type, *i.e.* the type and quality of the soil and the quality of available water. In the coastal area, Smajgl *et al.* (2015) pointed out that those environmental factors (*e.g.* saltwater intrusion, implicit effects of infrastructure planning, *etc.*) have a negative impact on the suitability and will then even indirectly lead to a change of land-use.

As we study the system for a short period of time, we assume that the soil type and depth are static and do not change over time. For to the studied area (the Mekong Delta), the main process that will have an impact on the soil suitability is the soil salinity evolution over years. The soil salinity is influenced by salt intrusions as a result of sea water level increase which is in turn due to climate change. Thus I introduce in the next section the soil salinity model.

3.2.2.2 Model design

This soil salinity evolution sub-model relies on a Cellular Automata. The conceptual model is designed in Figure 19. The input of the model includes GIS layers such as soil salinity layer, soil type layer, soil depth layer, river and canal vector layer and sluice gate layer.

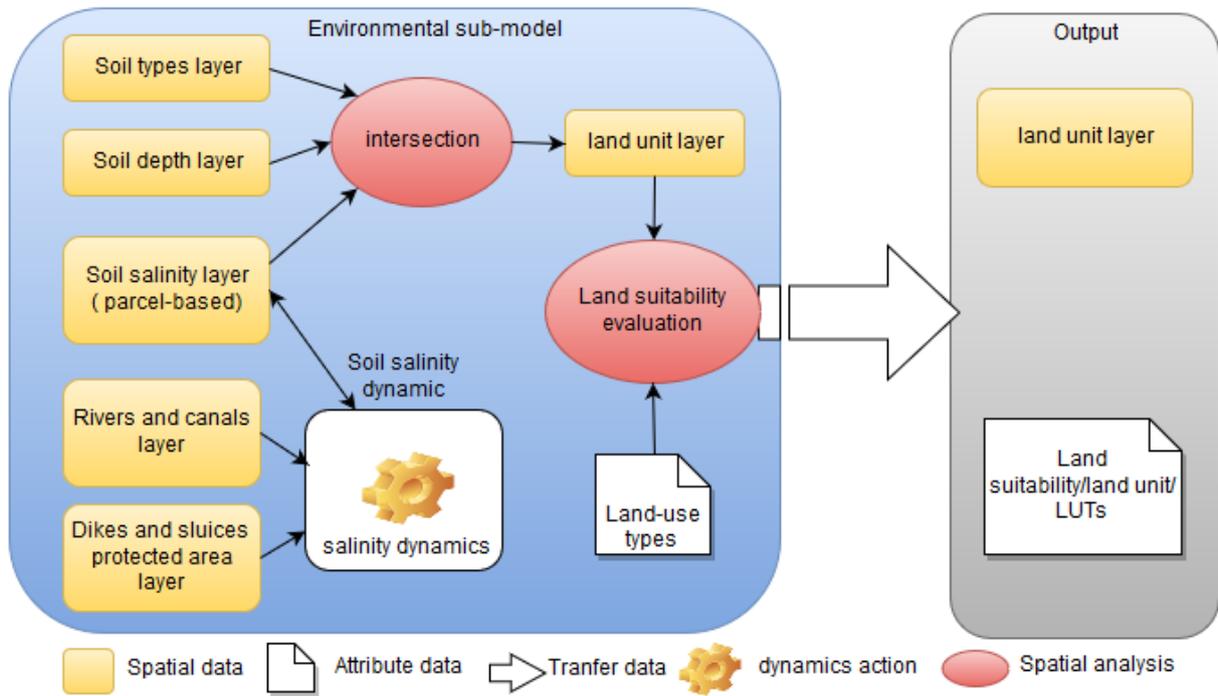


Figure 19. Conceptual model of environmental sub-model

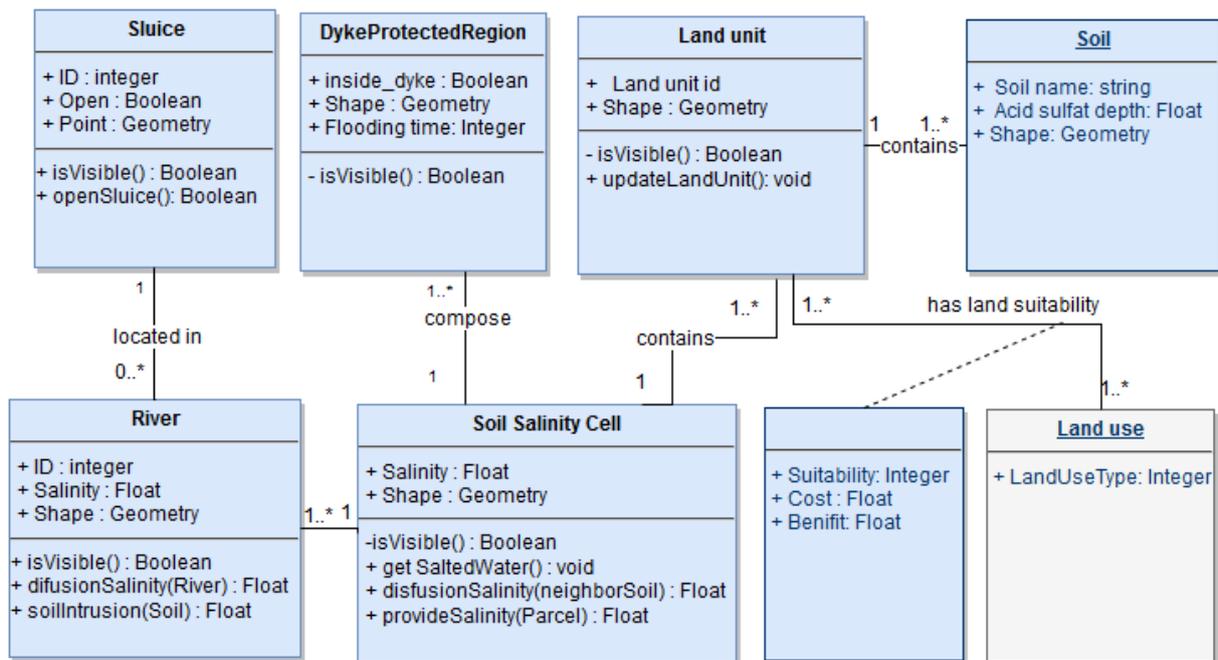


Figure 20. The UML diagram of the environmental sub-model

For more details, the UML class diagram of this sub-model is presented in Figure 20. In this sub-model, the main spatial units are the Soil Salinity Cells. These cells take the geometry object from the parcel objects. Each cell is located in one of the regions protected by dykes. Besides that, each cell can be bordered by one river. A river can have many sluice gates for protection against salt intrusion.

In the simplest cases, the Soil Salinity Cell in this sub-model can be implemented with static data of soil salinity. However, modelers can improve the model by replacing the soil salinity cells by a dynamic model of soil salinity.

Figure 19 presents the dynamics of the sub-model that is divided in 2 steps: soil salinity dynamics and land suitability evaluation.

In the first step, the dynamics of the model is voluntarily kept simple and deterministic: at each iteration (1 year) it reevaluates, like in a cellular automaton, the level of salinity of each parcel (here the cells are the parcels and are thus irregular). Salinity level of parcels that are protected by dikes does not change. The salinity of parcels bordering rivers automatically rise up by 12%. This evolution is a parameter of the sub-model and can be changed according to the region where the model is applied. In our case, these 12% correspond to the highest value of the soil salinity map (see Figure 21).

As shown in the UML class diagram, different classes have a role in the diffusion of the soil salinity. The rivers that are not protected by sluice gates will receive the highest salinity value diffused from the sea through the river systems (*diffusionSalinity(river)*). After that, the rivers diffuse the salinity to the cells (*soilIntrusion*). All cells that border a river will get the salinity from it (*getSaltedWater*). If a cell did not receive salinity from the river, its salinity is calculated by the average value of the salinity of its neighbors. The salinity is diffused in the remaining parcels using Equation 8 (Drogoul et al., 2016). The equation takes the previous salinity of the parcel and the salinity of its neighbor parcels excluding the ones inside the protected region. In detail, the salinity of a parcel is computed by using the previous salinity of the parcel plus the total salinity of the neighbor parcels at a distance of 100 meters, then by dividing it by the number of parcels. Note that this distance of 100m is only a parameter computed from the average area, which is around 0.4ha for us (calculated from the land-use map of the studied area).

$$salinity(x, t + 1) = \frac{salinity(x, t) + \sum salinity(y, t) | distance(x, y) \leq 100}{1 + |(y | distance(x, y) \leq 100)|} \quad (8)$$

With $x, y \in \text{Parcels}$

After having updated the salinity level of each parcel, the second step of the model concerns the land unit layer. The land unit layer is generated by computing the intersection of different layers of soil and water properties such as the soil type, the soil depth, the soil salinity, the flood depth layers and so on. The geometry object of the land unit layer is composed by the intersections of the composition layers. The attributes of the land unit

correspond to the attributes of the composition layers. This land unit will be the input data for the next process called *land suitability evaluation* as defined by FAO (1981). Land suitability represents the compatibility of a given land unit with the different land-use types. Based on the characteristics of the given land-use type for the soil and water properties, the land suitability is assigned 4 values (S1, S2, S3, N). S1 represents a high suitability. S2 represents a moderate suitability that will reduce the productivity and requires more investments. S3 means a low suitability and N means that the land unit is not suitable for the given land-use (FAO, 1981). Based on the type of soil and the level of salinity, the sub-model computes the suitability matrix for each of the land-use types considered in the region (*i.e.* Rice, Rice-Vegetables, Rice-Aquaculture, Aquaculture, Annual crops, Industrial perennial, Fruit perennial and Other perennial).

The output of the model is thus a land-unit layer that contains all the necessary data on the soil properties and land suitability for each land-use type. More details are given in the next section.

3.2.2.3 Details

The implementation is detailed using the data on the particular region of Thanh Phu in the coastal area of the Mekong Delta. Figure 21 shows the input data of this sub-model with the soil salinity maps of 2005 from Vo and Le (2006), the GIS data of dikes and dike-protected areas for the year 2010 (PCBT, 2011), the GIS data of parcels and the GIS data of rivers and canals. The soil salinity map in 2010 is used to evaluate the result of this sub-model.

The soil salinity layer is provided with a set of attributes, among which the salinity, classified into 4 levels (less than 4‰; 4–8‰; 8–12‰; greater than 12‰), whether or not it is in a dike-protected area, and whether or not it is bordering a river (obtained by overlapping the river and canal maps). In this sub-model, the input salinity map in 2005 (Figure 21 (1)) of the region is analyzed by GIS spatial analysis (intersection method) to obtain the salinity map at the parcel level. The salinity map in 2010 (Figure 21 (3)) is also intersected with the parcel map for calibrating the dynamics of the sub-model.

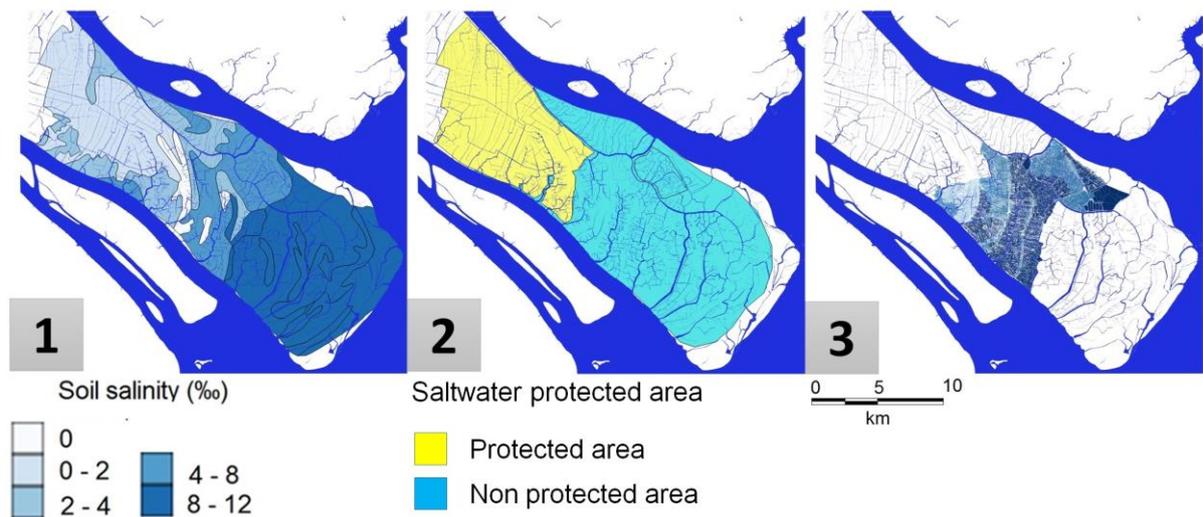


Figure 21. Spatial data for the land suitability model: (1) Soil salinity map in 2005, (2) Regions protected by dikes and sluices in 2010, (3) Soil salinity map in 2010.

As shown in the function of the sub-model defined in the previous section, the output of the salinity dynamics is used to create the land-unit layer. Then, the land units are continuously evaluated to receive the land suitability data for each land-use type. This information will be used by farmers to make their decision.

3.2.3 Sub-model of farmers' social influence

3.2.3.1 Overview

The decision of farmers is influenced by the decision of their neighbors (Case, 1992) or family. In Vietnam, for example, when farmers succeed with a new land-use type, they usually gain a lot of attention from their neighbors or through their social relationships. Moreover, numerous associations of farmers (and thus a number of social networks) exist in every villages, where they are encouraged to exchange their experiences and techniques of cultivation.

In Hamill and Gilbert (2009), the authors make the assumption of the existence of a network in which farmers can be influenced by, and can influence, their “neighbors”. This concept of “neighborhood” can take many forms, from topological or geographical relationships, which rely on the proximity between farmers, to familial or socio-economical ones, in which, for instance, the level of income would be used as a filter. A first assumption is made here: we consider that the familial network is superseded by the proximity network since, in Vietnam and especially in rural areas, it is common that members of the same family live next to each other. A second assumption is that the exchanges of experiences take place between farmers that belong to the same “social level” (or income group).

Some studies (VGSO, 2010a) have classified the incomes of people in Vietnam according to five groups: low-income (poor), below average income (nearly poor), middle income, standard income, high income (rich). Other published data considered only 2 levels (poor and not poor) (VGSO, 2012). In 2015, the Prime Minister of Vietnamese government decided to classify the income of household by poor, nearly poor, medium based on the average income household's members (Government of Vietnam, 2015). In this decision, the average income of a poor household is less than 700.000 VND per month (32USD/month⁶); a nearly poor household is from 700.000 to 1.000.000VND and a medium household is from 1.000.000 to 1.200.000VND. Thus, I distinguish incomes of farmer by three different profiles of farmers, essentially based on the range of income: (1) P1: rich and standard farmers, (2) P2: average farmers, (3) P3: poor and nearly poor farmers. I reuse this classification and couple it with the proximity network in order to produce an “influence network” for each farmer.

3.2.3.2 Model design

This network is recomputed at each year of the simulation (as farmers may change their income) and its main purpose is to serve as a “social topology” for farmers, *i.e.*, to modify the way they compute their set of neighbors. In the absence of this sub-model, the neighbors of a farmer are the farmers located in a radius of 100m around him. When this sub-model is used, the neighbors are defined as the farmers located in a radius of 100m and belonging to the same profile.

3.2.4 Farmer sub-model

3.2.4.1 Overview

In this sub-model, we make the hypothesis that the farmer's behavior is limited to land-use decisions. This decision-making process is based on a multitude of factors (discussed in section 2.2) and can be represented using a wide range of approaches. In order to compare some of them and to highlight the modular aspect of the integrated model, I designed several sub-models that represent farmers' decision-making process using different approaches. In all the following we consider that the people living on one parcel, *e.g.* a household or a family, are represented by a unique farmer. I have implemented two sub-models based on two non-cognitive approaches: The Markov-based selection and the multi-criteria selection. These sub-models rely on two main assumptions: (1) there is a 1:1 relationship between farmers and

⁶ 1USD \approx 21,840VND

parcels (one farmer only exploits one parcel); (2) the productivity of farmers remains constant and is not affected by technical progress or population growth. While these assumptions are mostly correct for the period of time of our study, they would need to be reevaluated for longer periods of time.

Implementing these two sub-models allows giving different options for modelers and evaluating whether these approaches are sufficient to represent the various aspects presented in Section 2.3.

The farmer sub-model considers two main entities that are the farmers and their parcels. Farmers are doing their aquaculture or agricultural activities on their parcels.

The general definition of the process is illustrated by the conceptual model of farmer (Figure 22). The farmer decision mechanism can be implemented using different approaches.

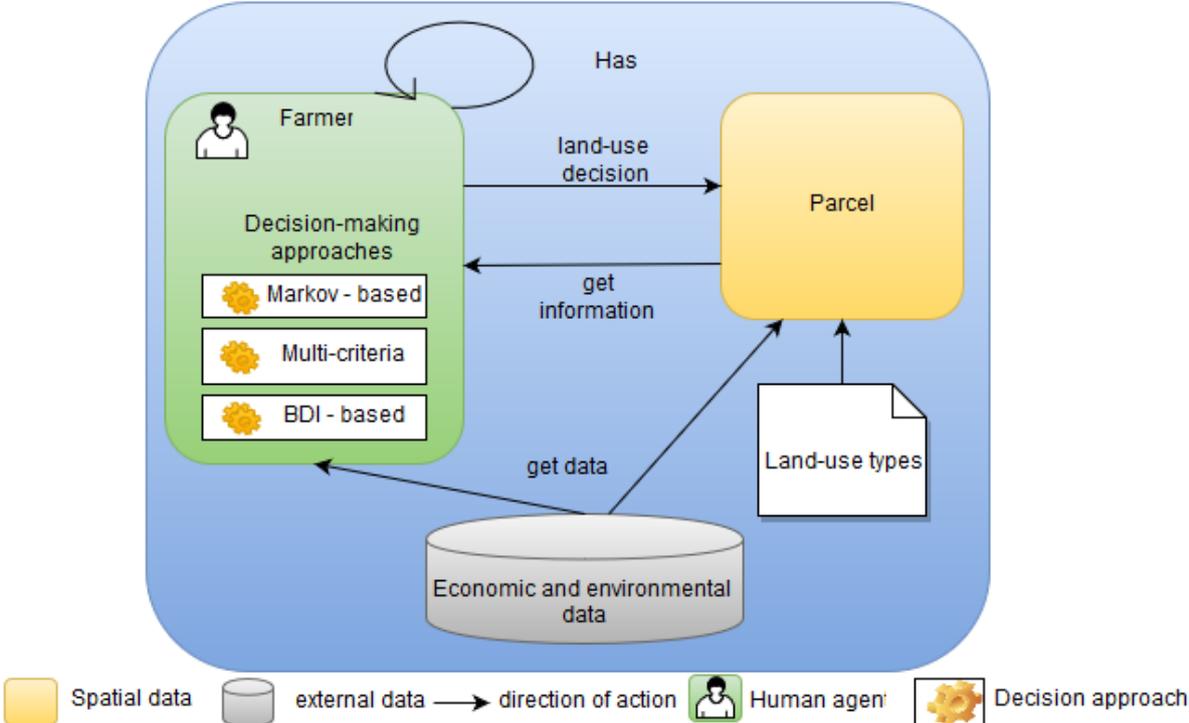


Figure 22. *The conceptual model of farmers.*

The environment in which land-use changes are simulated is represented by a set of parcels, that are initialized from a land-use map at village level (Figure 23). By combining this map with a land unit map, each parcel agent is provided with a given land-use type and other attributes such as its soil type, its level of salinity, and the extent and depth of flooding episodes on it.

In the next sections, I detail the two decision-making processes implemented.

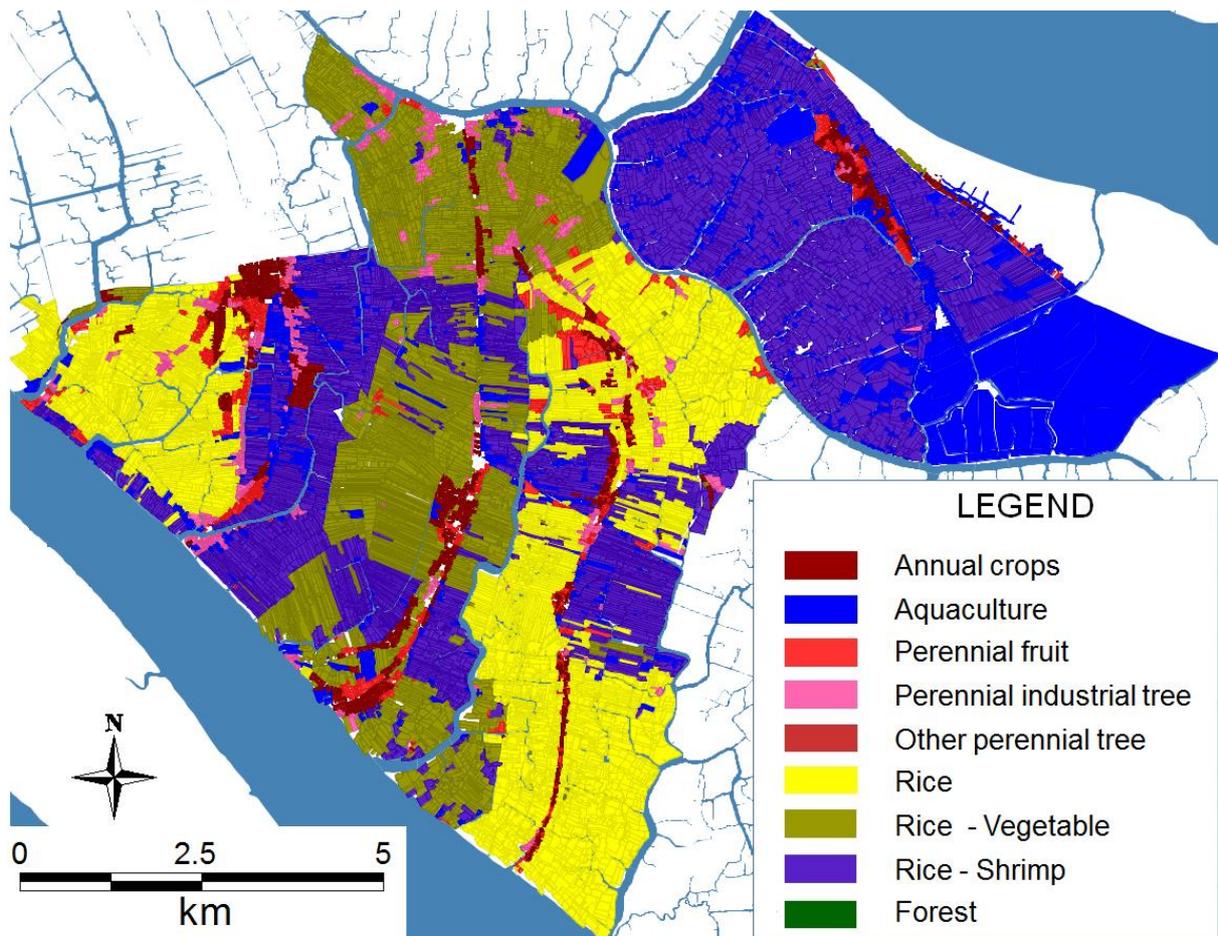


Figure 23. Land-use map of five villages (*An Thanh, Binh Thanh, An Thuan, An Quy, An Nhon, An Dien*) of Thanh Phu district in 2005.

3.2.4.2 Markov-based decision-making approach

The first farmer decision-making approach I introduce is the Markov-based decision-making process. This approach is quite popular in land-use planning and ecological models (Akinci et al., 2013; Bagheri et al., 2012; Elaalem et al., 2010; Nyeko, 2012; I. Santé & Crecente, 2005).

It is based on the Markov chain decision from a Markov transitions matrix. Agents choose randomly one land-use type given the probability included in the matrix. Then, the land suitability for the selected land-use is evaluated and the land-use type is kept only if it suits the parcel.

3.2.4.2.1 Markov matrix

The principal component of this approach is the Markov matrix that should be provided by the modeler. I added the possibility to compute the matrix based on two layers of land-use at two different time points (each layer must have a land_use field in its data structure). The algorithm counts the number of changes from one land-use to another one and the number of unchanged land uses. The numbers are normalized by the number of parcels to get the rate (assimilated to a probability) of change from one land-use type to another.

The structure of the matrix is provided in Table 3. It provides for each current land-use LUT_i the probability P_{ij} of change to a future land-use LUT_j . P_{ii} is thus the probability of remaining in the same land-use LUT_i .

Table 3. *Markov matrix*

		Future land-use			
		LUT_1	LUT_2	...	LUT_n
Current land-use	LUT_1	P_{11}	P_{12}		P_{1n}
	LUT_2	P_{21}	P_{22}		P_{2n}

	LUT_n	P_{n1}	P_{n2}	...	P_{nn}

(*LUT* : Land-use type; P_{ij} : Probability to change from LUT_i and LUT_j)

However, in the considered area, there are very different environmental conditions (fresh water, brackish water, salt water). As a consequence, I had to distinguish 2 very different areas, one inside the dikes and another outside the dikes, in which land-use changes are really different. For the region located outside the dikes, it is suitable for the brackish and salt water land-use types such as saltwater shrimp, rice+shrimp while the fresh water area inside the dyke does not allow these kind of cultivation. Thus, I created two matrices corresponding to the two regions.

3.2.4.2.2 Markov-based decision-making process

The decision-making behavior of the farmer agent is illustrated in the activity diagram of Figure 24. At each simulation step (*i.e.* each year), farmers will have a given probability of deciding to change the land-use of their parcel; this probability is a parameter of the simulation. If he decides to change, the farmer will choose randomly one of the land-use types according to the probabilities provided by the Markov matrix (thus, it depends on its

current land-use and on the location of his parcel). After having selected a land-use type, the farmer agent will check whether the land-use type is suitable for the environmental conditions of his parcel. If this land-use type is suitable (the suitability level is S_1 or S_2), the agent changes, otherwise it keeps its current land-use.

In the model, the change probability is implemented as a simulation parameter. This parameter will allow the model user to modify the simulation results depending on the input data. In my case study, I will explore this parameter in the experiment (Section 5.2.1) to select the best one.

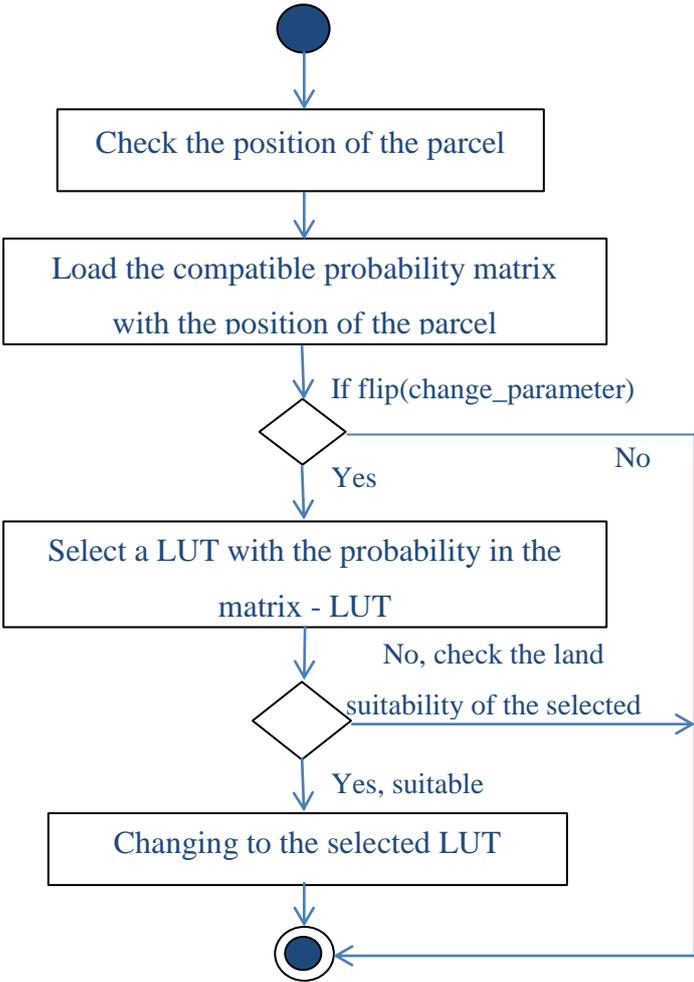


Figure 24. Activity diagram for the land-use selection with Markov-based decision

3.2.4.3 Multi-Criteria Decision-Making approach

In the second decision-making algorithm, the decisions of the farmer agent are made according to a multi-criteria analysis. This type of decision-making process is often used for land-use change models (see for example (Taillandier & Therond, 2011)). We defined three criteria for the decision: the expected benefit, the cost and the transition difficulty. Indeed, it is generally accepted that farmers tend to choose a production that maximizes their benefit,

minimizes the cost to avoid risky productions (Tri et al., 2013; Vu et al., 2014) and are easy to implement.

The UML class diagram of the sub-model of farmers based on the Multi-criteria decision approach is presented in Figure 25. The most important class is the farmer. Each parcel are carrying one land-use type at a time. Farmer agents have actions to compute price of products, cost of production, and benefit (represented for the land-use types). This information is used by farmers to choose a land-use for their parcel.

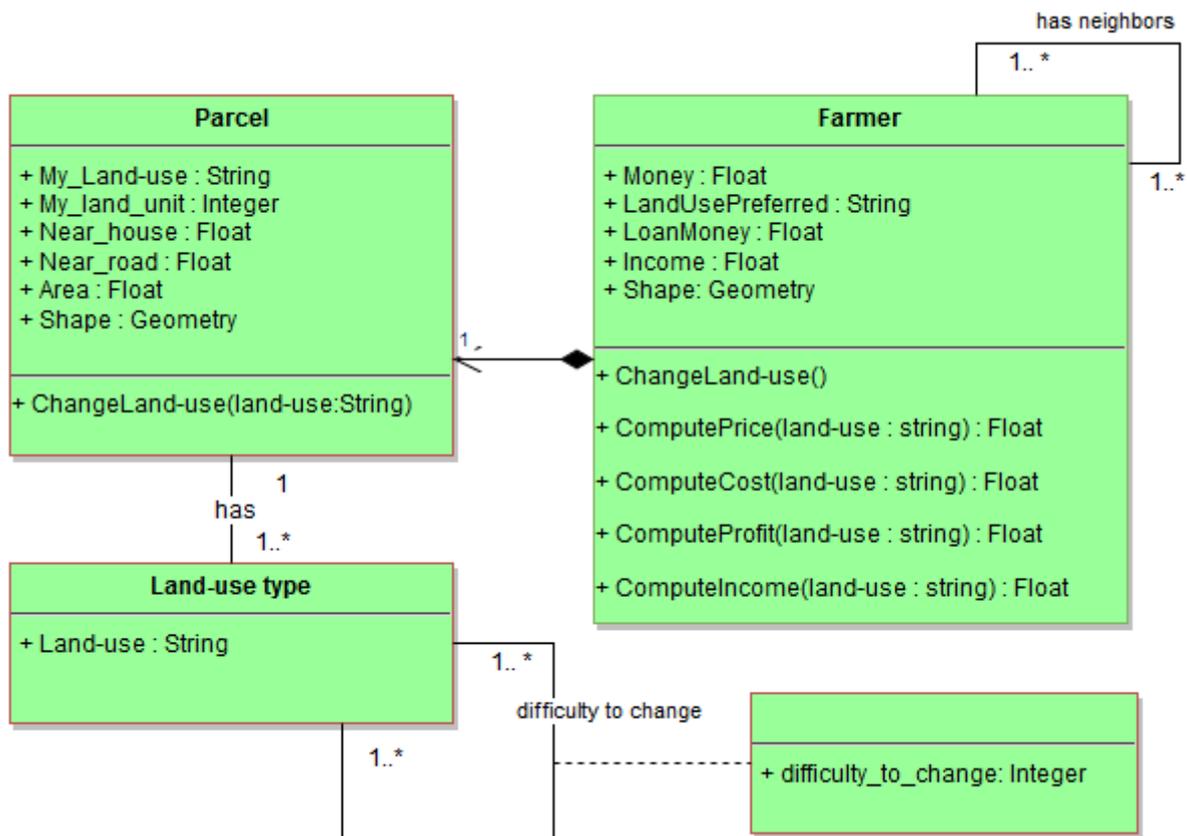


Figure 25. UML diagram of the farmer agent based on MCDM.

3.2.4.3.1 Definition of the fitness function

More precisely, I define a fitness function to find the most suitable land-use based on the land unit, cost, benefit and the difficulty of transition to that land-use. The fitness is defined (see equation 9) as a weighted arithmetic mean with three criteria: Expected benefit, Cost and Transition of the current land-use to another land-use. Each year, all the farmer agents compute the three criteria values for each of the six possible land-use types. Then, they choose the best land-use type, *i.e.* the one that maximizes the fitness function.

$$\begin{aligned}
& \text{Fitness}(\text{old_lu}, \text{lu}, \text{soil}, \text{year}) \\
& = W_{\text{Benefit}} \text{Benefit}(\text{lu}, \text{soil}, \text{year}) \\
& + W_{\text{cost}} \text{Cost}(\text{lu}, \text{year}) + W_{\text{transition}} \text{Transition}(\text{old_lu}, \text{lu})
\end{aligned} \tag{9}$$

3.2.4.3.2 Definition of the criteria

The first criterion, the expected benefit of the land-use, is calculated with the $\text{Benefit}(\text{lu}, \text{soil}, \text{year})$ function. This function evaluates the benefit of a land-use on a land-unit (soil) in a year. The benefit of a land-use type depends on the production yield of the soil for the land-use type. This value can be estimated thanks to the suitability of the soil for a production. Based on the classification of FAO (1981) (see section 3.2.2.2), we code the 4 levels of suitability by integer numbers (S1: 1, S2: 2, S3: 3, N: 4). The highest value means the worst suitability. The Benefit criterion is thus computed as a function of the land-use type, the soil type and the given year. It is calculated by dividing the benefit of the considered land-use type in the year by the maximum benefit of the year multiplied with the land suitability (equation 10).

$$\text{Benefit}(\text{lu}, \text{soil}, \text{year}) = \frac{\text{matrix_benefit}(\text{lu}, \text{year})}{\text{max_benefit}(\text{year}) * \text{matrix_suitability}(\text{soil}, \text{lu})} \tag{10}$$

$$\text{With: } \text{max_benefit}(\text{year}) = \max(\text{matrix_benefit}(\text{lu}, \text{year})) \tag{11}$$

The second criterion for the decision is the cost of the land-use calculated by Equation 12. This equation is based on the normalized production cost of the land-use type in the year. In addition, to combine all the criteria in the fitness function (that we want to maximize), the cost criterion is normalized and increases when the land-use cost decreases (*i.e.* to minimize the land-use cost, the Cost criterion should be maximized).

$$\text{Cost}(\text{lu}, \text{year}) = 1 - \frac{\text{matrix_cost}(\text{lu}, \text{year})}{\text{max_cost}(\text{year})} \tag{12}$$

$$\text{With: } \text{max_cost}(\text{year}) = \max(\text{matrix_cost}(\text{lu}, \text{year})) \tag{13}$$

When shifting from a land-use type to another land-use type, a farmer has to take into account the technical difficulty to carry out such a change. For example, it is possible to shift from rice to perennial fruit, even if this process is quite hard, but it is nearly impossible to shift from perennial fruit to rice. The third criterion measures the difficulty of changing. The difficulty to shift from one land-use to another one was evaluated by domain-experts as showed in the Table 4 where we using 3 values: 1 means that it is the easy to change; 2 means that it is difficult but possible; 3 means that it is nearly impossible. The transition criterion function that is based on this difficulty of changing is provided in Equation 14.

$$Transition(old_lu, lu) = \frac{3 - transition_matrix(old_lu, lu)}{2} \quad (14)$$

Table 4. The difficulty matrix when shifting from a land-use to the others land-use types

Land-use type	Rice	Rice - vegetable	Rice - Shrimp	Annual crops	Perennial industrial tree	Shrimp	Other perennial tree	Perennial fruit
Rice	1	1	1	2	3	2	3	3
Rice - vegetable	1	1	3	2	2	3	2	2
Rice - Shrimp	3	3	1	3	3	2	3	3
Annual crops	1	1	3	1	2	3	2	2
Perennial industrial tree	3	3	3	2	1	2	1	1
Shrimp	3	3	3	3	3	1	3	3
Other perennial tree	3	3	3	2	1	2	1	1
Perennial fruit	3	3	3	2	1	2	1	1

3.2.4.3.3 Weighting of the criteria

As I choose to use a weighted arithmetic mean to combine the various criteria, an important aspect is to choose the appropriate weights to give the best simulation results. As I have considered three criteria, the fitness function has thus three weights that the users can tune depending on his/her purpose. In Chapter 5, these weights are calibrated by exploring the domain of parameters.

3.2.5 Discussion about the farmer decision-making agent

After having implemented two decision-making algorithms for the farmer agents, I can now draw the main benefits and drawbacks of each of them.

The Markov-based approach is the easiest to implement and is well adapted to regions where the land-use does not change too much. A limitation of this approach is that the main Markov matrix of land-use shift probabilities cannot take into account any new land-use types (that does not exist in the data). Note that in our implementation, if the environmental factors were well taken into account, I was not able to integrate the economic factors. Another limitation of this approach is that a parcel can change its land-use type many times during the simulation (and possibly at every step), which is not realistic. The Transition criterion in the multi-criteria decision-making approach has been introduced to limit this unexpected behavior.

The multi-criteria decision-making, on the other hand, allows the modeler to implement both economic and environmental factors. These factors are evaluated as criteria for the decision of farmers. However, this method does not allow to reproduce the farmer reasoning in its planning and social aspects. Indeed, in some cases, farmers make choices based on wrong belief about the world. They can also imitate their neighbors. In addition, farmers can follow a long-term strategy (*e.g.* choice of a specific production) that requires to carry out some sub-objectives (*e.g.*, get a loan, learn new farming techniques...). While following his general strategy, this one can be postponed or cancelled if he perceives new information. This kind of behavior cannot be easily defined and implemented with equations. Indeed, the social behaviors of human that I have collected from our survey could not be represented in these approaches. In addition, the multi-criteria approach requires weights that should be calibrated to give a good fitness function. This difficulty becomes higher when the number of criteria increases. They should thus be chosen with caution to avoid introducing unneeded complexity and computation.

3.3 Conclusion

In this chapter, I have presented the general MAB-LUC that I propose. This integrated model is composed of a set of modular components. This model partially answers the research question on how to build a land-use model that could support land-use planning tasks. I have presented in detail each of these components and their interactions. In addition, I have proposed one or several implementations of the processes involved in each component to show that what I have proposed is not a specific model but a more general model that can be applied on various case studies and in which each dynamics can be complexified at will.

However, I have also shown that a non-cognitive representation of human decision-making is too limited to simulate human being decision-making in terms of land-use change. This limitation led me to propose a new model of farmers using a BDI architecture as presented in the next chapter.

CHAPTER 4 INTEGRATING A HUMAN DECISION- MAKING MODEL INTO AN AGENT BASED MODEL

In Chapter 3, I have presented the MAB-LUC integrated model and argued about the necessity of using a BDI architecture for human agents to improve their decision-making process. However, because of the lack of generic tools to support the definition and implementation of BDI agents that simultaneously support the representation of complex data (in particular spatial data) and the modeling of complex behaviors, the use of a BDI architecture by modelers is not so common and can be difficult. This chapter focuses on the presentation of the BDI architecture integrated into GAMA to benefit from its spatial explicit/multi-modeling/multi-scale underpinnings. Then, I propose to improve the farmer model in the MAB-LUC with this architecture.

The integration of the BDI plugin into the GAMA platform is part of a collaborative work funded by ANR (ACTEUR Project⁷) that regroups researchers from different research units (IDEES⁸, IRIT⁹, LRI¹⁰, LIG¹¹ and LITIS¹²). I have contributed to the development of the conceptual design of the plug-in. I have also tested and validated it in the case study presented in this manuscript and have contributed to some of the papers published on this extension to GAMA. In order to distinguish my contributions from the contributions of my fellow researchers, I will use the subject “I” when describing my personal contributions, and “we” for the collaborative achievements. The architecture is described in more details in Caillou et al. (2015) and Taillandier et al. (2016).

This chapter is organized as follows: Section 4.1 first details the conceptual architecture used to represent human beings in socio-environmental models. Then, Section 4.2 describes the BDI extension of the GAMA platform. Finally, Section 4.3 shows how this BDI architecture was integrated into the farmer sub-model.

⁶ ANR-ACTEUR: Agents Cognitifs Territorialisés pour l’Etude des dynamiques Urbaines et des Risques

<http://acteur-anr.fr>

⁸ IDEES : UMR 6266 IDEES- Identité et Différenciation de l’Espace, de l’Environnement et des Sociétés.

<http://www.umr-idees.fr>

⁹ IRIT : Institut de Recherche en Informatique de Toulouse. <https://www.irit.fr>

¹⁰ LRI : Laboratoire de Recherche en Informatique. <https://www.lri.fr>

¹¹ LIG : Laboratoire d’Informatique de Grenoble. <http://www.liglab.fr>

¹² LITIS : Laboratoire d’Informatique, du Traitement de l’Information et des Systèmes, <http://www.litislab.fr>

4.1 Principles of the human decision-making architecture

Having an agent architecture integrated in a modeling platform is not only necessary for land-use change modeling but also, more generally, for any socio-environmental study. The requirements presented in Chapter 3 and arguments given in Chapter 2 in favor of the choice of a BDI agent architecture to represent the human decision-making led us to integrate a BDI architecture into the GAMA platform. The next paragraphs of this section give more details concerning the choices we made for this architecture.

Figure 26 summarizes the proposed architecture. This architecture allows using both the classic reflex behaviors of GAMA and a BDI reasoning engine.

The first component of the architecture is the Belief base of the agent (block number 1). This base contains the knowledge of the agent. Note that one of the specific features of beliefs is the possibility for the agent to create and add new beliefs anytime during the simulation whereas it is not possible to add new attributes to the agent. This gives more flexibility to the agent but requires the agent to be able to deal with all these possible new beliefs.

The second element of this agent architecture is the base of Desires and related intentions (the block number 2). The desires are the facts that the agent wants to become true. The intentions correspond to the desires that the agent is currently trying to fulfill. An intention to be fulfilled can require to first fulfill some sub-intentions: for instance, in order to fulfill the intention to produce shrimps, the farmer could first have to fulfill the intention to get money (*loan_money_from_banks* for instance).

The next elements of the architecture are the plans of the agents (block number 3). Plans are composed of actions (in block number 4) that the agent will perform. By default, the plans in this architecture are linked with an intention. Each plan refers to an intention but conversely an intention can be fulfilled by many plans. During the simulation, the plans of the current intention are executed until the current intention (or its related desire) is removed or until the plans are finished. When a new intention is added, the agent can suspend its current intention and try to fulfill first the new intention. Thus, the plans associated with the new intention will be executed in the next iteration.

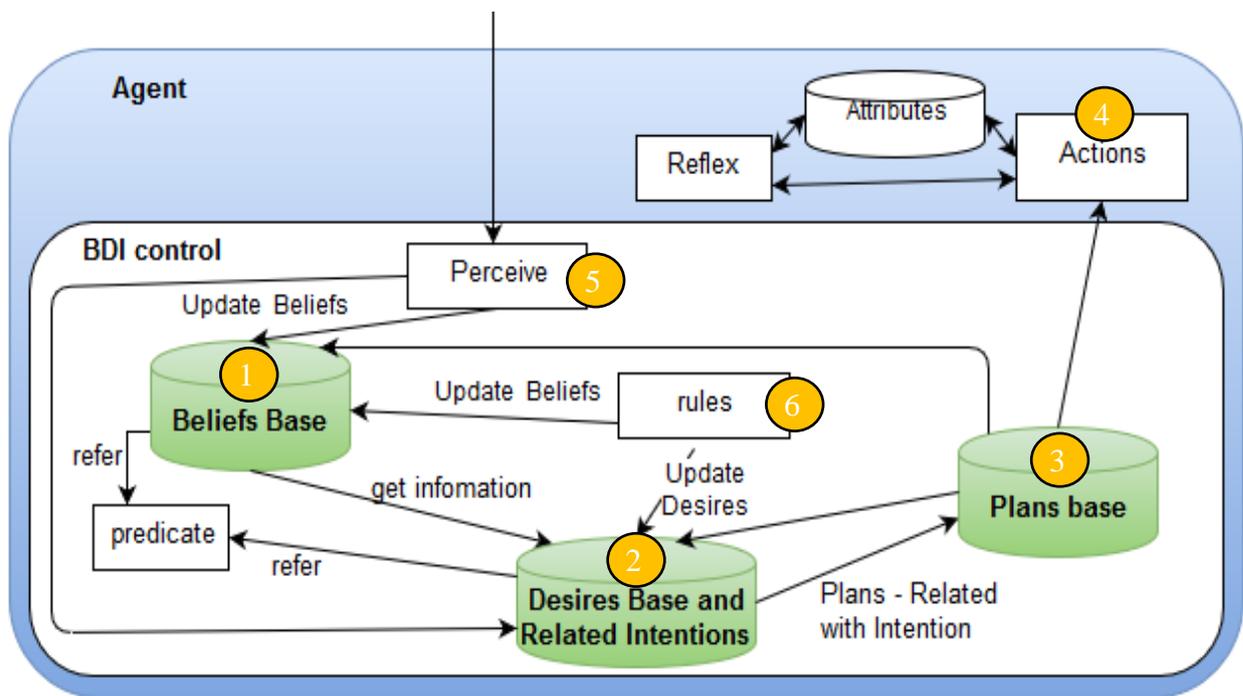


Figure 26. *Human decision-making agent framework for social environment model*

The block number 4 represents the attributes, actions and reflexes. These components are the ones shared by all agents in GAMA. In GAMA (Grignard et al., 2013) the attributes represent the information of an agent while actions and reflexes show the behaviors of an agent. A reflex is a specific behavior of agents, it is executed automatically each simulation step, it can call many actions. Inversely, an action is a possible action of agent that is called from a reflex or from the other actions. Indeed, the modelers can reuse all the features already included in the GAMA platform, which can be very useful to define some specific reactive behaviors. In addition, the BDI plug-in provides some new behaviors to establish a link between the environment and the agent cognition. One of these behaviors is the perception of the agent (block number 5). With this behavior, an agent can receive information from the environment or from the others agents and automatically add new beliefs to its belief base.

Another new behavior provided by the BDI plug-in is the rule (block number 6). A rule allows to automatically inferring new pieces of knowledge (beliefs or desires) from previous beliefs or desires. For instance, if the agent has the belief that it will need 1000\$ to implement its new production and the belief that it has only 500\$, we can define a rule to infer the desire to get 500\$.

4.2 Presentation of the GAMA BDI plug-in

The architecture proposed has been implemented as a GAMA plug-in as part of the ACTEUR ANR project that gathers many researchers as mentioned in the introduction of this chapter. The architecture has been used in several works dealing with different case studies: city evacuation, bush-fire spreading, urban growth... I used a preliminary version of it to compare three architectures for farmer agents in the context of agricultural land-use change dynamics (Truong et al., 2016). The model implemented concerned 5000 parcels in the Binh Thanh commune, Thanh Phu district, Ben Tre province in the Mekong Delta, Vietnam. Under the support of the ANR-ACTEUR project, the architecture has been improved and presented in Caillou et al., (2015). This version integrates a better management of the belief, desires and intention bases, but was still difficult to use, in particular by modelers that were not experts in BDI architectures. In addition, it was very time-consuming in terms of computation. These previous versions helped us to improve our model of farmers' behaviors (Drogoul et al., 2016).

With the recent updates of Taillandier et al, (2016), the BDI architecture is now fully integrated into GAMA and a lot more optimized in terms of memory and computation time. It is now possible to run simulations and smoothly explore the model parameter space with large data. Note that the current version of the plug-in integrates an optional emotional module for the agents (Bourgais, Patrick, & Laurent, 2016).

In the following section, I will present the latest syntax of the architecture that I have used to implement the farmer sub-model of the MAB-LUC.

4.2.1 Representation of knowledge of GAMA BDI agents

4.2.1.1 Declaration of a BDI agent

The GAMA BDI plugin provides data structures and statements (more generally extensions of the GAML language) to be able to develop agents whose behavior is designed using the BDI paradigm. In particular, it provides an architecture, called *simple_bdi*, that can be added to a species of agents and that allows modelers to combine in their agents the advantages of the classical GAMA agents (with all their features and their default reflex architecture) and a BDI reasoning engine.

This following code in GAML shows the declaration of the species of agents *FarmerBDI* that uses the new BDI architecture.

```
species FarmerBDI control: simple_bdi{
}
}
```

When a species of agents is defined using the *simple_bdi* architecture, all the agents of this species gain new knowledge bases and possible behaviors. The knowledge bases are the Belief, Desire and Intention bases and the new behaviors are the perception, rule and plan behaviors. In the following sections, I will present the way the agents' knowledge and behaviors are represented (and described in the GAML language) in our architecture.

4.2.1.2 Predicates

The knowledge of an agent is represented by a new data type called *predicate*. The predicates, which usually represent a combination of attributes and perceptions of the agent, are used to track which belief, desire or intention should be made active.

```
predicate earn_the_highest_possible_income <-
  new_predicate("select_highest_income");
```

A predicate has a name, may have a value (with no constraint on the type), some parameters (each defined by a name and a value), can be true or false and has a priority. The following example defines a predicate “*has_loan_money*” that is called “loan” and has a value of 1000 and a priority of 1.

```
predicate has_loan_money<-new_predicate("loan",1000)with priority 1;
```

4.2.1.3 Belief base

The beliefs of an agent are composed of a set of predicates representing the internal knowledge of the agent about the world.

The belief base is a part of the memory of BDI agents. During a simulation, the agent can update its belief base by adding or removing beliefs. These mechanisms permit agents to easily update their knowledge. For example, an agent can add a new belief or update a belief with the following syntax (where *has_loan_money* is a predicate. After the belief has been added, it will be stored in the belief base of the agent):

```
do add_belief(has_loan_money);
```

The following statement will remove a belief from the belief base:

```
do remove_belief(has_loan_money) ;
```

Note that modelers can update beliefs anywhere: in a rule statement, a perception, a reflex, a plan....

When checking its knowledge, an agent can ask if it has a belief or not with the operator *has_belief(predicate)*. If its belief base contains at least one belief that correspond to the one given as operand, the operator returns true. Note that two beliefs are similar if they have the same name and eventually the same values if these ones are defined for both predicates. For instance, in the following example, if the agent has in its belief base the belief *loan_money*, the operator *has_belief(new_predicate("loan"))* will return true as the agent has already in its belief base a predicate with the same name.

```
has_belief(new_predicate("loan")) ;
```

4.2.1.4 Desire base

The desire base of the agent represents its objectives and contains desire predicates. It can be added with the statement:

```
do add_desire(earn_the_highest_possible_income) ;
```

In the GAMA BDI architecture, a desire is fulfilled in two cases. The first case is when the associated predicate is added into the Belief base (which means that the agent believes that an objective is true). The second case is when a desire is manually removed from the desire or intention bases.

```
do remove_desire(earn_the_highest_possible_income) ;
```

Or:

```
do add_belief(earn_the_highest_possible_income) ;
```

Note that it is possible for a modeler to define a reflex for updating desires that will manually remove the given desire. The modeler can also use rules to do it automatically as it will be presented in Section 4.2.2.2.

Desires can be linked by hierarchical links, which means that desires can have sub-desires. Sub-desires allow agents to define intermediary objectives. For example, when a farmer has an objective of changing its land-use to another one providing a higher income but he does not have enough money for shifting, he can ask money from a bank. In that case, in order to fulfill its main objective, the agent can add an intermediary desire that it will try to fulfill first.

Desires have a priority value that can be dynamic. It is used to select a new intention from the desire base. The priority of a desire is determined by the priority of the corresponding predicate.

4.2.1.5 Intention base

Intentions represent what the agent has chosen to do. In the GAMA BDI architecture, the intentions are chosen among the agent's desires. When an agent has more than one desire, the desire chosen as the new intention is the one with the highest priority value. The current intention will determine the plan that is going to be executed. If the desires have the same priority value, one of them is randomly selected. Note that the modeler can choose, by just changing the value of a Boolean parameter, to replace this deterministic way of choosing intentions by a probabilistic one.

An agent can add a new sub-intention to its current intention. The following example shows the syntax that an agent can use to add a sub-intention `loan_money_from_banks` as a hierarchical link of the intention `earn_the_highest_possible_income`. After adding a new sub-intention, the current intention is put on hold, and the sub-intention becomes the current intention. When the sub-intention is removed (or finished), the agent will return to its intention `earn_the_highest_possible_income`.

```
do add_subintention(predicate: earn_the_highest_possible_income,  
    subintentions: ask_money_from_banks, add_as_desire: true);  
do current_intention_on_hold();
```

4.2.2 Behavior of agents

4.2.2.1 Perception

The perception has been implemented as a specific behavior of the GAMA BDI architecture. At each iteration, the agent executes all its perceptions.

Since the update of the architecture proposed by Taillandier *et al.*, (2016), agents can perceive the environment and other agents based on perception conditions and automatically add corresponding beliefs. This behavior allows simplifying a lot the writing of the agent perceptions.

The following example illustrates the fact that an agent perceives the farmers in a radius of 100m and updates its belief about the cost of production. In that case, it updates the perceived beliefs of the farmers by adding a belief that the current land-use type of his

neighbors does not give a good benefit anymore because its production cost was higher than the income.

```
perceive target:farmer in: 100 when: has_belief(cost_higher_income) {  
    focus "cost_higher_income" var:landuse;  
}
```

4.2.2.2 Rule

A rule is a specific behavior of the GAMA BDI architecture that was integrated in the last update of the architecture (Taillandier *et al.*, 2016). It allows to infer or remove desires or beliefs from the agent's current beliefs and desires, *i.e.* a new desire or belief can emerge or disappear from the existing ones. At each iteration, the agent executes all its rules (just after its perceptions).

The following example illustrates the fact that if an agent has the belief that it does not have enough money, it will automatically add a desire to loan money.

```
rule belief: new_predicate("not_enough_money") new_desire:  
loan_money;
```

4.2.2.3 Plans

The modeler has to define for his/her BDI agents a set of plans to fulfill its desires. A plan is a set of instructions that is designed to fulfill an intention of the agent. A plan has a name, can have an intention to fulfill, an ending condition, a priority, a condition of activation and can be instantaneous or not (*i.e.* take a complete simulated step when activated or not). When a plan is designed with an intention, the plan will be executed when the intention is the current intention of the agent.

The following statement gives an example of a plan (named `change_to_highest_income`) of a farmer for changing its land-use type to the one with the highest expected income. This plan will be executed when the farmer have the intention "`earn_the_highest_possible_income`" as its current intention and will be dropped when the agent changes its land-use to its favorite land-use. In BDI terms, this plan will be finished when the agent believes that `have_changed_to_favorite_land_use` is true.

```
plan change_to_highest_income intention: earn_the_highest_possible_income  
priority:1
```

```
finished_when: have_changed_to_favorite_land_use  
  
{ // GAML code }
```

Each intention can have many plans. Each plan has a priority value that is 1 by default and that can be dynamic. It is used to select a plan when several possible plans are available. Besides that, a plan can be instantaneous, which means that during the same simulation step, the agent will be able to activate several plans.

To conclude this section, we have developed a new BDI architecture that is integrated into GAMA and I used this architecture to build a farmer model for the MAB-LUC. This BDI farmer sub-model is described in the next section.

4.3 Integrating the BDI architecture into the sub-model of Farmers

In Sections 2.5 and 3.4, I have compared various agent formalisms for farmers in land-use change modeling. I claimed that the BDI architecture is the most appropriate one to represent social agents like farmers. Thus, in this section, I will implement the decision-making behaviors of farmers using the BDI architecture that has been integrated in GAMA and presented in the previous section.

Going back to the roles of farmers in land-use decision-making (Section 2.2), I designed an agent-based model where farmers (or households) are represented as agents that have been provided with behaviors expressed in the BDI formalism.

The data used to define these behavioral components are based on a survey of twenty-five households who have changed at least two times their land-use from 1997 to 2014. All of farmers come from the Binh Thanh commune, Thanh Phu district, Ben Tre province. The pie chart in Figure 6 depicts the results of this survey. The results show that the change was due to a diversity of motivations and expectations. Looking for a higher benefit is important, but following what the neighbors do or according to the land suitability are also frequently cited.

4.3.1 Conceptual model of the farmers based on the BDI architecture

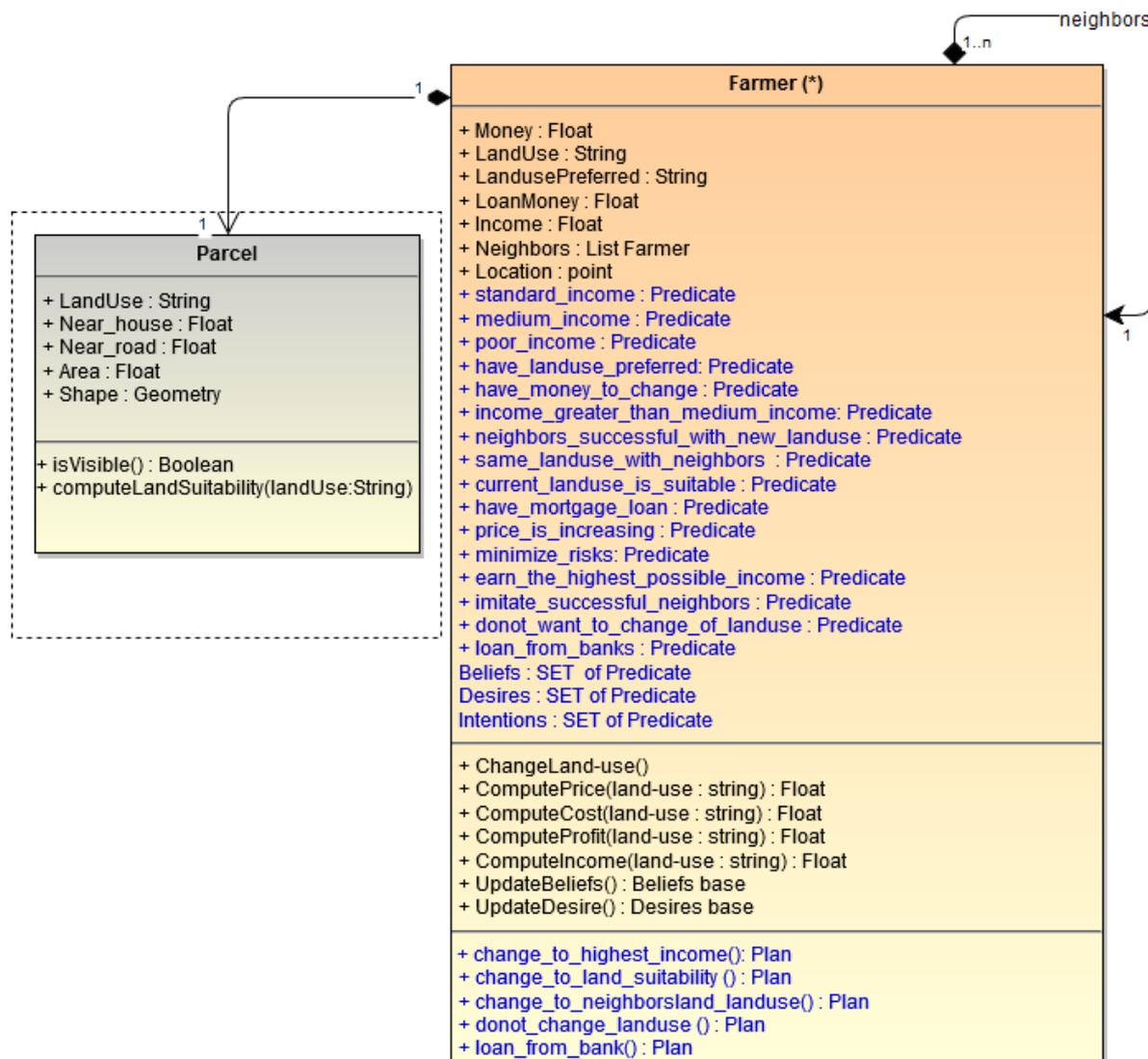


Figure 27. UML class diagram of the BDI farmer sub-model

The UML class diagram of the farmer sub-model is presented in Figure 27. Each farmer has one parcel. A parcel is represented by a polygon and has attributes such as a land-use type, an area, a land unit that the parcel is overlapping.

Farmer agents are defined using the GAMA BDI architecture with their attributes, potential actions, predicates, belief base, desire base, intention base and potential plans.

The belief base is updated by a reflex called *update_beliefs()* at initialization and after each step of the simulation. The beliefs of the farmer agent are defined in Table 5 together with the conjunction of conditions required to make each belief become true. The three first beliefs are computed based on the available amount of money of farmers. The others are based on the perception of the farmer agent regarding the prices of products, the costs of production and the land suitability of their parcel.

Table 5. Beliefs base of farmers and conditions for the update_beliefs function

Belief	Condition to set
standard_income	Money in standard money interval
medium_income	Money in medium money interval
poor_income	Money in poor money interval
have_landuse_preferred	landUsePreferred \neq ""
have_money_to_change	Money-costs(NewlandUse) >0
loaning_from_banks	loanMoney >0
neighbors_successful_with_new_landuse	averageIncome(neighbors, landuse) \geq income(landuse)
same_landuse_with_neighbors	Landuse \neq neighbors.landuse
have_mortgage_loan	loanMoney =0 and mortgaged=True
current_landuse_is_not_suitable	computeSuitability(landuse) >2
income_greater_than_medium_income	Income $>$ mean(income)
price_is_increasing	If exist price(landuseTypes(i,step) $>$ price(landUseTypes(i,step-1)

4.3.2 Desires base of farmers

Desires represent a set of objectives that the farmer would like to achieve, based on its beliefs. Each desire has a priority, which is used to choose the next intention of farmers. Based on our survey data shown in Figure 6, each farmer can have different desires that are not necessarily exclusive. The desires of farmers are listed in Table 6. The desire base is updated by a reflex called *update_desires()*.

Table 6. Relationships between Beliefs and Desires for farmers agents

Beliefs	Desires and corresponding Intentions	Plans
not have_money_to_change income_is_greater_than_medium_income same_landuse_with_neighbors not price_is_increasing	donot_want_to_change_of_landuse	donot_change_landuse()
medium_income price_is_increasing not current_landuse_is_suitable	minimize_risks	change_to_land_suitability() ()
standard_income price_is_increasing	earn_the_highest_possible_income	change_to_highest_income() ()
poor_income neighbors_successful_with_new_landuse	imitate_successful_neighbors	change_to_neighbors_landuse() ()
not have_money_to_change have_mortgage_for_loan not loaning_from_banks	loan_money_from_banks	loan_from_banks() ()

- Desire 1: Farmers donot want to change of landuse.

Every farmer can have this desire (it is their initial desire), notably after they have changed to their preferred land-use. During simulations, this desire is added to the base when a farmer believes that it does not have enough money to change, or that its income is greater than the average income, or that it uses the same land-use as its neighbors, or, finally, that the price of the product has not changed.

- **Desire 2: Farmers want to *minimize_risks* (of environmental and financial ones).**

This desire concerns the farmers who believe that they belong to an average category, that the price of their products is increasing, and that they do not have enough money to select another land-use type. It is also influenced by the belief regarding the suitability of their parcel. If it appears to be (or to have become) not suitable for their current land-use, they will add the desire to change to another one, even if it does not provide the highest income.

- **Desire 3: Farmers want to *earn_the_highest_possible_income*.**

Usually, the land uses that require high investments will provide higher incomes. This desire is used by standard farmers who believe that they have enough money to shift to a land-use type providing the highest possible benefit.

- **Desire 4: Farmers want to *imitate_successful_neighbors*.**

This desire concerns farmers who believe that they are poor. If they perceive that their neighbors have changed their land-use and that they have been successful in doing so, then they have the desire to change to the same land-use. This desire will also trigger the desire to loan money from banks if the shifting cost is higher than their capital.

- **Desire 5: Farmers want to *loan_money_from_banks* in order to shift to a new land-use type.**

After a farmer selects a land-use type different from the one it currently undertakes, if it believes that it does not have enough capital to change, it adds a temporary desire to loan money from a bank, which is provided with the highest priority until it can effectively change to its new land-use.

4.3.3 Intentions base of farmers

The intention base contains the desire that the agent is currently trying to achieve. When the agent has no current intention, it randomly chooses as its new intention one of the desires that have the highest priority. The current intention will determine the selected plan. Plans are a set of actions, which can be executed over the course of several steps of simulation until its post-conditions become true or the related intention is removed from the base of intentions. The relationships between Beliefs, Desires and Intentions are shown in Table 6. For example, when a farmer intends to change its land-use to *earn_the_highest_possible_income* but do not *have_money_to_change*, it desires to

loan_money_from_banks, which triggers the corresponding plan *loan_from_banks()* and postpones *change_to_highest_income()*.

4.3.4 Set of plans defined for farmers

To fulfill their intentions, farmer can carry out several plans associated with their intentions as defined in Table 6.

Plan 1: *change_to_land_suitability()*

This plan is executed when "*minimize_risk*" is set as the current intention of farmers. In this plan, the farmer agent selects a new land-use type based on the criteria of land suitability to minimize the potential risks, even if the expected income is not the highest.

- **Plan 2: "*change_to_highest_income()*"**: This plan is executed when farmers have the intention "*earn_the_highest_possible_income*". The activity diagram of the plan is shown in Figure 28. In this plan, farmer agents select a land-use type that is expected to provide them with the highest income even if it is risky (if the land is not really suitable, for instance). If farmers do not have enough money to shift, they add a sub-intention "*loan_money_from_banks*" and postpone the current intention.

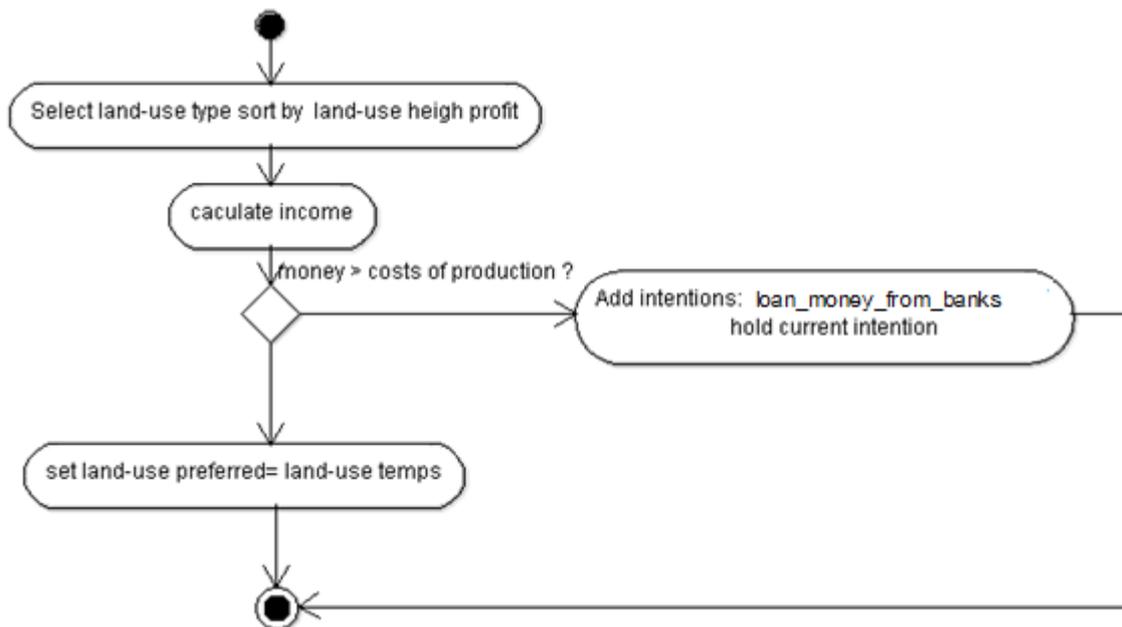


Figure 28. Activity diagram when farmers change to a highest income land-use type

-**Plan 3: "*change_to_neighbors_landuse()*"**: This plan is executed when farmers have the intention "*imitate_successful_neighbors*". In this plan, the farmer undertakes the necessary actions to change to the land-use type chosen by their immediate (geographical)

neighbors who have earned a higher income than them. The diagram shown in Figure 29 illustrates the process of selection of the land-use type. Then, if the farmer does not have enough capital, it tries to get a loan from banks (“*loan_money_from_banks*” intention) and postpone its current intention until it gets the loan or believes that it cannot borrow from banks.

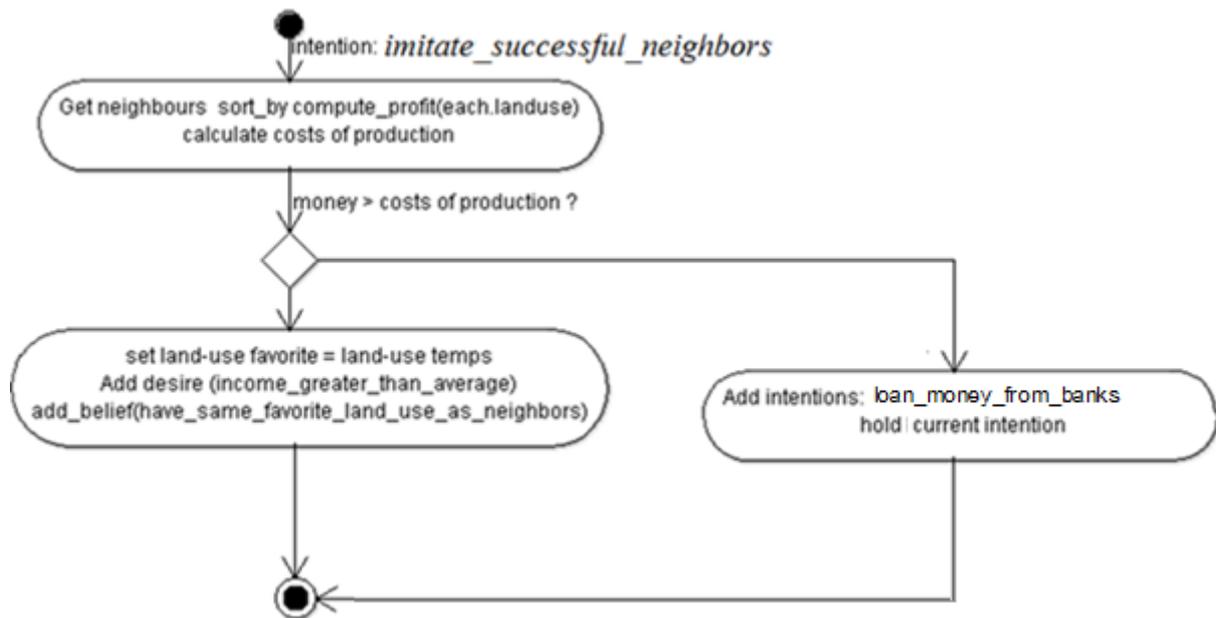


Figure 29. Activity diagram when farmers imitate their neighbors

- **Plan 4: "loan_from_banks()"** : In this plan, the farmer requests an investment budget from banks when it has planned to change his land-use but does not have enough capital to invest in this shift. This request is not automatically fulfilled; as it is the case in reality, this intention is added hierarchically when farmers execute the intentions “*imitate_successful_neighbors*” and “*earn_the_highest_possible_income*”.

The result of a borrow request is computed by the use of a probabilistic function. The money requested from banks is very important for farmers when they want to implement a land-use type that needs a large investment. The proportion of successful borrows is a parameter that can be modified to simulate the role of the government in controlling the economic policy in land-use change.

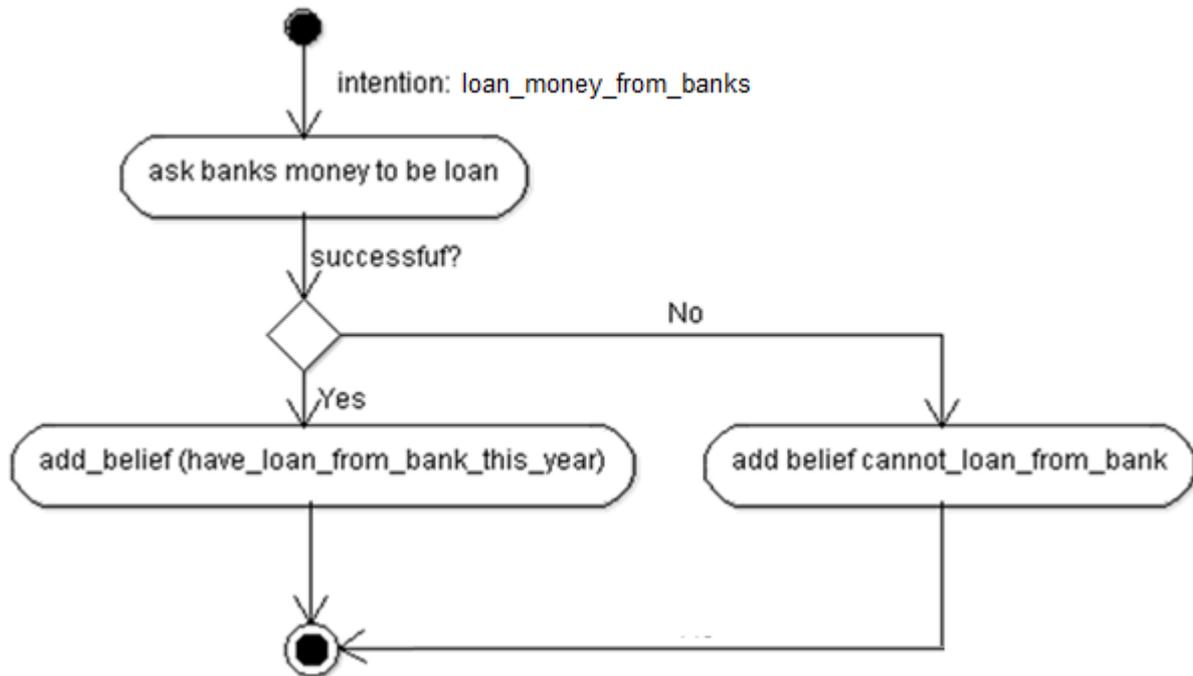


Figure 30. Activity diagram of the plan “loan_from_banks” of farmers

- **Plan “donot_change_land_use()”** : This plan is executed when farmers have the intention to "donot_want_to_change". Farmers only calculate their income.

In addition to the plans the farmers are going to execute, each farmer agent undertakes a number of mandatory actions every simulation step (reflexes) such as paying back loans to the bank or computing their income.

4.4 Conclusion

In this chapter, I have introduced a new agent architecture that can be used for socio-environmental and socio-ecological modeling. This architecture was fully implemented as a new GAMA plugin in the context of a collaborative work (ACTEUR ANR project). This architecture provides modelers with an easy way to represent the knowledge and the behaviors of human agents through the GAML language.

Based on this architecture, I proposed and implemented a new sub-model for the farmers for the MAB-LUC. This implementation shows a natural way to represent the farmer behavior that is close to the reasoning process of farmers that I collected with interviews. This sub-model will be assessed in the next chapter.

CHAPTER 5 VALIDATION OF THE COGNITIVE AGENT IN LAND-USE CHANGE MODELS

In this chapter, I validate the relevance of the BDI architecture in representing the farmers' behaviors in land-use change models. A real dataset (taken from a coastal district of the Mekong Delta) is used to calibrate the different sub-models and to validate their outputs. Thanks to the modularity of the integrated framework, I am able to conduct a fair comparison between the three behavioral models I implemented. This comparison shows that the BDI-based approach allows obtaining more realistic outcomes.

5.1 Description of experiments

Chapter 3 presented my proposed land-use change integrated model, called MAB-LUC, in which users can represent the decision-making in the farmer model by three different approaches: Markov-based decision process, Multi-criteria decision-making (MCDM) and BDI-based decision process. This chapter describes the validation of the MAB-LUC with three experiments corresponding to these approaches. The first experiment analyzes the farmer decision model using the Markov-based decision process defined in section 3.3.4.2. The second experiment studies the MCDM approach presented in section 3.3.4.3 for the decision making in the model of farmers. The third experiment verifies the relationship between the land-use and the behaviors of farmers based on the BDI architecture.

In order to evaluate the different approaches for modeling the farmer decision making, in the following subsections, I describe the dataset as well as the indicators which are used to assess the results of the experiments.

5.1.1 Experiment data

As shown in Chapter 3, our land-use change model is composed of four different sub-models: economic, environmental, farmer network and farmer models. Table 7 presents the input data for each sub-model as well as the corresponding years in which the experiment data were taken. For example, the economic model requires the price and cost of products related to the land-use types as input. The experiment data for this sub-model is taken from 2005 to 2010.

Table 7. *Input data for each sub-model of the land-use change model and the corresponding years used in our experiments.*

Sub-model	Input data	Year
Economic	Price and cost of products related to the land-use types	Price and cost of products taken from 2005 to 2010
Environmental	Land-unit map (generated from soil, salinity and soil depth layers) Protection dikes and regions protected by dykes	Land-unit maps in 2010
Farmer network	List of neighboring farmers (within a default distance of 100m from each farmer)	
Farmers	Parcel land-use maps	Parcel land-use maps in 2005 and 2010

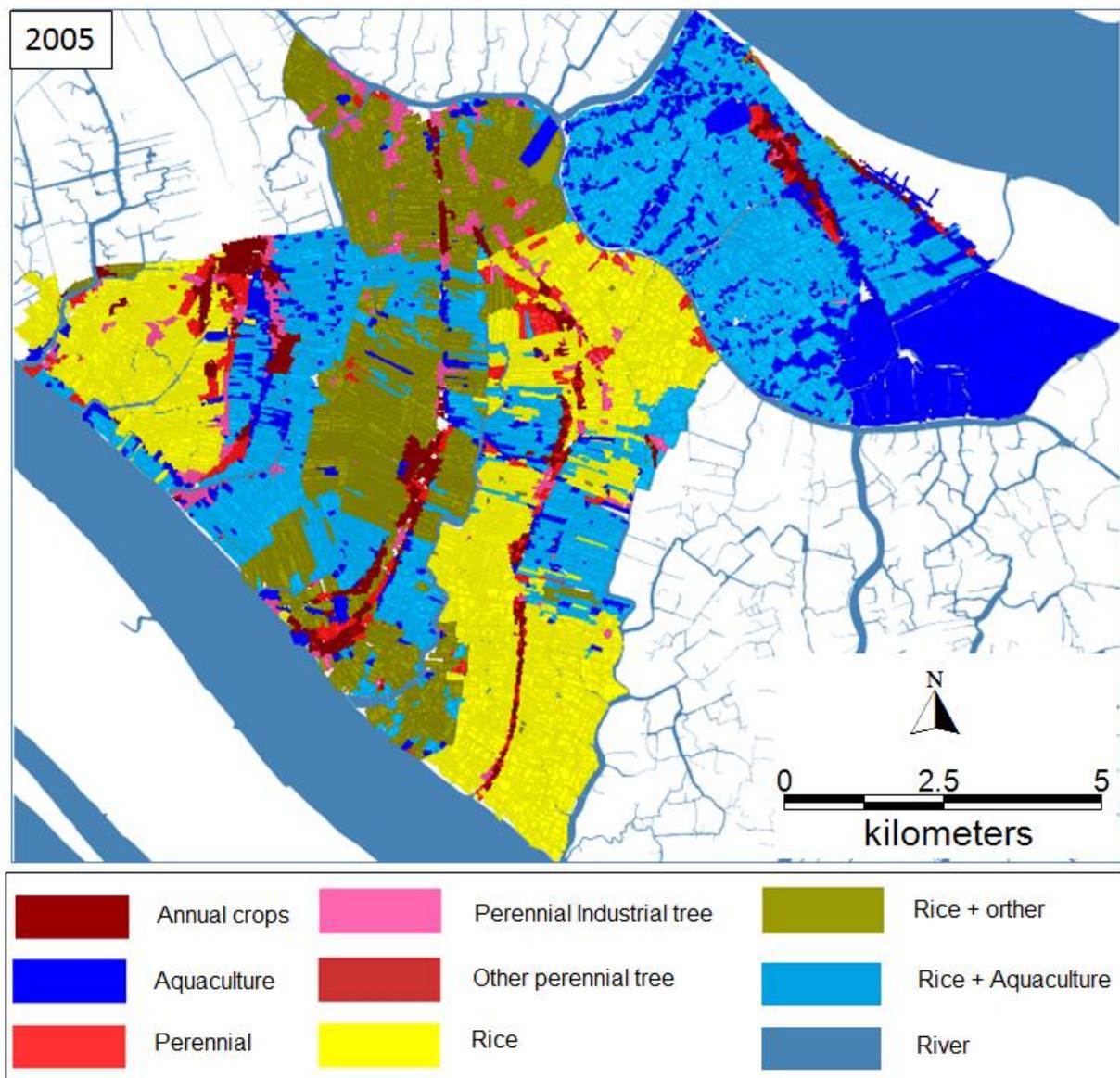


Figure 31. *Land-use map in 2005 of 5 villages of Thanh Phu district.*

For the farmer model which is the main component of our integrated model, data are taken from the land-use map of five villages of Thanh Phu district, Ben Tre province in the Mekong Delta. This land-use map is composed of 18400 parcels of the villages An Thanh, Binh Thanh, An Thuan, An Quy, An Nhon and An Dien. Figure 31 shows the land-use map in 2005 for the initialization of the model and **Figure 32** shows the land-use map in 2010 used for the validation of the model.

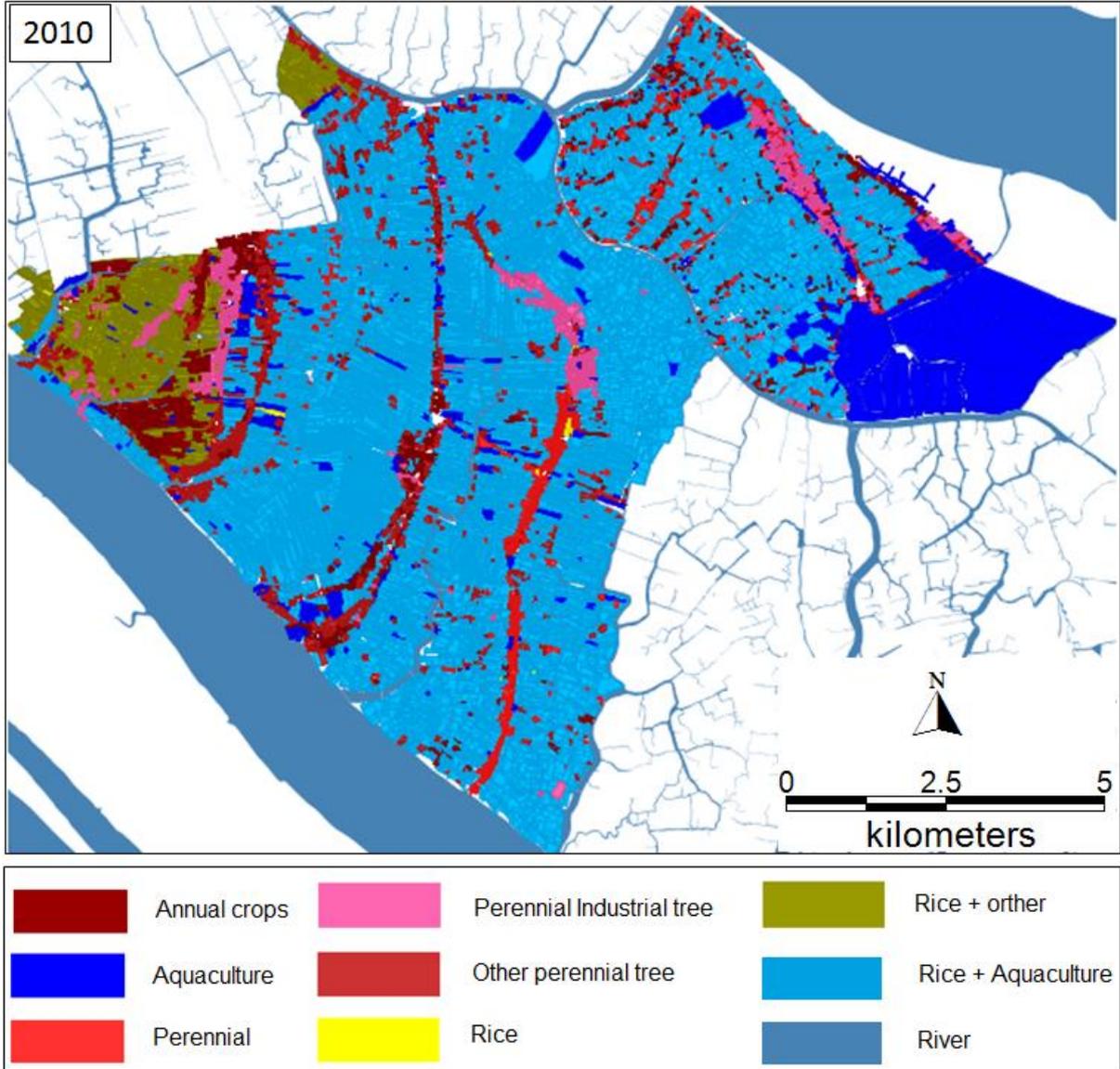


Figure 32. Land-use map in 2010 of five villages of Thanh Phu district.

5.1.2 Indicators for simulation assessment

The main outcome of each experiment of the MAB-LUC is the land-use map at each simulation step. To assess its validity, two indicators, Fuzzy Kappa and Absolute Deviation Percentages (ADP), are used for comparing the simulated map in 2010 to the land-use map observed in 2010.

The Fuzzy Kappa indicator is based on the Kappa indicator (J. Cohen, 1960), which evaluates the correlation between the global precision of the simulated result and the accuracy determined by the hypothetical probability (random change). However, the Fuzzy Kappa indicator measures their similarity based on local correlations. This indicator is often used to evaluate land-use change models (Visser & de Nijs, 2006). The higher the Kappa/Fuzzy Kappa value the better the result.

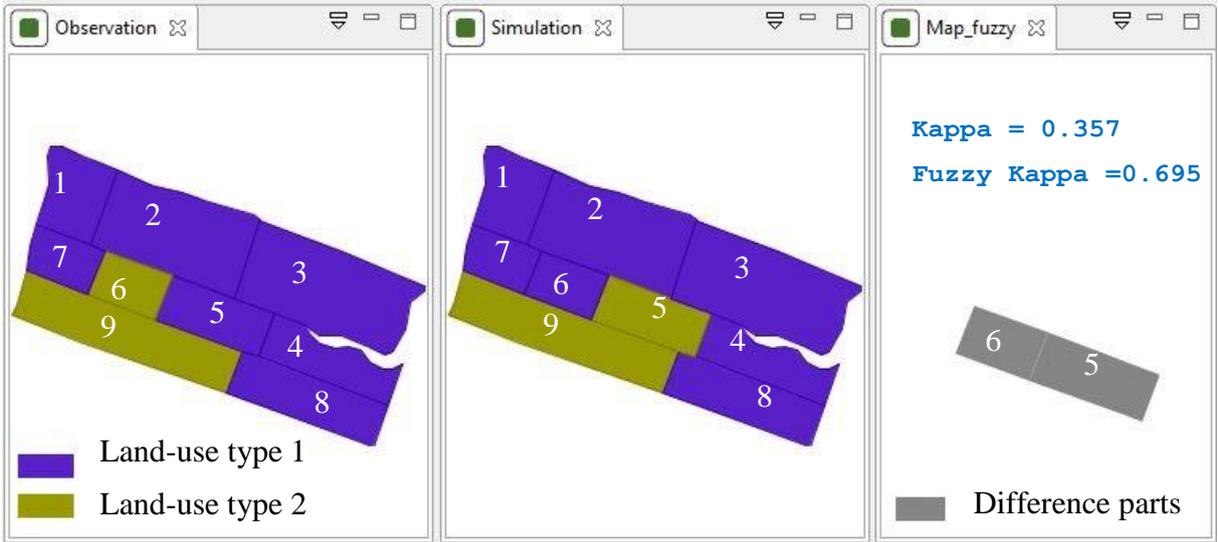


Figure 33. Fuzzy Kappa calculation

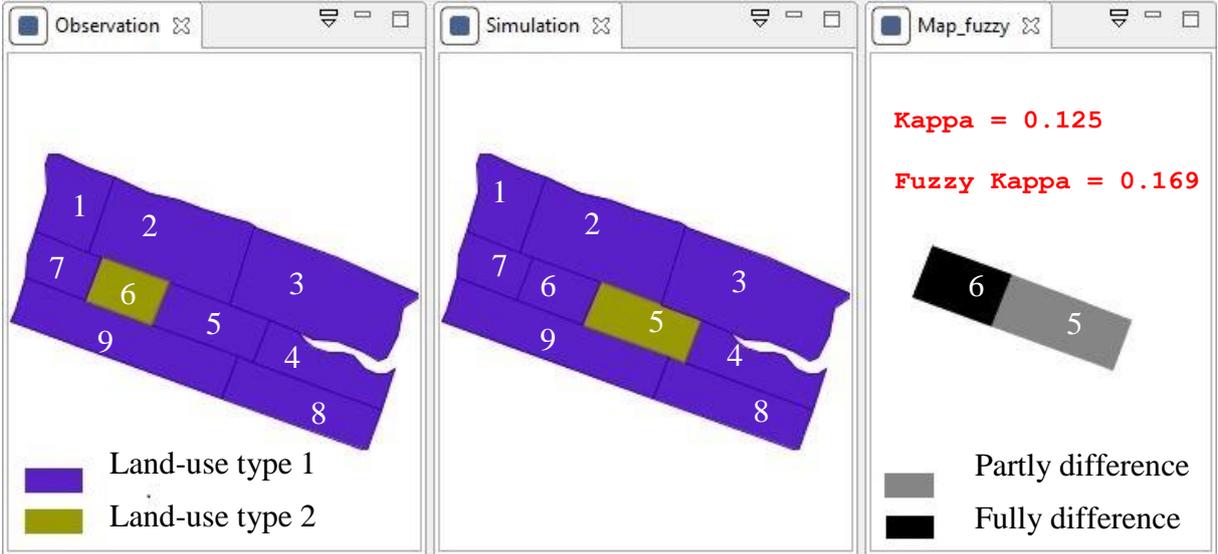


Figure 34. An example on the issue of Kappa and Fuzzy Kappa indicators.

Although the Kappa and Fuzzy Kappa indicators are often used to measure the similarity of maps, in the specific cases where the numbers of elements in the observed groups are not equivalent, these indicators could give bad results. For example, in Figure 34,

the simulated map and the observed map are very similar but the Kappa indicator equals only 0.125 and the Fuzzy Kappa indicator is just a little better (0.169).

The limitations of the Kappa and the Fuzzy Kappa indicators make it difficult to explain the simulation results, as in the example of Figure 34. That led me to introduce a second indicator for evaluating the simulation result: The Absolute Deviation Percentages (ADP) indicator. It measures the global absolute difference between the simulated map and the observed map. The ADP indicator is calculated by Equation 15.

$$ADP(\%) = 100 \frac{\sum_{i=1}^n |X'_i - X_i|}{\sum_{i=1}^n X'_i} \quad (15)$$

where X_i is the observed quantity of parcels with land-use type i and X'_i is the simulated quantity of parcels with land-use type i . The smaller the ADP value is, the better the result. Thus, the accuracy in term of surface equal 100% minus ADP.

These indicators are already implemented in the GAMA platform. Thus, I used both the ADP and the Fuzzy Kappa indicators for analyzing the results of the experiments.

5.2 Calibration of the sub-model of the MAB-LUC

Since the economic and the environmental sub-models mainly use collected data, the dynamics of these models are quite simple. Thus, I focus on calibrating the farmer sub-models where the Markov-based decision, the MCDM and the BDI-based decision approaches are used for the decision making of farmers.

Regarding the datasets for the calibration process, the farmer sub-models use the same datasets of the economic and environmental sub-models. Concerning the spatial data of parcels, these calibration experiments use 5000 parcels randomly extracted from the land-use map.

5.2.1 Calibration of the model of farmers using Markov-based decision approach

As presented in Section 3.3.4.2, the farmer sub-model using the Markov-based decision approach has a parameter controlling the process of changing the land-use of farmers. This parameter receives values from 0.1 to 1. Thus, we chose to manually explore this parameter by using a discretization step of 0.1. For this sub-model, the parameter exploration is done by using a batch experiment and the Exhaustive method implemented in GAMA.

The exploration process automatically repeats the experiment with the parameter increasing from 0.1 to 1. The Exhaustive algorithm then scans the value range of the parameter. In each iteration, the parameter value is increased by 0.1 and the fitness value (the ADP indicator) of the simulation is measured. The value of the variable *para_probability* corresponding to the smallest value of the *adp_indicator* will be chosen as the most appropriate parameter of the model.

The exploration results show that the minimum value of the ADP indicator is 24.9% (surface accuracy = 75.1%) when the parameter *para_probability* is 0.4.

5.2.2 Calibration of the model of farmers using MCDM approach

In the sub-model of farmers using the MCDM approach presented in Section 0, I have defined 3 main parameters representing the weights of the criteria which evaluate the decision given by the model. For calibrating these parameters with the data of the studied regions mentioned in section 5.2.1. The three parameters evaluated in this experiment are *weight_benefit*, *weight_cost* and *weight_implementation* which represent respectively the weights for the benefit criterion, for evaluating the cost and for the transition. These parameters vary from 0.1 to 1 by 0.1 increments. The calibration aims at selecting a set of parameters which minimizes the ADP indicators.

With the set of parameter values, we could run up to 1000 simulations by using the Exhaustive algorithm. The execution time could be high when applying this algorithm with large models. Thus, instead of the Exhaustive algorithm, we used a Genetic algorithm, which exists in the GAMA platform, to calibrate the model. The exploration with the Genetic algorithm in our experiment gives a best fitness of 7.47% and the best parameter values are: *weight_benefit* = 0.3; *weight_cost* = 0.5; *weight_implementation* = 0.6.

5.2.3 Calibration of the model of Farmers using the BDI-based decision approach

The decision making of the farmer sub-model uses the BDI-based approach presented in Section 4.3 of Chapter 4. In this approach, the sub-model has four parameters representing respectively the proportions of rich, standard, medium and poor people. These proportions represent the social profile of farmers situated in the studied area. The corresponding parameters are: *w_rich*, *w_standard*, *w_medium* and *w_poor*. The total of these proportions must be 100%. In the model, the *w_poor* parameter is not explored but it can be deduced from the three first parameters.

Theoretically, these proportions should be collected from the statistical data of the studied area. However, as these statistical data are aggregated for the whole province, they are not appropriate for local communes. Thus, I set these proportions as parameters. Based on the statistical data of the district, the parameter values could be assigned as follows:

- w_{rich} : 0.1 to 0.3
- $w_{standard}$: 0.2 to 0.5
- w_{medium} : 0.2 to 0.5

In this calibration experiment, the Genetic Algorithm provided by GAMA is also used since it supports well the optimization of the fitness and reduces the computation time for the users.

The calibration gives as results a set of parameter values: $w_{rich} = 0.1$; $w_{standard} = w_{medium} = 0.4$. The best fitness value in this case is 9.27%

In the evaluation of decision making approaches in the next section, the explored parameter values are used as the default values of the model.

5.3 Evaluation the MAB-LUC

This section presents the evaluation of three experiments of the MAB_LUC framework. In this framework, the decision of human farmers is simulated by the decision making model with three different approaches. The evaluation is done by comparing the simulation results with the real land-use map in 2010 in the studied region. The farmer's decision-making implemented with the BDI-based approach is compared to the experiments implementing the Markov-based decision and the MCDM approaches proposed in Section 3.1 of Chapter 3.

5.3.1 Experiment 1: The MAB-LUC using Markov-based decision approach

In this first experiment, I focus on the results of the MAB-LUC using the Markov-based decision approach. This approach is the most widely used method for land-use change simulation.

The Markov matrix is built based on land-use data in 2005 and 2010 of 5 villages of Thanh Phu district, in the Mekong Delta. This region is composed of fresh water areas protected by dykes, brackish water areas and salt water areas. Thus, the model allows users to automatically generate Markov matrices for differences regions. The Markov matrix is built

by calculating the proportion of each land-use type which has changed to another type. Table 8 presents two Markov matrices corresponding to the inside dyke region (region protected by dykes) and the outside dyke region (region which is not protected by dykes). The value at row *i* and column *j* of the Markov matrix represents the proportion of the land-use type in row *i* which has changed to the land-use type in column *j*.

Table 8. *Markov matrixes representing the transition among land-use types*

	Region	Annual crops	Perennial industrial tree	Rice – Shrimp	Rice – vegetable	Rice	Aquaculture	Perennial fruit
Annual crops	Inside dyke region	154	13	52	0	6	1	0
Perennial industrial tree		13	19	41	0	35	2	0
Rice – Shrimp		0	0	0	0	0	0	0
Rice – vegetable		17	2	0	0	115	0	0
Rice		226	72	66	5	972	19	1
Aquaculture		7	10	3	0	8	2	0
Perennial fruit		32	51	88	0	20	0	3
Annual crops	Outside dyke region	717	202	106	104	1	35	228
Perennial industrial tree		57	360	162	105	3	14	72
Rice – Aquaculture		0	2	0	3400	0	52	0
Rice – vegetable		8	155	1	3017	61	54	1
Rice		47	140	184	2685	100	87	217
Aquaculture		302	235	57	0	20	523	337
Perennial fruit		42	134	163	117	2	10	228

The simulation of the model is shown in Figure 35. We can intuitively see that the simulated land-use map in 2010 is very different from the real land-use map. The simulated map shows that the Annual crops and the Perennial fruit areas are distributed randomly in both protected and unprotected regions. However, the Rice – Aquaculture areas are quite well distributed in the regions which are not protected by dykes. Note that in the implementation of this approach, we have introduced an evaluation of land suitability after a random choice in

the Markov matrices, this evaluation makes the result of the Markov-based approach better than the one of the random choice.

In fact, the location’s accuracy (Fuzzy Kappa) is 49% and the error is quite high (the ADP indicator is 25.2%). Figure 36 shows the obtained fuzzy map. This map shows the differences between the simulated map and the real map in 2010. The colors of parcels vary from black to light gray. The simulated land-use type of black parcels is totally different from the real one. The simulated land-use type of grey parcels is also different from the real one but some of their neighbors have the same simulated land-use type.

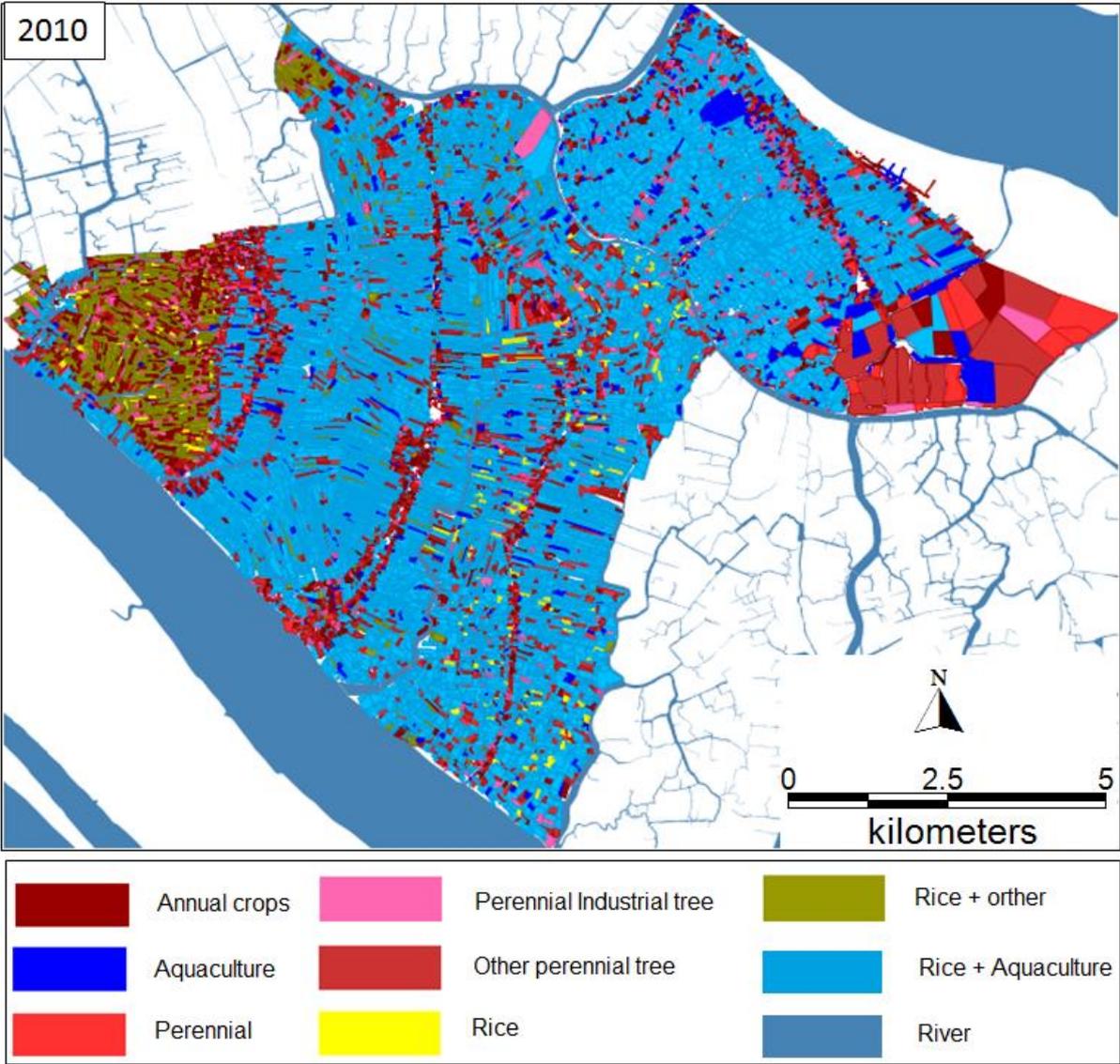


Figure 35. *The simulation result in 2010 of MAB-LUC using the Markov-based decision approach.*

Because the approach is stochastic, only one analysis on the land suitability constraints are not enough for a good distribution. As shown in the red circles on Figure 36, the regions that contain a lot of errors consist of two main land-use types (Annual crops and Perennial

fruit). When these land use types are well suitable for the regions, a random distribution will give a bad result.

Based on the probability of land-use changes in the past, the Markov – based solution can give a good description of the land use changes in the regions where the economic and environment are stable.



Figure 36. *The Fuzzy map of the farmer’s decision making using the Markov decision approach.*

5.3.2 Experiment 2: The MAB-LUC using the MCDM approach

The second experiment focuses on the farmer’s decision making based on the MCDM approach presented in Section 3.2.4.3.

The simulation is done with the weight values W_c , W_p , W_T determined by calibration. Figure 37 shows the simulation results in 2010. The simulated results are almost very accurate except for the two areas in the region protected by dykes (illustrated by the red circles). In these small regions, the main areas are the Rice areas while in the real map (Figure 32) these regions are mainly occupied by the Rice + Other crops. Looking closer step by step on the simulation process of the MCDM approach, the simulated results in Table 9 show a

phenomenon where the land-uses inside of the red circle area have been changed back and forth many times between two land-use types “Rice” and “Rice – other crops”. This unstable result can be explained by the evaluation mechanism of the criteria determining a land-use type. In this case, the same land suitability value for many land-use types (except the ones needing salted water), the dynamics of the cost - benefit and the ease of change between these two land-use types affected the evaluation of the fitness function.

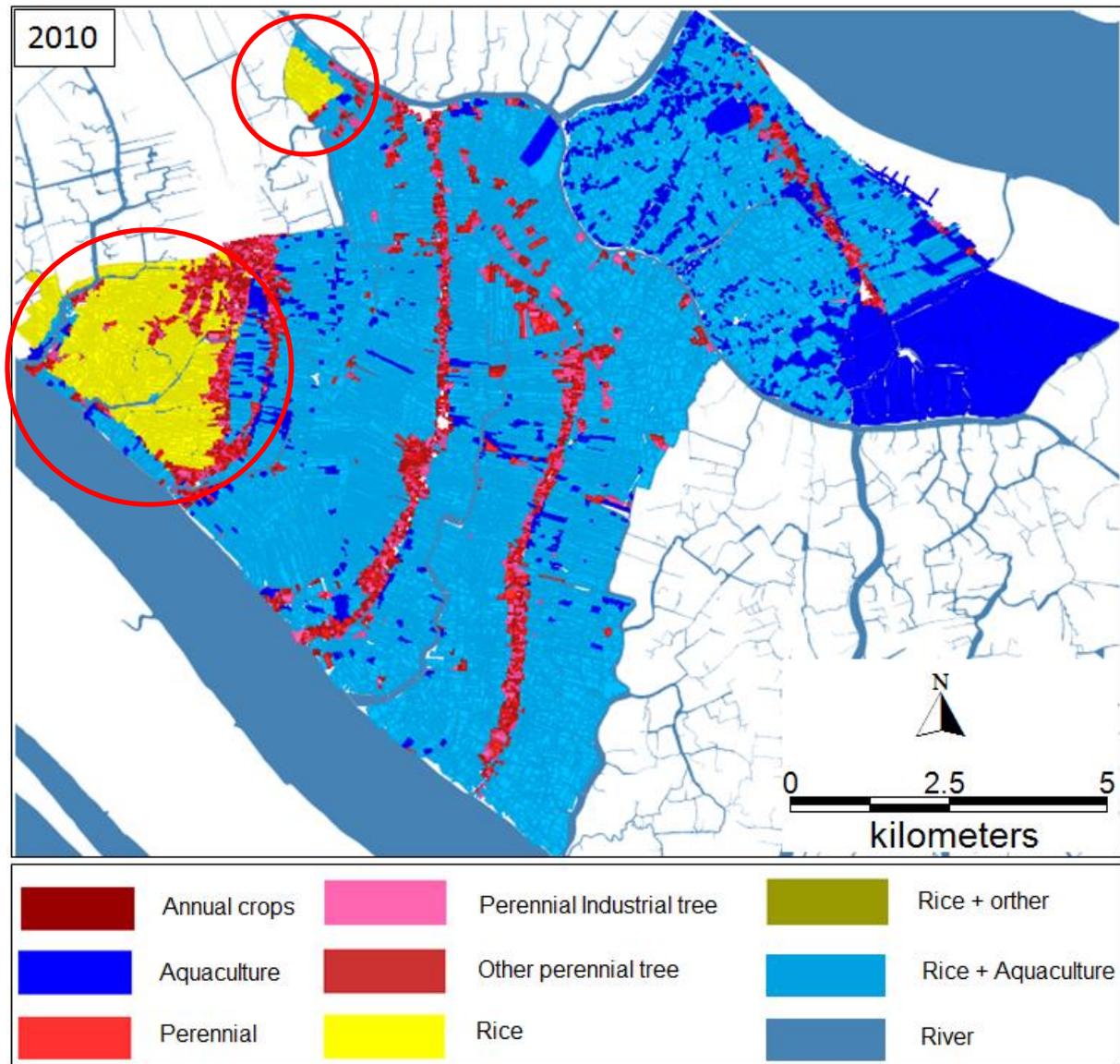


Figure 37. Simulation results of the MCDM approach in 2010.

This phenomenon, which occurs in some local areas as can be seen on Figure 37 is the main reason that reduces the value of the Fuzzy Kappa indicator. That explains why the value of the Fuzzy Kappa indicator of the MCDM approach is low while most of the areas are well simulated. The simulated results illustrates also a limitation of this approach in representing the human behaviors that the people who have the same land-use type in a region have changed simultaneously their land-use type to other type. This simulated behavior of farmers

is not realistic but it can be explained by the mechanism of the MCDM approach, which selects the land-use type based on a fitness function. The modification of influencing factors such as the price or cost of products could strongly affect the value of the fitness function of all farmers who have the same economic and environmental conditions at the same time.

Table 9. Area of the land-use types from 2005 to 2010 simulated with the MCDM approach

Land-use type	Simulation result (ha)					Observed land-use areas in 2010 (ha)
	2006	2007	2008	2009	2010	
Annual crops	19	19	0.1	0.1	0	282.4
Perennial industrial tree	215.2	253	241.3	257	250.3	160.1
Perennial fruit	373.7	483.1	494.8	479	485.7	463.6
Rice – Aquaculture	3966.5	5549.1	5549.1	5575.6	5575.6	5500
Rice	1695.4	0	95.7	69.2	551.5	4.8
Rice + Other crops	1117.9	1117.9	964.3	964.3	0	920.1
Aquaculture	1004.8	970.5	970.5	970.5	970.5	961.7

The Fuzzy Kappa and the surface accuracy indicators given by the MCDM approach are respectively 42.1% and 79.7% (ADP = 20.3%). According to the Fuzzy Kappa measure, the Markov-based decision approach is better than the MCDM approach. However, in visualization, most of the areas in the Fuzzy Kappa map of the MCDM approach (Figure 38) are better simulated than the Markov-based one (illustrated by the white color). The ADP indicator of the MCDM approach (20.3%) is better than the one of the Markov-based decision approach (25.2%).

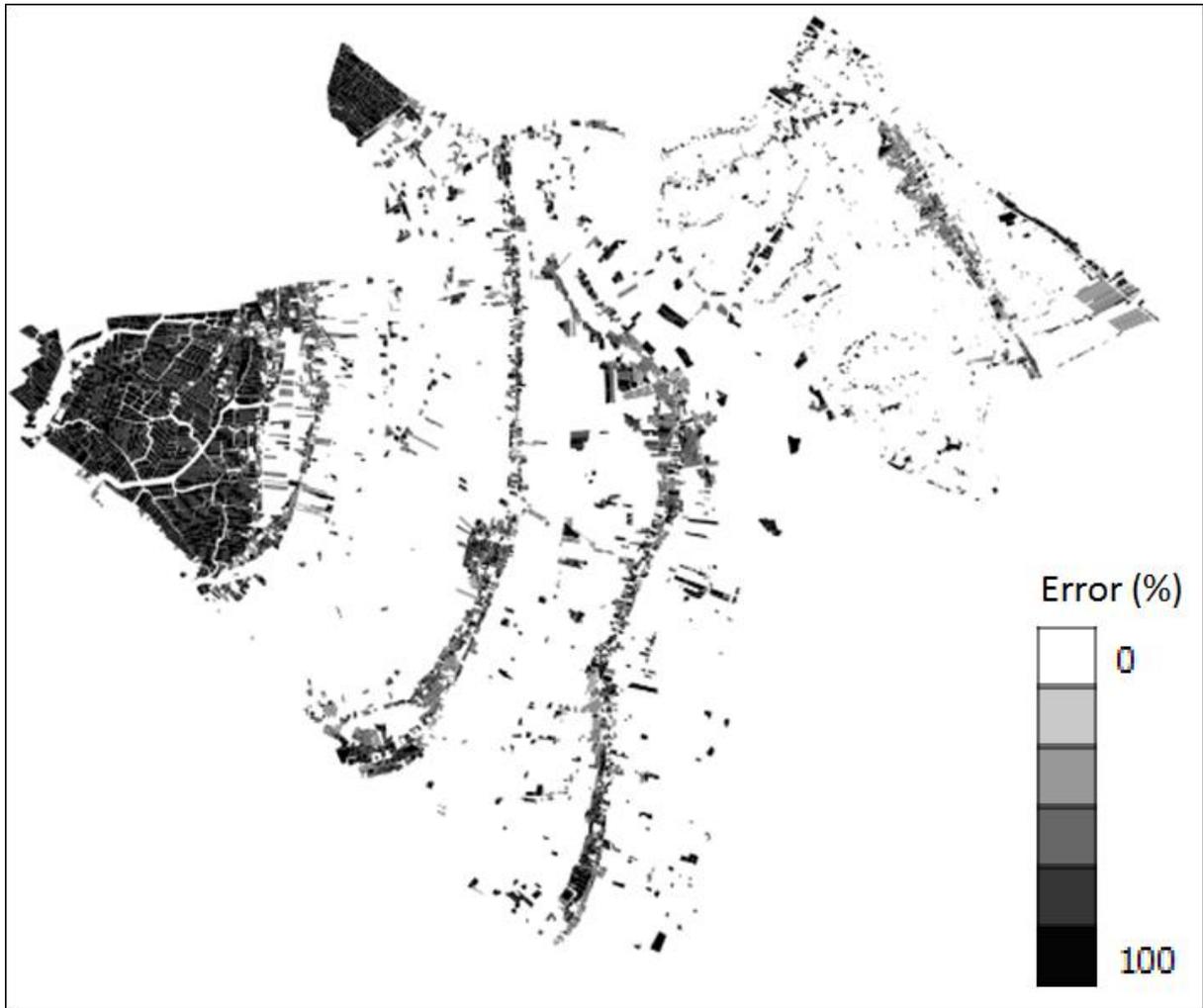


Figure 38. *The Fuzzy Kappa map of the MAB-LUC using the MCDM approach.*

Overall, these results are not very different from the ones obtained with the Markov-based decision approach, but regarding the spatial distribution of the land-use types on the fuzzy maps (Figure 36 and Figure 38) and the ADP indicator, the MCDM approach is better than the Markov-based decision approach. However, the MCDM approach still cannot represent realistic behaviors of farmers. The next section analyzes the MAB-LUC using the proposed BDI - based decision approach presented in Chapter 4.

5.3.3 Experiment 3: The MAB-LUC model using the BDI - based decision approach

The two classic decision-making approaches do not give good results in our experiments. Hence, in this section, I analyze the experiment of the MAP-LUC with the proposed BDI-based decision approach. It will allow verifying if this cognitive approach could be a good solution to represent the farmers' behaviors.

Figure 39 shows the simulation of the land-use change in 2010 using the MAB-LUC with the BDI-based approach. By comparing with the observed map in 2010 (Figure 32), the

simulated map is almost similar with the observed one. However, the result in the areas within the red circles in Figure 39 are not good: the parcels are not correctly changed from Rice+other crops to Rice + Aquaculture.

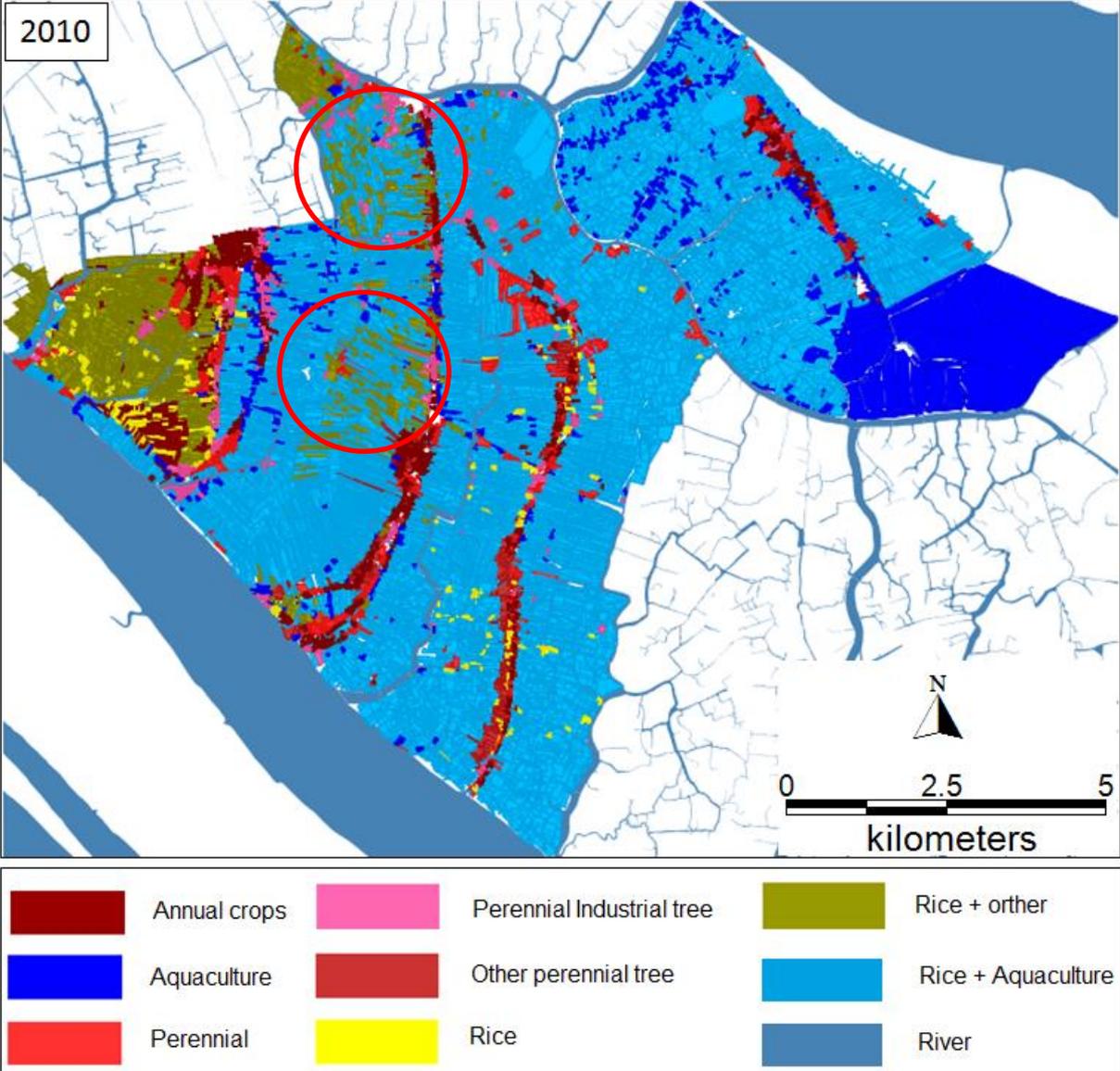


Figure 39. Simulation results of the BDI-based decision approach over 5 years.

Regarding in detail the simulation results from 2006 to 2010 of the BDI-based approach in Table 10, we found that the trend of land-use change is similar to that of the previous years. The Rice and the Rice + Other crops decrease while the Rice + Aquaculture increases. The other land-use types are slightly changed.

Table 10. Area of the land-use types from 2006 to 2010 simulated with the BDI - based decision approach

Land-use type	Simulation result (ha)					Observed land-use area in 2010 (ha)
	2006	2007	2008	2009	2010	
Annual crops	255.2	297.7	297.7	280.8	281.4	282.4
Perennial industrial tree	173.5	150	150	137.4	129	160.1
Perennial fruit	190.5	340.8	340.8	352.7	362.6	463.5
Rice – Aquaculture	2567.4	4867	4867	5074.4	5162.1	5501
Rice	1979.5	438	438	307.1	234.3	4.8
Rice – Other crops	3229.2	1684.9	1684.9	1631.3	1617.3	920.1
Aquaculture	1053	897.7	897.7	865.5	855.5	961.7

Regarding the reason of the simulated results, the behaviors of farmers in their land-use selection are summarized in the chart of farmers' desires during the simulation (Figure 40). At the beginning, the desires of farmers are initialized based on the profile of farmers. During the simulation, some farmers could change their land-use type if they satisfy all the conditions of the new land-use type and their desire is changed to "Stay on current LU", which means that they desire to keep this new land-use type from now on. The conditions of a land-use type are evaluated by the price and cost of products. Some farmers may not have enough money to change to their preferred land-use. They will add a new desire "Ask for loan" and the corresponding sub-intention, which means that they ask for a loan from the bank and wait to execute this sub-intention next year. In the next years, if these farmers receive a loan from the bank, they will remove the sub-intention and return to the first intention. For farmers who have the desire "Stay on current land-use", they continue their current land-use and update their profile. According to the price of products and the state of the neighbors, some farmers can change their desires based on the main behaviors of their profile. The behaviors of farmers appear to be quite realistic, and this allows modeler to test different control policies on land-use, which can prove very useful in land-use planning process.

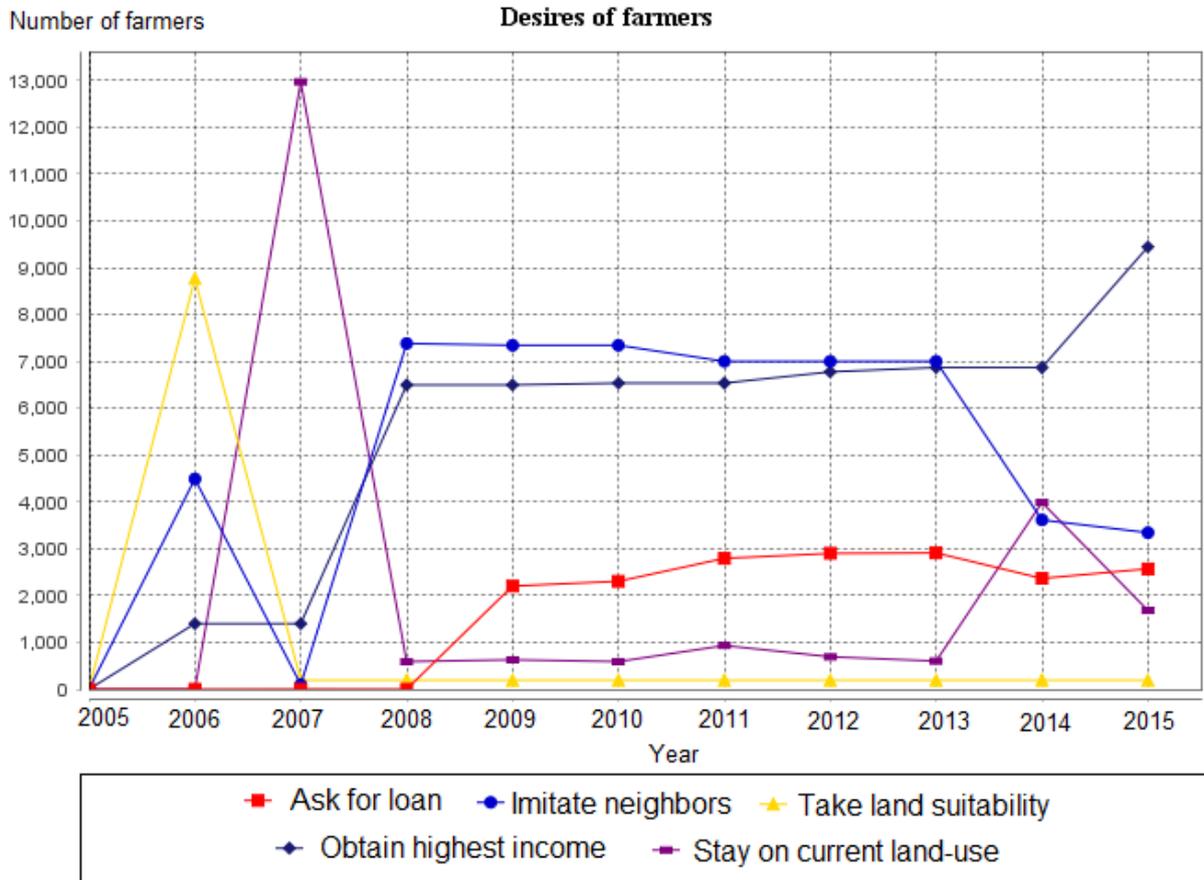


Figure 40. Chart representing the number of farmers corresponding to each desire.

Figure 41 shows the Fuzzy map produced by the MAP-LUC model with the BDI - based decision approach. Comparing the Fuzzy Kappa maps, the BDI-based approach (Figure 39) is better than the MCDM approach one (Figure 37) for the whole map. In visualization, most of the parts in the Fuzzy Kappa map of the MCDM approach seem better than the BDI ones. However, in calculation, the values of the Fuzzy Kappa and the surface accuracy indicators of the BDI-based approach are respectively 50.6% and 89.9% (ADP=10.1%), which shows the best simulated land-use change among the results of the three approaches.

In the next section, we will verify if the simulated results of the three approaches are significantly different in order to recommend the best one for planners.

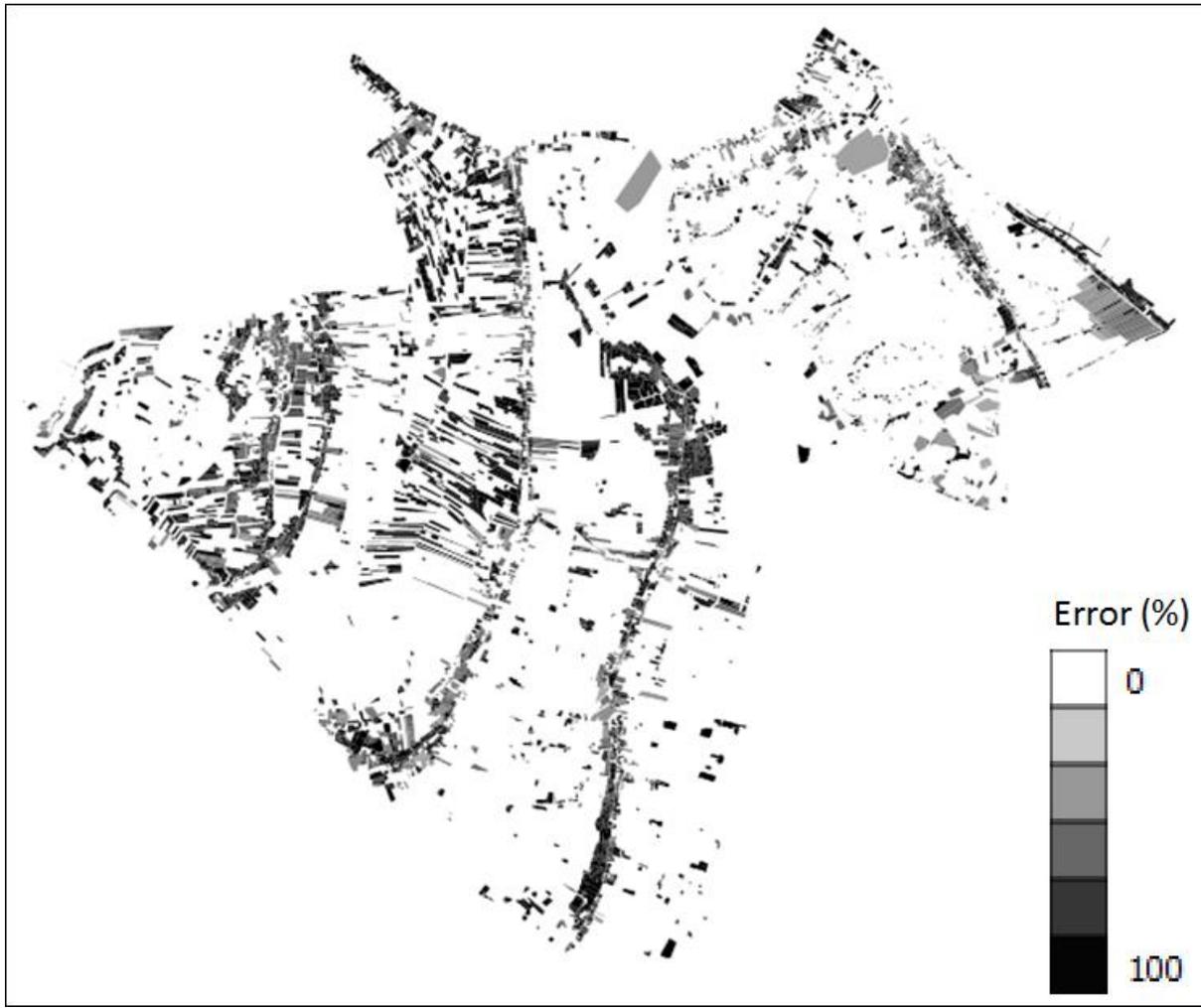


Figure 41. *Fuzzy Kappa map of the MAB-LUC model using the BDI-based decision approach.*

5.4 Assessment

In the previous sections, three different farmer decision-making approaches are explored through three experiments. Figure 42 shows the comparison of these approaches based on the Fuzzy Kappa and the ADP indicators. Because of the possible stochasticity of some approaches, 100 simulations are launched for every experiment to check the significance of the results. The results of these 100 simulations are then analyzed by the one-way analysis of variance ANOVA using SPSS statistics in order to determine whether there are any significant differences between the mean results of these simulations. The one-way ANOVA is applied separately to each of the two indicators: Fuzzy Kappa for the accuracy in term of location and ADP for the accuracy in term of surface. Note that the two evaluation indicators have opposite meanings. The higher Fuzzy Kappa and surface accuracy (100%-ADP) values are the better results.

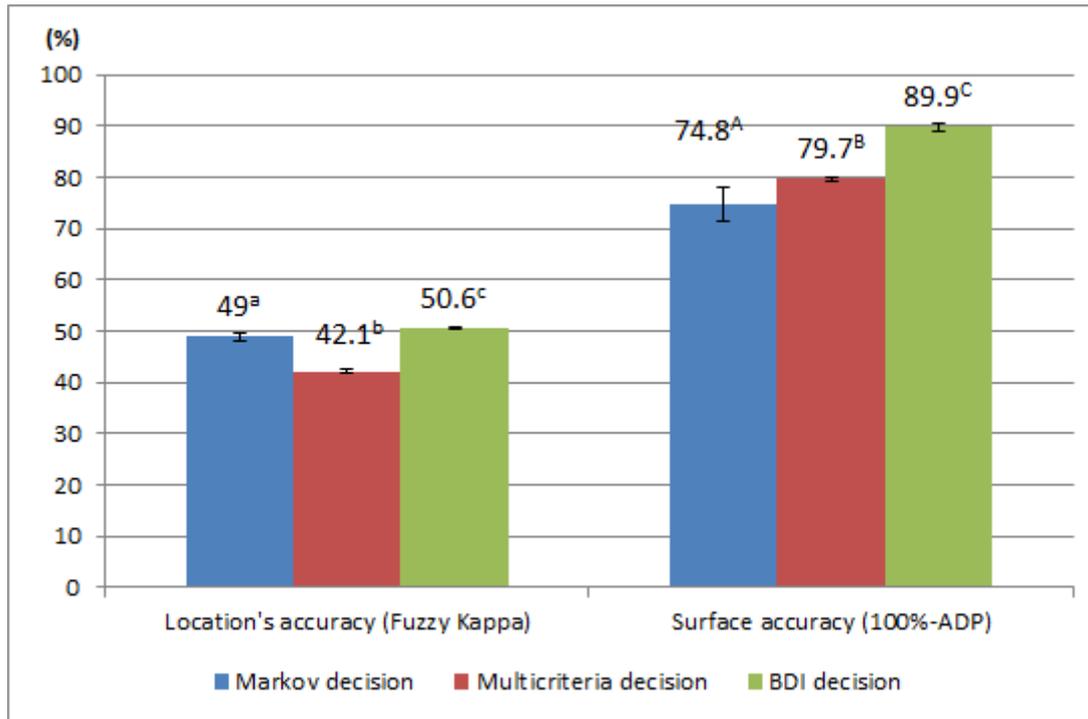


Figure 42. Comparison of farmer decision making approaches using one-way ANOVA with SPSS statistics.

The comparison of the three farmer decision making approaches using one-way ANOVA is shown in Figure 42. The column chart shows, for each approach, the mean and standard deviation values of 100 simulations of each indicator. The value of each column represents the mean value while the black error bar at the top of the column represents the standard deviation. The small letters (a, b, c or A, B, C) at the top of the mean value labels denotes whether the mean values of the three approaches are significantly different. Different letters denote that the corresponding results are significantly different while the same letters denote that the results are not significantly different. Figure 42 shows that there are significant differences between the results of the three approaches for both the position's accuracy (Fuzzy Kappa) and the surface accuracy (100%-ADP) indicators.

Figure 42 shows that, according to the Fuzzy Kappa indicator, the BDI-based approach is a little bit better than the Markov-based decision and the MCDM approaches. However, when looking on the Fuzzy Kappa maps, the BDI-based approach is significantly better than the others.

As mentioned in section 5.1.2, sometimes the Fuzzy Kappa indicator is not good, especially when the numbers of elements in the observed groups are not equivalent. Thus, the

ADP indicator is considered. The comparison chart (Figure 42) shows that, although the result is not bad, the Markov-based decision is the worst approach (the accuracy in term of surface is 74.8%). The MCDM approach is better (surface accuracy = 79.7%) and the BDI-based approach is still the best one (surface accuracy = 89.9%).

As a conclusion, we can say that the three approaches give all quite realistic (or at least credible) simulation results and that the BDI-based approach gives significantly better results of accuracy in terms of location and surface than the two others.

5.5 Conclusion

This chapter compares the simulated land-use maps produced by three human decision-making modeling techniques (Markov-based decision, Multi-criteria decision and BDI-based decision) with the real land-use map of the studied area. The Markov-based decision and the MCDM decision approaches are quite easy to implement. However, these approaches do not provide neither a good simulation result nor a good representation of the farmers' decisions. The BDI-based approach gives the best results (with an accuracy indicator equals to 89.9%). The simulated trend of land-use change is close to the real land-use change of farmers.

The experiments show that the proposed MAB-LUC integrated model allows, by taking into account the human decision-making, to simulate land-use change in a quite accurate way. In the next chapter, I propose a method to integrate the MAB-LUC into the LUP process for appraising the alternatives of the land-use plan with human-economic and human-environmental criteria.

CHAPTER 6 INTEGRATION OF THE LAND-USE CHANGE MODEL INTO THE LAND-USE PLANNING PROCESS

One of the main challenges of the FAO land-use planning process (see Figure 1) is to be able to assess the future impacts of alternative options or land-use policies, which corresponds to the 6th step of the LUP process. Based on the results analyzed in Chapter 5, I first present how to integrate the MAB-LUC in the 6th step of the LUP process. Then, I explore how my integrated model could be used to perform this assessment, and finally I present two practical examples. The first one analyses various economic policies regarding the accessibility of farmers to credit. The second one analyses the construction of infrastructures such as sluice gates to change the environmental conditions. At last, I propose some hints concerning the use of the MAB-LUC for land-use planning under climate change, especially under a Sea Level Rise scenario.

6.1 Integration of the MAB-LUC into the land-use planning process

As I argued in Chapter 1 (section 1.1), the previous studies on land-use planning did not propose a dynamic appraisal of social, economic and environmental factors. As a consequence, it is a big challenge for planners to propose suitable plans. Regarding the previous land-use planning works, most of them focused on improving the land suitability evaluation (the 5th step of the Land-Use Plan of FAO) with multi-criteria approaches (AHP, linear programming) to provide land-use plan options. However, many land-use types can be suitable for the same land unit. Thus, the planners have to select an option among the set of possible ones based on their own criteria and knowledge. For solving this limitation, some researchers (Cao et al., 2011; Cao, Huang, Wang, & Lin, 2012; Memmah, Lescouret, Yao, & Lavigne, 2015; Porta et al., 2013) applied linear programming and genetic algorithms to determine the total area of each land-use type for each land unit, but they do not propose any solution for land-use allocation. Besides that, some studies focus on the spatial allocation of land-use type by the use of a multi-criteria analysis (LIU, WANG, & GUO, 2006; LIU et al., 2006; Inés Santé & Crecente, 2007; Santé-Riveira, Crecente-Maseda, & Miranda-Barrós, 2008; Wang, Yu, & Huang, 2004). However, these studies are limited to the accounting of the farmer's behaviors in the allocation of land-use types.

In order to overtake these limitations, I propose to use the MAB-LUC for appraising the different alternatives in the land-use planning process. This contribution concerns the 6th step of the FAO’s LUP process.

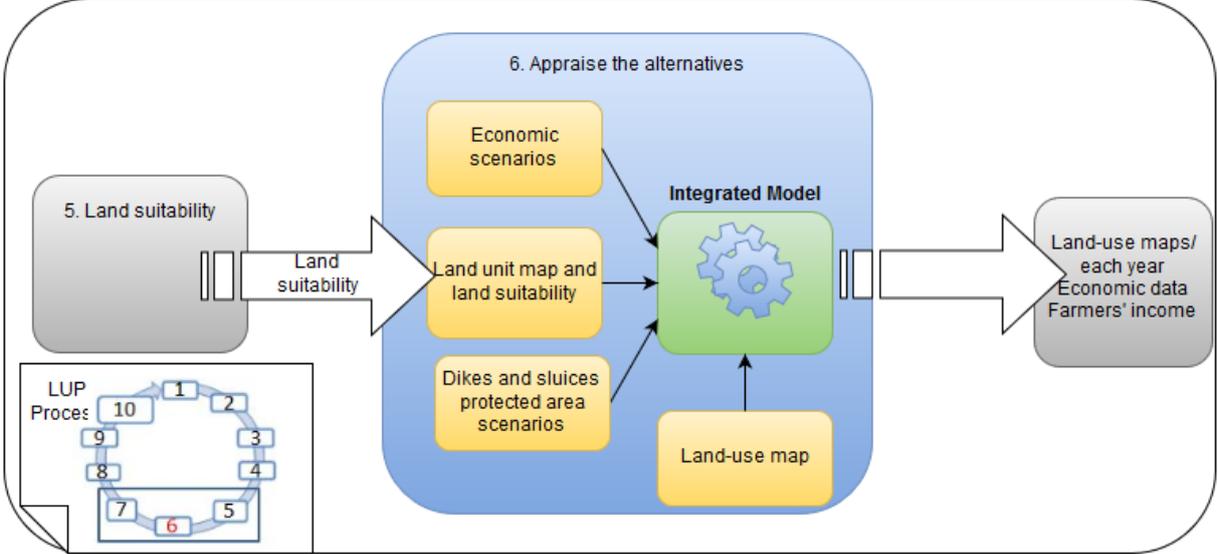


Figure 43. LUP process with MAB-LUC framework

The proposition is detailed in Figure 43, where the MAB-LUC integrated model with the BDI decision-making approach is integrated into the land-use planning process to simulate the possible land-uses under the effect of human, socio-economic and environmental factors. The five first steps of the land-use planning (LUP) process are kept unchanged. The 5th step provides a land unit map and the land suitability dataset for each land-use types. Then, in the step 6, different economic scenarios such as scenarios of the evolution of costs and prices of products during the planning period, investment credit policies, environmental data (land unit map and land suitability of the land-use types) and the land-use map (at parcel level) are introduced to the MAB-LUC. The MAB-LUC allows planners to test as many scenarios as needed and to obtain for each of them a very detailed map of land-use type allocation.

The steps 7 to 10 are the same as in the normal LUP process of FAO. In the 7th step, planners can select the most appropriate land-use option for being their land-use plan.

In the next sections, I apply the process in the context of two case studies: (1) the first one relies on the loan policy of the government; (2) the second one concerns changes in the infrastructure.

6.2 Appraisal of socio-economic factors for land-use plans

This section focuses on testing a dynamic appraisal of socio-economic factors using the LUP process proposed in the previous section. The land-use options are tested in a scenario where product price increase from 2010 to 2020 and the loan policies from the banks change. The scenario analyses the behaviors of farmers and the results of land-use change when applying different credit controlling policies.

Regarding the input data, the scenario assesses the land-use change from 2010 to 2020 with the MAB-LUC using the BDI-based approach for farmer decision-making. I use the initial land-use map in 2010, the dynamic prices of products in 2020 provided by the economic sub-model and the environmental data of 2010. In this experiment, I assume that the environment data do not change during the simulation. Based on the calculation in Chapter 3 (Figure 17, page 51) the average benefit of aquaculture (shrimp) production is around 24000VND/m² (~ 1.1USD/m²) with a standard deviation around 2000VDN/m². Thus, for this scenario, I consider that the benefit of aquaculture production will continue to increase about 2000VND/m² per year, and that the benefit of the other kinds of productions will not change. Moreover, the investment capital of farmers will mainly come from banks through loans. Thus, the benefit of aquaculture is expressed in Equation (15) where x is the step of the simulation.

$$benefit_aqua = (24000 + 2000x) \quad (15)$$

When the benefit of aquaculture increases, as a social consequence, farmers will tend to change their land-use type to aquaculture. However, the cost of aquaculture production being very high, farmers need to ask investment money for changing to this kind of production.

The scenario will be tested with 4 credit policies: no credit control; 2.5% of farmers can receive a loan per year; 5% of farmers can receive a loan per year; and 10% of farmers can receive a loan per year.

The simulation results of land-use in 2020 corresponding to the different credit policies are shown in Figure 44. The simulated maps show that aquaculture (the blue area) occupies most of the studied area when every farmer has access to investment credit each year (no control of investment). In the case where the number of farmers who can receive a loan per year is limited, aquaculture area increases slowly during ten years.

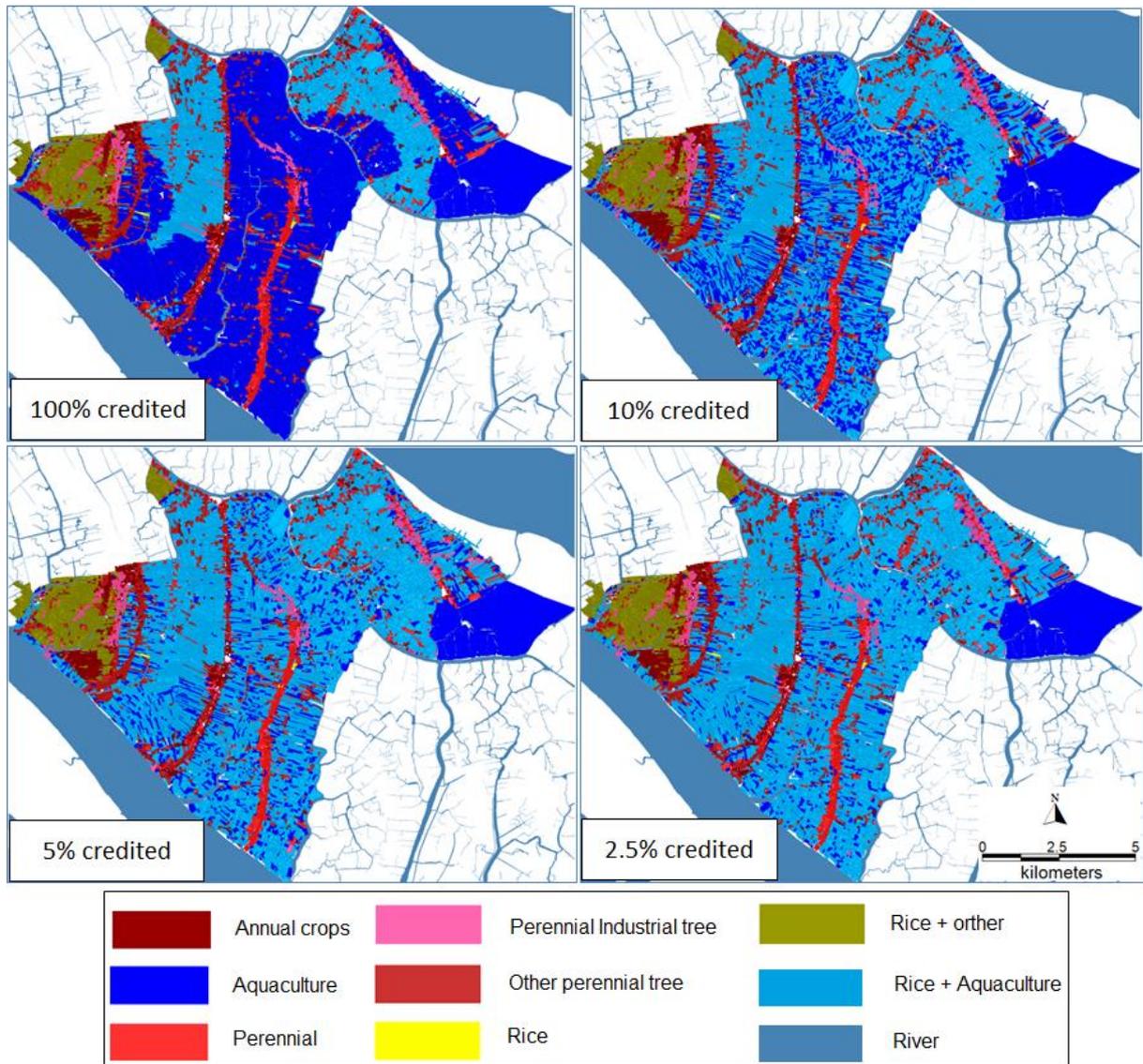


Figure 44. Simulated maps in 2020 with different loan policies.

The chart in Figure 45 shows the total area for each land-use type in 2020 simulated with the 4 different loan policies. The two main land-use types are rice-shrimp and aquaculture. If there is no control on loan (100% of farmers can have a loan), everybody can change to his/her favorite land-use type, the total area of aquaculture in this case reaches 4369.7ha. Aquaculture area is quite small when only 2.5 % or 5% of farmers have access to investment money each year. Aquaculture area covers 1093.5ha (respectively 1347.9ha) in the case that 2.5% (respectively 5%) of farmers can benefit from credit each year. When the percentage of farmers who can receive a loan from banks increases to 10%, the aquaculture area increases to 1886ha (nearly a half of aquaculture area in the case where there is no control of investment credit).

Regarding the behaviors of farmers in the model, the credit policy indirectly affects the desires of farmers as shown in Figure 46. With the strictest loans control policy, which

gives investment credit to only 2.5% of farmers each year, in 2020, there still are many farmers waiting for a loan from banks.

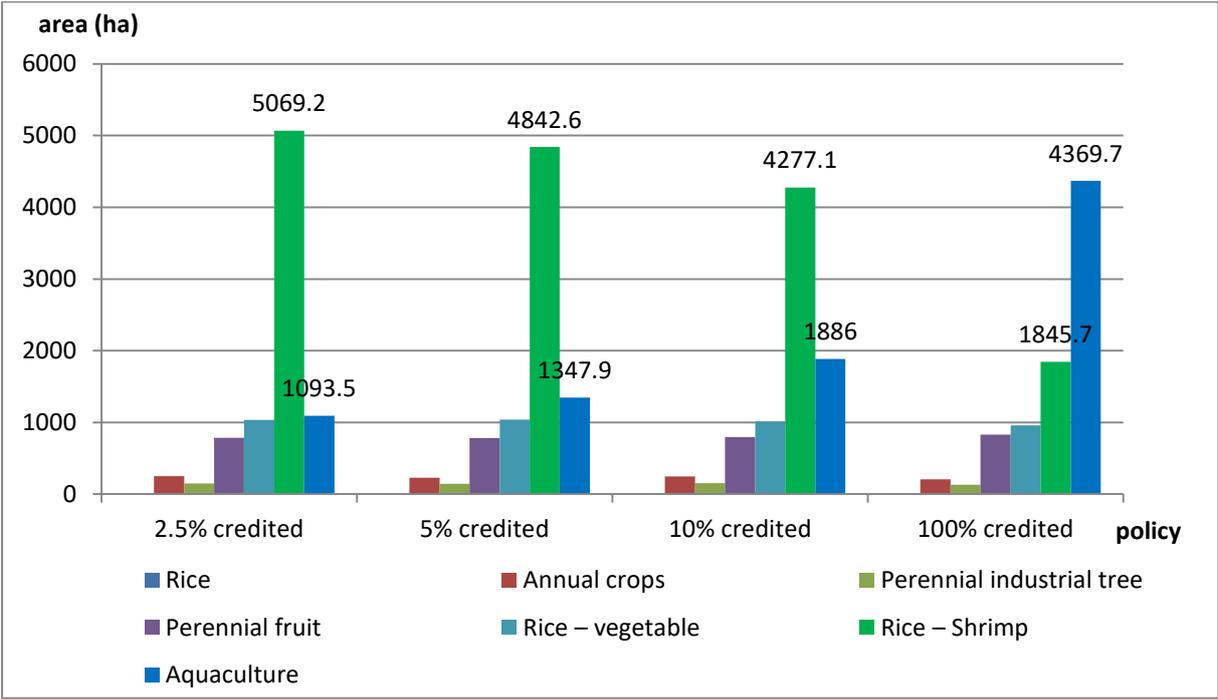


Figure 45. Area of land-use types according to different credit policies in 2020

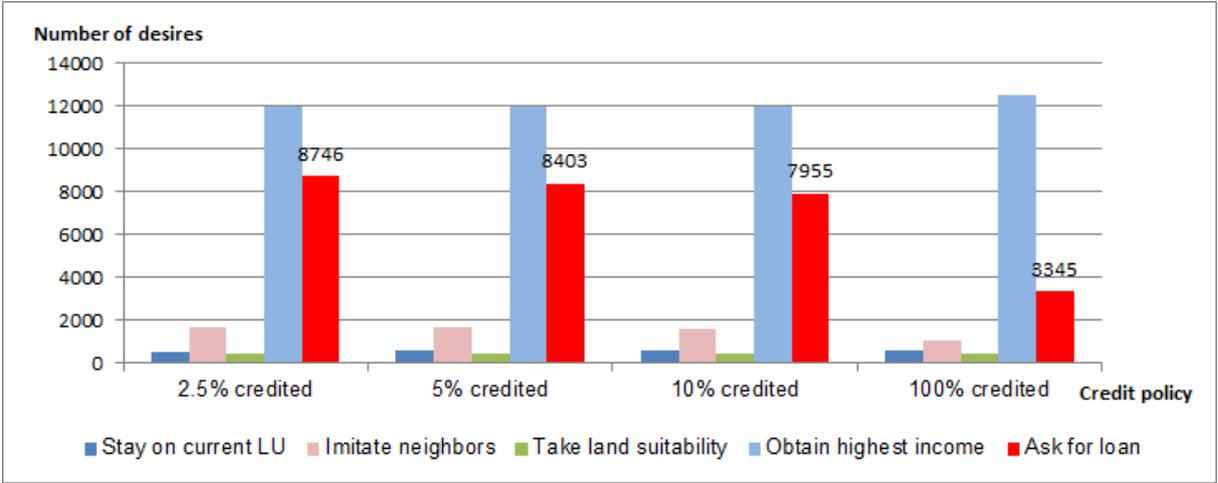


Figure 46. Desires of farmers according to different credit policies in 2020

This result allows planners to assess the simulated land-use plan and analyze the influence of social- economic factors on farmers’ behaviors in land-use change.

The next section presents a socio-economic and environmental appraisal of land-use planning.

6.3 Appraisal of both socio-economic and environmental factors for land-use plans

In order to assess both socio-economic and socio-environmental factors, I present a second scenario with two assumptions: (1) the economic scenario is the same as the one of Section 6.2, (2) the environmental scenario relies on changes of infrastructure such as sluice gate control system.

In the Mekong Delta region, the systems of sluice gates and dykes play an important role in protecting the region from the salinity intrusion. In the dry season (from November to May of the next year), the sluice gates are closed for protecting the region from salted water. On the one hand, the sluice gates protect the rice area, but on the other hand they also indirectly prevent farmers in the salt protected area from doing shrimp production. As a scenario for testing the infrastructure management, we consider that the sluice gates in the region bounded by the red circle in Figure 47 are opened in the dry season. As a consequence, the soil salinity of this local region increases which makes the region become more suitable to aquaculture production.

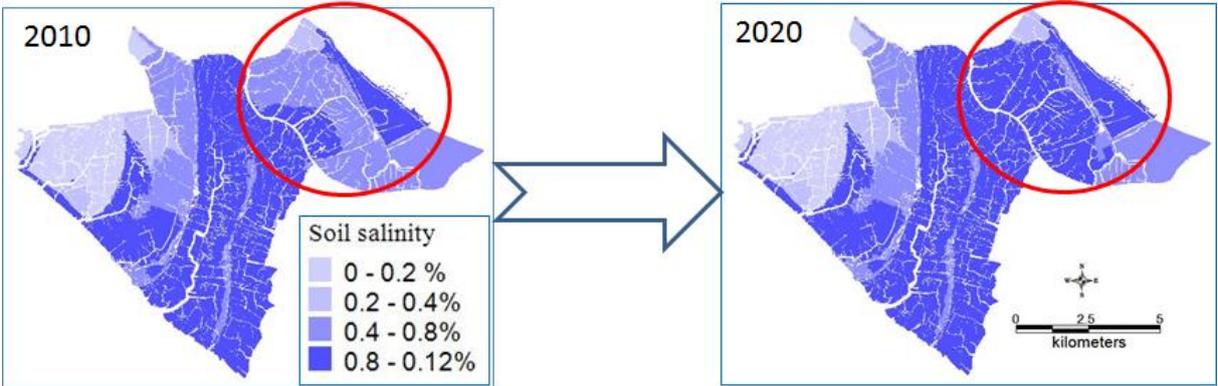


Figure 47. A scenario of changing soil salinities of the region

The simulation results with environmental changes corresponding to different investment credit policies are shown in Figure 48. If there is no control on credit, people whose current land-use type is rice-aquaculture will mostly change to aquaculture (5134.1ha). This land-use change tendency is stronger than in Scenario 1 (4367.9ha). If the percentage of farmers who can receive a loan from banks is limited at 2.5% per year, only about 1100ha will be changed to aquaculture while most of land-use area will still be rice-aquaculture.

Regarding the farmers' behaviors, Figure 49 shows that the number of farmers who need loans to change to the highest income land-use, is also very high. In fact, in the case

where only 2.5% of farmers can receive a loan, at the end of the simulation period, there are still 9901 farmers waiting for a loan decision from banks. The aquaculture area in this case is only 1161.5ha (Figure 48). Moreover, the results in Figure 48 and Figure 49 show that when the investment credit policy is less strict, the number of farmers who wait for a loan decision decreases while the aquaculture area increases. We can say that the loan policy strongly affects the decisions of farmers even if the environmental conditions are suitable for the land-use change.

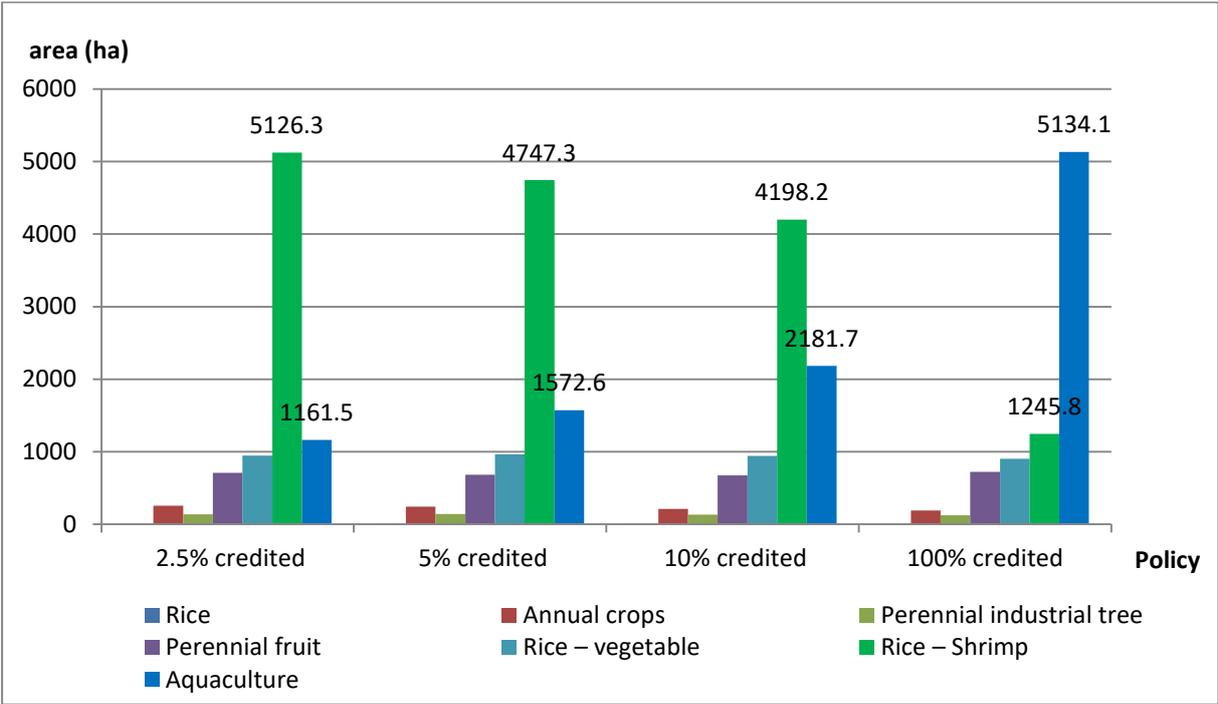


Figure 48. Area of land-use types in 2020 according to the scenario 2

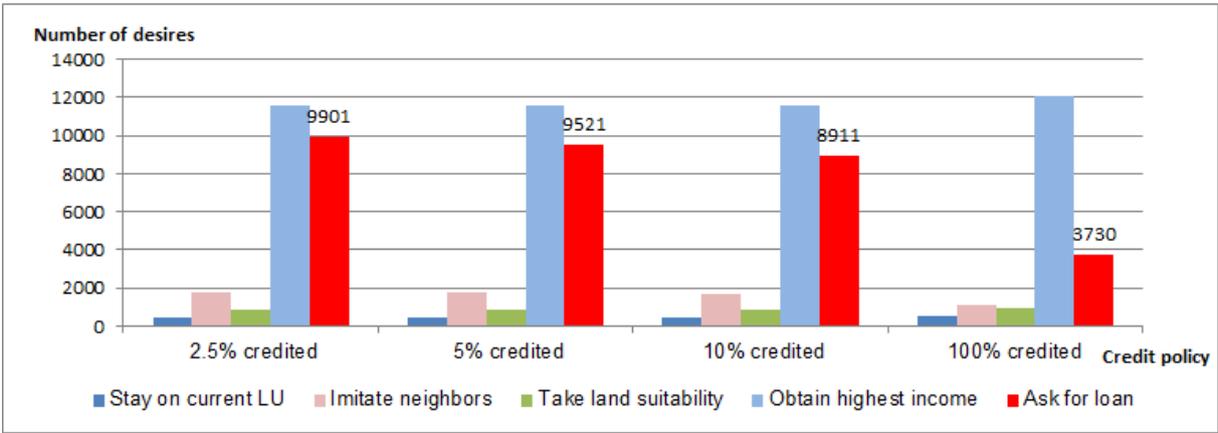


Figure 49. Desires of farmers in 2020 according to the scenario 2

The results of the two scenarios of socio-economic and socio-environmental appraisal of alternatives allow planners to propose many different plans according to the different economic and environmental conditions. The MAB-LUC model using the BDI-based decision

approach provides planners with not only land-use plans but also a tool for testing different economic policies and infrastructure plans.

6.4 Assessment of land-use plans under climate change

According to (Wassmann, Hien, Hoanh, & Tuong, 2004), the Mekong Delta region will be heavily influenced by the effects of global climate change. Indeed, the sea level rise and salinity intrusion will strongly impact the life of people and the situation of agricultural production (Smajgl et al., 2015). Based on the analysis of Smajgl et al. (2015), the agricultural area of the Mekong Delta of Vietnam will strongly decrease because of the salinity intrusion.

Land-use plans are built for a 10 years' period. Climate change could strongly affect future plans. To provide the basis for the assessment of climate change in Vietnam, the Ministry of Natural Resources and Environment (MONRE) of Vietnam have built scenarios of floods and salinity intrusion with a sea level rise of 30cm, 50cm and 100cm (MONRE, 2009a). These scenarios are evaluated at the national and regional scales, in which the Mekong Delta is the most interesting region. The MONRE's Circular N^o 29 dated on 02 June, 2014 (MONRE, 2014) requires an appraisal of the impact of climate change, especially the rising of sea level and the salinity intrusion, on land-use plans.

To assess the land-uses under the impact of climate change, a big challenge is to be able to predict the land-use change, which is difficult because of the lack of tools to simulate the self-adaptation to the socio-environmental factors of farmers. Most of the studies have targeted vulnerability assessment with GIS tools and provided some solutions for climate change mitigation and adaptation (Lin et al., 2013; Mani Murali & Dinesh Kumar, 2015; Marfai & King, 2007; Nhan, Trung, & Sanh, 2011; Wassmann et al., 2004). The static spatial data assessment of these studies is done by overlapping the current land-use map with the SLR maps without taking into account the dynamics of land-use. Another assessment of agricultural land-use change based on scenarios was proposed by (Meiyappan, Dalton, O'Neill, & Jain, 2014). Although this research does not focus on the farmers' roles, it also proposes to test the impact of policies in the context of climate change.

Following the same idea as these works, it is possible to use the MAB-LUC to assess land-use plans under impact of environmental change with SLR scenarios. The full assessment process, shown in Figure 50, is composed of the three following steps:

(1) The first step is the land-use planning process using the MAB-LUC model to appraise the alternatives. This proposal is presented in Section 6.1.

(2) The second step is the GIS data processing. In this step, a spatial analysis with a GIS tool is proposed to prepare land-unit maps under climate change. The land unit maps are created by overlapping (using union method) the 3 main layers: the flooding map, the salinity intrusion map and the soil map. To assess the two scenarios of SLR in 2030 and 2050, two land-unit maps related to these scenarios are needed.

(3) The last and main step of the appraisal is the assessment process. It requires as input the output data of the two previous steps: the land-use options and the land-unit map. The land-unit map provides the characteristics of the soil, time and depth of flood and salinity in 2030 (and in 2050). In addition to the environmental factors, the economic evolution and credit policy could affect the land-use plan under different SLR scenarios. Each land-use option provided from the LUP process in the first step is tested sequentially by an experiment in this third step. For each experiment, a land-use map is produced.

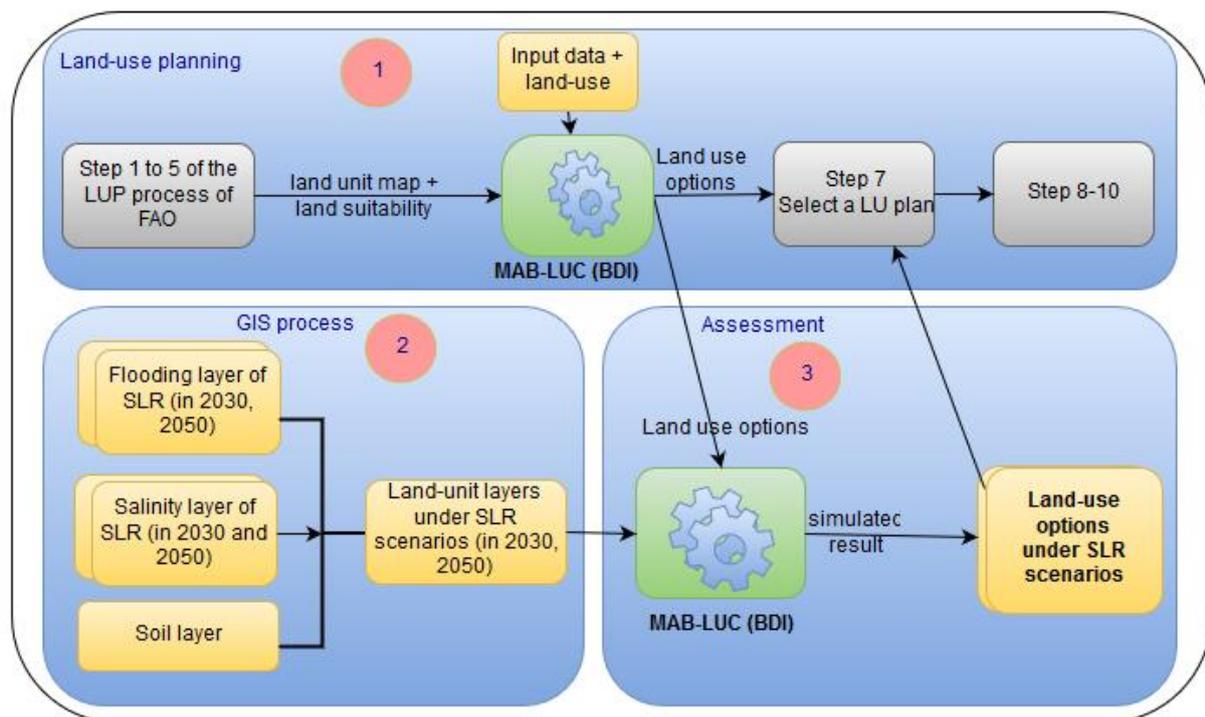


Figure 50. Assessment of land-use plans under SLR scenarios

Finally, the results obtained in the third step are given back to the 7th step of the LUP process. In the 7th step, the assessed options with SLR scenarios can be compared to provide authorities with advices concerning the adaptation and mitigation of climate change.

6.5 Conclusion

This chapter aimed at answering the research question of this thesis by providing an integrated model to assess the different alternatives of the land-use planning process. Indeed, I propose to use The MAB-LUC in the 6th step of the FAO's LUP process to appraise the possible land-uses with both socio-economic and environmental factors. The application ability of the proposed solution is illustrated by two assessment scenarios. The first one analyses the effect of investment credit policies on land-use plans, while the second analyzes the effect of both economic and environmental factors on land-uses. The results of the two scenarios show the capability of the MAB-LUC to provide possible land-use plans and to test the economic and environmental control policies.

Concerning the assessment of land-use planning under climate change, the MAB-LUC that takes into account the farmer behaviors can be a good solution for land-use plan assessment in the context of salinity intrusion, especially in the Mekong Delta of Vietnam.

CHAPTER 7 CONCLUSION

This chapter summarizes the contributions of this thesis and discusses the future works for improving the land-use planning and extending the results to similar works.

7.1 Contributions

As presented in Chapter 1, this thesis has four main objectives that interest both the artificial intelligence and environmental resource management disciplines: (1) proposition and integration of a human decision-making process model into an agent-based platform; (2) design and implementation of an agent-based integrated model for land-use change (MAB-LUC) that takes into account the complexity of the farmers' decision-making process; (3) validation of the proposed model by simulating the land-use change in the Mekong Delta and (4) integration of the MAB-LUC into the 6th step of the LUP process of FAO.

This section summarizes the main contributions of this thesis in both fields: agent-based modeling and environmental land-use planning.

7.1.1 Contributions to agent-based modeling

The first contribution of this thesis is a human decision-making modeling framework in which the BDI architecture is used to define the cognitive architecture of socio-environmental agents.

The second contribution is the integration of the proposed framework into the GAMA agent-based platform. We have contributed to the development of an extension of the GAMA platform that provides a generic BDI architecture. This architecture is based on the GAMA meta-model and can be used through the GAML modeling language, and thus allows to democratize the use of such an architecture for non-computer scientists.

7.1.2 Contributions for LUCC, LUP and assessment on impact of climate change

Regarding the contributions made to the domain of Land-Use and land Cover Change (LUCC), I have proposed an integrated model for land-use change modeling named MAB-LUC. It has been built to be generic, flexible and to solve complex land-use planning problems. This model represents the farmers' decision making process with three different approaches: Markov-based decision approach, MCDM approach and BDI-based decision

approach. The MAB-LUC has also been calibrated and validated with the data of the studied region (Thanh Phu district, Ben Tre province in the Mekong Delta).

The integrated model is divided into different sub-models corresponding to the different socio-economic and environmental factors affecting farmers' decisions. This modularity increases the flexibility and the reusability of models. Each sub-model manages one or several factors and could be modified or replaced by more complex ones. The most important of them, the model of farmers, is implemented using a BDI architecture, which allows to represent farmers as complex actors whose beliefs help them to arbitrate between several, sometimes contradictory, desires.

Regarding the contribution to land-use planning, the novel approach integrating the BDI architecture into the MAB-LUC allows providing more accurate land-use change maps (see Chapter 5). This accuracy makes the MAB-LUC particularly interesting to support the 6th step of the land-use planning process of FAO: appraisal of the alternatives with socio-economic and environmental factors. The ability to test economic and environmental policies of authorities, including environmental policies in the case of Sea Level Rise (SLR), have been demonstrated with the MAB-LUC (cf. MONRE requirements).

7.2 Perspectives

7.2.1 Improving the integrated model regarding the usage of uncertain data

As this thesis does not focus on economic modeling, the price dynamics in the economic model is still very simple. It is integrated only to provide the near future price dynamics corresponding to the land-use planning period. To be able to better take the economic factors into account, and in particular the uncertainty of the prices evolution, it is important to improve this economic model. Several works propose methods to predict the price of agricultural products by taking into account the uncertainty of such dynamics. For example, Bond et al. (2004) propose to use a Monte Carlo method and Nguyen and Tran (2015) proposed the maximum likelihood estimation method. It could be possible to build a model using such methods to provide different scenarios of product price and cost evolution.

7.2.2 Extending the integrated model to similar works

The model proposed in this thesis could be extended and be used for similar socio-environmental problems such as the environmental assessment of sustainable aquaculture or the analysis of forestry economic services.

7.2.2.1 Environmental assessment of sustainable aquaculture

Aquaculture activities give the highest income to farmers. Many people in coastal areas would like to change to shrimp farming (Johnston, Trong, Tien, & Xuan, 2000). However, intensive shrimp farming has negative impacts on the environment especially on the soil salinity and water quality. Inversely, environmental pollution could cause serious damage to this activity. In fact, shrimp cultivation is facing many risks. The biggest problems come from environmental factors and in particular the salinity and pollution of water sources (pollution and virus). Yield losses due to shrimp diseases lead farmers into debt and poverty (Chanratchakool & Phillips, 2002). A review of Walker and Winton (2010) showed several reasons for the shrimp diseases to rapidly and widely break out in a large region. The poor knowledges on pathogens, critical epidemiological factors, geographical range and individual behaviors are the key reasons. In addition, farmers play a very important role in the process of pathogen transmission to the supply water system.

While most of the Mekong Delta regions are not well adapted for the shrimp cultivation, it is necessary to supply these regions with clean water and drainage systems. Due to the lack of irrigation systems, polluted wastewater from shrimp ponds could be discharged into water supply canals and then could be reused as supply water by everyone. Thus, planning and implementing irrigation canal systems for sustainable shrimp farming areas will be a challenge for the authorities. Planners need to know and simulate the shrimp cultivation behaviors of farmers in relation with the environment such as the water supply canal system.

A solution could be to extend the current works concerning the modeling of interactions between farmers during their shrimp cultivation and the effect of the irrigation systems. For more details, the environmental model can be extended to simulate the distribution of pollution (shrimp's pathogens) discharged from the shrimp ponds to the river and canal systems. After that, several scenarios for irrigation canals could be used to appraise the best plans that can reduce the risk of disease.

The results of this kind of work could help authorities to effectively invest in the irrigation system to support not only sustainable aquaculture but also sustainable agriculture.

7.2.2.2 Analysis of forestry economic services

One of the land-use types that are not taken into account in this thesis is the mangrove forest. According to the MARD of Vietnam (2010), the saline soil area in the Mekong Delta is around 373.301ha including 128.537ha of mangroves, 179.081ha of aquaculture and 65.683ha

of non-mangrove forest area. There are two kinds of mangrove forests in the Mekong Delta: protected forests and productive forests. The productive forests are contracted by farmers to protect mangrove forests and exploit fishery resources. Figure 51 shows a schema of the location of the farming systems and the mangrove forest in a region of the Mekong Delta.

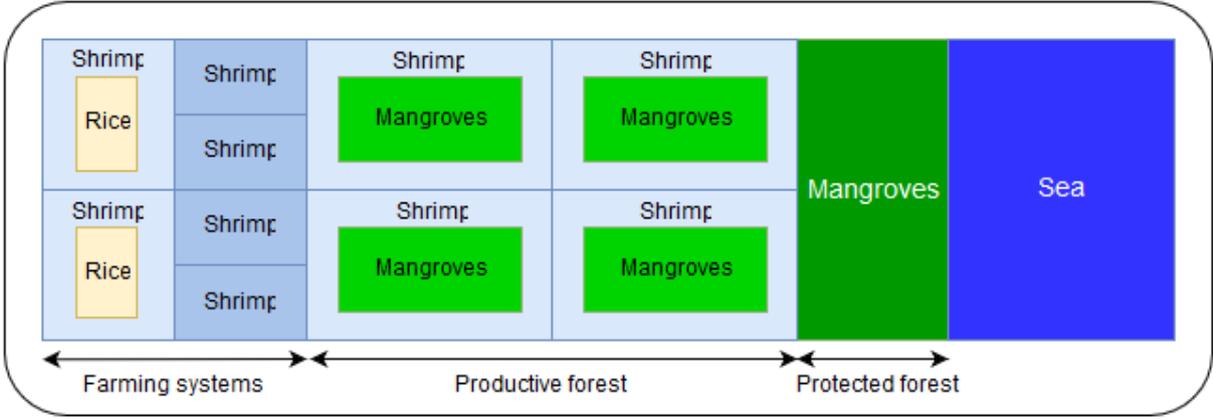


Figure 51. *Shrimp-mangroves systems in the Mekong Delta*

Before 2000, the mangroves forests in the Mekong Delta decreased considerably because of the deforestation to do intensive brackish water aquaculture. This action has not only increased the coastal erosion and the salinity intrusion but also led to environmental degradation in the Mekong Delta (Johnston et al., 2000). Thus, protecting mangroves and increasing the people’s life quality are the two challenging objectives of authorities. A solution to this in the Mekong Delta lies in mixed shrimp-mangrove systems. Each productive mangrove parcel is divided into mangrove (60% of surface, in the center) and shrimp farming (40% of surface, around the mangrove area) (Bui & Huynh, 2008).

Kuenzer and Tuan (2013) pointed out that mangrove ecosystem services with the mixed shrimp-mangrove systems provide high economic values and support forest protection. Quoc Vo et al. (2015) indicated that expanding intensive aquaculture would reduce the benefit of local communities and increase the risks for both mangrove and aquaculture activities. For this problem, Bui and Huynh (2008) indicated that the misplanned area for intensive aquaculture and the mixed shrimp-mangrove lead to pollution and create a risk for both types of production.

The authorities are facing the requirement of sustainable land-use plan which aims at reducing the risks for shrimp farming and the mixed shrimp-mangrove region.

To face this challenge, we propose to extend the current work of this thesis to simulate the activities of both intensive shrimp farming and shrimp-mangrove farming. The aim is to

model the impacts of the behaviors of two kinds of corresponding farmers on mangrove areas. Moreover, we aim at analyzing the impacts of control policies, which decide the proportion between mangrove and shrimp areas on shrimp cultivation. The scenarios that the authorities could use for testing their control policies are: (1) testing the risks for both economy and mangroves of the whole region when farmers increase the proportion of shrimp cultivation in the mixed shrimp-mangrove systems (40% of the parcel area by default); (2) assessing control policies to change from intensive shrimp cultivation to mixed shrimp-mangrove system on the sustainable development of farming systems.

In conclusion, the proposed MAB-LUC with the BDI architecture allows us to answer questions in LUCC and land-use planning that require to take into accounts the socio-economic, environmental and human decision factors. The integrated model could also be used with some adaptations to answer questions for other similar socio-environmental modeling problems.

A APPENDIX A: GLOSSARY

The key terms discussed in this thesis, that is relevant to the land-use planning, land-use change, cognitive model and agent-based simulation.

Key term	Description
Land-use planning, land-use change	
Commune	An administrative level lower than district (Source: The JTD courses ¹²).
Costs of production	The total costs during production .
District	An administrative level lower than province (or independent municipality) in Vietnam (Source: The JTD courses ¹²).
Farmer	A person who is doing the agriculture (or aquaculture) production.
Land evaluation	The assessment of land performance when used for specified purposes (FAO, 1981).
Land suitability	The fitness of a given land-use type for a defined use (FAO, 1981)
Land unit map	The map created to represent the potential uses of a "unit" of land (Regions, provinces, districts) (Source: The JTD courses ¹²).
Land–use plan	A plan to manage the land development (Source: The JTD courses ¹²).
Land-use	The usage of land by humans.
Land-use change	A type of human activity that transforms the landscape.
Land-use planning	The systematic assessment of land and water potential, alternatives for land use and economic and social conditions in order to select and adapt the best land-use options (FAO, 1993)
Land-use type	A combination of land use that farmer takes.
Layer	(GIS) A set of geometrical objects that share the same type of geometry (<i>e.g.</i> a layer of buildings) (Source: The JTD courses ¹²).
Mortgage	Properties of borrower put in place for a loan from a bank. These properties allow the lender to take possession and sell the secured property (Source: Wikipedia.org).
Parcel	A single unit of land that is created by a partition of land (Source: The JTD courses ¹²).
Price of products	Market price of products
Province	An administrative level in Vietnam that is managed directly by the

	government.
Spatial analysis	Examination of the spatial pattern of natural and human-made phenomena using numerical analysis and statistics (Source: The JTD courses ¹²).
Villages	An administrative level lower than district in Vietnam.
Agent-based model	
Agent	The representation, in a model, of a single entity of the modeled system. Agents belong to species in GAMA (Source: The JTD courses ¹³).
Belief	An element of a BDI agent that represents the knowledge of agent.
Calibration	The action of setting the value of parameters of a model (Source: The JTD courses ¹¹).
Cognitive agent	An agent that is capable of acting and interacting to the environment for cognitive development and learning ¹⁴ .
Desire	A piece of knowledge of a BDI agent that represents a goal of the agent.
Intention	A piece of knowledge of a BDI agent that represents what agent is going to do.
Reactive agent	An agent that reacts based on the perceived information from environment.
Sub-model	In this thesis, it is a model that can work both as an independent model and as a component of another model.
BDI control and related keyword in GAMA	
action	A statement for define an action of agent. It composes a set of instructions.
add_belief	A statement for adding a new belief to the beliefs base of a BDI agent.
add_desire	A statement for adding a new desire to the desire base of a BDI agent.
add_subintention	A statement for adding a sub intention to the current intention.
control	A facet for the specific agent architecture in GAMA.
has_belief	An operator in BDI control for testing if an agent have a belief.

¹³ Glossary of the JTD courses, www.tamdaoconf.org

¹⁴ <http://www.igi-global.com/dictionary/cognitive-agent/50949>

has_desire	An operator in BDI control for testing if an agent have a desire.
new_predicate	A statement for creating a new predicate.
perceive	A specific behaviors of a BDI agent, executed every iteration for perceive information from agents.
plan	An action of a BDI agent would do to fulfill a goal (in the context of BDI architecture).
predicate	A data type of BDI agent represents a combination attribute of agent.
reflex	The simplest form of behavior an agent uses (Source: The JTD courses ¹²). A reflex is executed for each simulation cycle.
remove_belief	A statement for removing a belief of agent.
remove_desire	A statement for removing a desire of agent.
rule	A specific behavior of a BDI agent for updating desires or beliefs, it is executed after the perceptions of agents.
simpleBDI	The BDI control for agent in GAMA, agents can use the specifics behaviors of the BDI control.
species	A statement for declaring an agent in GAMA.

B APPENDIX B: PUBLICATIONS

1. Truong, Q. C., Taillandier, P., Gaudou, B., Vo, M. Q., Nguyen, T. H., & Drogoul, A. (2016). Exploring Agent Architectures for Farmer Behavior in Land-Use Change. A Case Study in Coastal Area of the Vietnamese Mekong Delta. In B. Gaudou & J. S. Sichman (Eds.), *Multi-Agent Based Simulation XVI* (Vol. 9568, pp. 146–158). Cham: Springer International Publishing. Retrieved from http://link.springer.com/10.1007/978-3-319-31447-1_10
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