Exploring Agent Architectures for Farmer Behavior in Land-Use Change. A Case Study in Coastal Area of the Vietnamese Mekong Delta

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Abstract. Farmers are the key actors of land-use change processes. It is thus essential to choose a suitable architecture for farmer behavior to model such processes. In this paper, we compared three models with different architectures to model the farmer behavior in the coastal areas of the Ben Tre province: (i) The first one is a probabilistic model that allows farmer to select the land-use pattern based on land change probability; (ii) The second model is based on multi-criteria decision making and takes into account the land suitability of the parcel and the farmer benefit; (iii) The third model used a BDI (Beliefs - Desires - Intentions) architecture. For each of these models, we have compared the difference between simulated data and real data by using the Fuzzy Kappa coefficient. The results show the suitability of the BDI architecture to build land-use change model and to support decision-making on land-use planning.

Keywords: Agent-based simulation · Agent architecture · BDI architecture · Land-use change · Mekong Delta

1 Introduction

The Mekong Delta region will be heavily influenced by the effects of global climate change [23]. Indeed, the sea level rise and saltwater intrusion will strongly impact the life of people and the situation of agricultural production [9,20]. Nhan *et al.* [12] pointed out that the environmental conditions significantly impact the agriculture and fisheries and that ordinary people tend to spontaneous change the land-use, which causes difficulties for land resource management and cultivation of farmers. Another difficulty comes from the behaviors of farmers that tend to adapt their food production to the market [19]. The question for planners is how to simulate the behaviors of the farmer to understand land-use and land cover (LULC) change in the next years to build a successful land-use plan. In this context, the choice of an agent architecture to model the farmer behavior is particularly important.

In this paper, we propose to compare three classic agent architectures defined to model human beings behaviors: the first model is based on a probabilistic model, the second one is based on multi-criteria decision making and the last one is based on the BDI paradigm. The comparison is done on an example model simulating the land-use change due to farmers' decisions in the coastal areas of the Ben Tre province (Mekong Delta, Vietnam). The objective is to determine among these three architectures the one that seems the most adapted to model the farmer behavior.

This paper is organized as follows: Sect. 2 presents a state of the art of the existing models of land-use change and an overview of agent architectures used to model such processes. Section 3 is dedicated to the presentation of the three farmer models that have been implemented and of results of their comparison. Finally Sect. 4 proposes a conclusion and offers some perspectives.

2 State of the Art

2.1 Modeling of Land-Use Change

For years, the follow-up study of land-use changes have been mainly based on monitoring the changes in the past using diverse tools related to GIS and Remote Sensing. These tools do not allow to model the dynamic but only to describe the changes. Some researchers have also proposed models based on the combination of GIS, Cellular Automata and Markov chain [11,24] to monitor and to predict the land changing in the future. Although these models give good results for monitoring the past time, they show their limitations to predict the future due to complex behaviors of the social actors in the real world that is not captured by these models. Concerning the modeling of actors involved in LULC changes, Agent-Based Models (ABM) have been heavily used [8,14]. However, most of these models remain simple models based on probabilities. They do not allow to take into account the behavior complexity of the various stakeholders.

In order to represent in a more realistic way the behavior of the different stakeholders, some research works have proposed to use BDI (Belief, Desire and Intention) agent architecture [16] for LULC modeling. In this cognitive agent architecture, agents have beliefs (pieces of information they believe to be true in the world), desires (how they desire the world to become) driving their long-term activities, and intentions of short-term actions to perform to make the world compliant with desires they have chosen and which they commit to achieve. Besides that, agents can change their behaviors and update their beliefs according to what they perceive from the environment. This architecture has been applied to simulate human behavior in many different fields [1]. Concerning land-use planning, Behzadi *et al.* [3] have proposed a BDI architecture applied to city planning. In this model, the planer is the main agent of the model and decides most effective plans to apply according to its beliefs and its goals. Another BDI architecture, based on the belief theory and on a multi-criteria decision-making process, has been proposed in [18] in yearly cropping plan decision-making. This architecture has the advantages to be quite light (it allows to simulate simultaneously thousands of BDI agents) and easy to use by modelers. However, this architecture does not propose any specific formalism for the definition of beliefs and plans and was very specific to its application context.

Only few models have been developed to simulate LULC changes in Vietnam. Among them, the model presented in [4] concerns the planning scenarios in the northern mountains of Vietnam. Another one aims at studying the evolution of cultivation field patterns in the central mountains [7]. However, these models do not rely on real management data from the province departments of natural resources and their case studies are mostly concentrated in the mountains. Almost no study has been carried out about the Mekong Delta, especially the coastal areas affected by saltwater intrusion whereas there are important needs of this type of models.

2.2 Existing Agent Architectures to Model Land-Use Change

Balke and Gilbert have pointed out in an article presenting 14 agent architectures [2] how human beings are very complex machines and difficult to model. However, many agent architectures have attempted to model them. These architectures are often divided in two groups:

- *Reactive architectures*. The agent directly responds to the environment stimuli, without taking into account event history. This architecture is often used in large-scale model. Many of these architectures use production rules where the behaviors are based on "if - then" rules [13].
- *Cognitive architectures*. These agents have reasoning capabilities. They can memorize the past and display complex social behavior. The BDI architecture belongs to this group.

If many complex agent architectures have been proposed, it is not always essential to use them to model the human behaviors, as the human decision-making process is often based more on many sources of information rather than on complex deliberations [5]. Concerning LULC modeling, even if some models propose to use a BDI agent architecture [3,18], most of the are still using simple architectures based on probabilities or on multi-criteria decision-making algorithms [8,14]. The main aims of this paper are thus to compare these three types of architectures on a case study concerning the coastal area of the Vietnamese Mekong Delta and establish recommendations for LULC modeling.

3 Comparison of Agent Architectures to Model Actors Involved in LULC Changes in Coastal Area of the Mekong Delta

3.1 Land-Use Change in Coastal Area of the Vietnamese Mekong Delta

In Vietnam, the land-use zoning policy that defines the type of developments allowed on parcels is defined for 10 years and at four administrative levels: country, province, district and village. The zoning policy is detailed by two plans (five years per plan) under instructions of the Circulars of Ministry of Natural Resources and Environment [10,22]. However the province land-use changes often do not fit with plans. This phenomenon is particularly visible for the Ben Tre province: the total cultivated area planned for 2010 was 175,824 ha, and reached in reality 179,671 ha (102 %); the rice area reached 38,000 ha compared with the 30,000 ha planned; the aquaculture land was planned to be 39,200 ha but only reached 30,289 ha; at last the forest area only reached 1.30 ha compared with 350 ha planned [15]. This difference of planned and real developments can also be observed at the village level. This unpredictability of the land-use change accentuates the need of reliable tools to simulate the land-use changes to support decision-making process.

3.2 Land Suitability Analysis

As stated in the previous Section, it is important to be able to understand processes underlying land-use changes at the village level in order to be able to predict the evolution of land-use change at province level. In this context, we chose to study the evolution of land-use in the village of Binh Thanh. This coastal village of the Ben Tre province of the Mekong Delta is representative of the region as it contains a mix of brackish and fresh water. In such area the land-use is strongly impacted by the irrigation.

We have collected data concerning the land-use of each parcel of this village in 2005 (Fig. 1) and in 2010 from the Department of Natural Resources and Environment of the Ben Tre province. In this area, six **land-use** types have been defined:

- Rice,
- Rice - Vegetable,
- Rice - Shrimp,
- Annual crops,
- Industrial Perennial tree,
- Aquaculture.

We collected as well the soil map, the saltwater map and the flood map of the regions and define from them six **land-unit** types (a value per land-unit type). From each of these land-unit types, we defined with the help of domain-experts a suitability value for each land-use type. This suitability, which was evaluated by using fourth values, represents the adequacy between the land unit type and the land-use type. For instance, producing industrial perennial tree on a salty soil is very difficult and the yield will be very low.

We also built with domain-experts a transition matrix for each land-use-type. This matrix allows to represent the technical difficulty to change from one land-use type to another one. This difficulty was evaluated using three values (1: easy, 2: medium, 3: very difficult).

At last, we collected data concerning the evolution of benefit and cost of each land-use type for a hectare from 2005 to 2010.

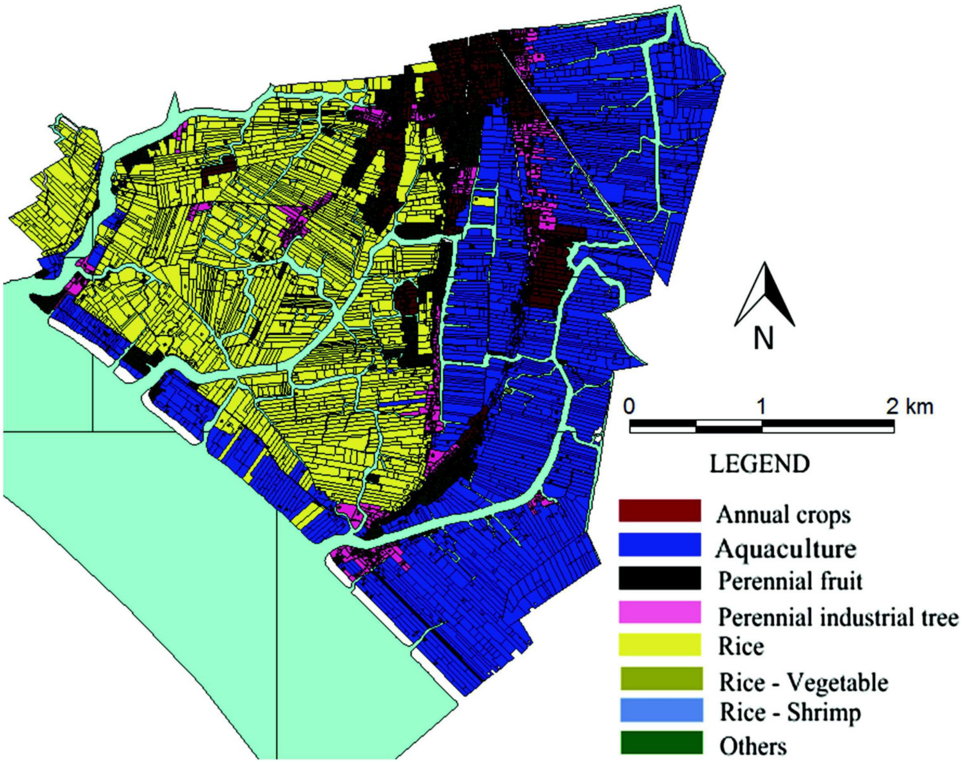

Fig. 1. Land-use map of Binh Thanh in 2005. *source: department of environmental and natural resources of Ben Tre province, Vietnam.*

3.3 Tested Agent Architectures

The next section describes the general model that was used for the test. We describe then the three architectures that have been implemented (the simplest one based on transition probabilities, a more complex architecture) based on multi-criteria decision-making process and the most complex BDI architecture. In this work we only focused on simple architectures with few parameters, as we aim at testing different kinds of architecture and not at defining a very complex and realistic model.

Model Description. The model was defined in order to simulate the evolution of the land-use of the Binh Thanh village. We make the assumption that each farmer has only one parcel and that he has to make a decision concerning the land-use of the parcel every year. A simulation step in this model represents thus 1 year.

In this simple model, the main species of agents is the parcel species that represents the farmer and his/her parcel. A parcel agent has the following attributes:

- *shape*: geometry of the parcel (static),
- *land unit type*: type of soil for the parcel (static),
- *region*: is it inside or outside the dykes (static),
- *neighbors*: list of parcels at a given distance that have the same land unit type (static),
- *land-use*: type of production (dynamic).

In addition to parcel agents, we define a world agent that contains all the global variables:

- *profit_matrix*: for each year (from 2005 to 2010) and for each land-use type the benefit that can be expected from 1 ha of production,
- *cost_matrix*: for each year (from 2005 to 2010) and for each land-use type the cost of 1 ha of production,
- *suitability_by_landuse*: for each land unit type, the suitability to produce a given land-use type,
- *transition_matrix*: difficulty to change from a land-use to another one.

At each simulation step (i.e. every year), each parcel agent is activated in a random order. When activated, a parcel agent (embedding the farmer making decision) chooses its new land-use (that can be the same as the previous one) and changes to it if necessary.

The different models presented in the following sections deal with this choice of a new land-use. Note that all the agent attributes defined here will not be used in all the models. For instance the *neighbors* attribute will only be used by the BDI model.

Decisions Based on Transition Probabilities. In the first farmer behavior model, farmer decisions are based on land change probability. A matrix of probabilities to shift from one land-use type to another was built using the data from 2005 and 2010 and more particularly the number of parcels that changed from 2005 to 2010 (Table 1). As the study area is composed of 2 very different regions - one inside the dykes and the other one outside - we chose to create two matrices corresponding to each region.

The decision-making behavior of the agent is very simple: at each simulation step (i.e. each year), a parcel agent has the probability 0.2 to change its land-use. Each time, it chooses to change its land-use, it draws randomly its new land-use according to the matrices previously defined. From the data we can observe that parcels have changed their land-use on average once during the

Table 1. Land-use changed from 2005 to 2010, counted by number of parcels

		Land-use in 2010 (out-inside dykes)					
		A. Crops	Trees	Rice-Shrimps	Rice-Vege	Rice	Aquaculture
Land-use in 2005 (in-outside dykes)	A. Crops	77-134	64-13	39-0	0-6	0-0	8-1
	Trees	20-8	151-29	3-0	0-31	1-0	2-2
	Rice-Shrimps	0-100	0-0	0-0	0-1016	0-0	0-21
	Rice-Vege	0-0	0-0	1-0	0-0	0-0	0-0
	Rice	0-80	35-67	8-0	17-48	0-0	2-2
	Aquaculture	17-4	173-8	1123-2	1-0	7-0	88-2

5 years of observations. As a consequence, we consider that each parcel has the probability 1/5 of changing land use type at each step. As a consequence, during a simulation some parcels can change their land-use multi times and others not, which is the observed process.

Decision Model Based on Multi-criteria. In the second model, the parcel agent decisions are made according to a multi-criteria analysis. This type of decision-making process in often used for land-use change models (see for example [17]). We defined 3 criteria for the decision: the profit, the cost and the transition difficulty. Indeed, it is generally accepted that farmers tend to choose a production that maximizes their profits, that minimizes the cost - avoidance of risky productions - and that are easy to implement. More precisely, the criterion values are computed as follows for a given transition from *old_lu* to *lu* and a given *soil* type (i.e. land unit type) and a *year* number:

$$Profit(lu, soil, year) = \frac{matrix\_profit(lu, year)}{(max\_profit(year) * matrix\_suitability(soil, lu))} \quad (1)$$

With:

$$max\_profit(year) = max(matrix\_profit(lu, year)) \quad (2)$$

$$Cost(lu, year) = \frac{matrix\_cost(lu, year)}{max\_cost(year)} \quad (3)$$

With:

$$max\_cost(year) = max(matrix\_cost(lu, year)) \quad (4)$$

$$Transition(old\_lu, lu) = \frac{(3 - transition\_matrix(old\_lu, lu))}{2} \quad (5)$$

At each year, every parcel agents computes for each of the six possible land-use types the values of the three criteria. Then, using a weighted mean (see

Eq. 6), it chooses the best land-use type (the one that maximizes the fitness).

$$Fitness(lu, soil, year) = W_{profit}Profit(lu, soil, year) + W_{cost}Cost(lu, year) + W_{transition}Transition(old\_lu, lu) \quad (6)$$

Decision Model Based on a BDI Architecture. In this last model, we propose to use a BDI architecture to model the behavior of the parcel agents. The choice of the land-use type will be based on the three criteria defined in the previous section. However, instead of considering that all the parcel agents have a precise idea of the expected profit according to their land unit type, we consider in this model that the knowledge of the agents is imperfect. It is only when they will have tested a particular land-use type that they will know the real profit that could be obtained from it. We consider as well that a parcel agent can give information to their neighbors concerning their profit. Indeed, in Vietnamese village, the social links between farmers are particularly strong and they often share advices and knowledge.

Figure 2 presents the UML activity diagram of our BDI architecture. First, the agent tests a probability to change or not its current plan. If it keeps the plan, it continues to execute it. Otherwise, it tests a probability to change its goal. If it does not keep its goal, it selects a new goal among the desires with the highest priority and adds it to its intention base. If several desires have the same priority, the goal is randomly chosen among them. Once a goal has been selected (or if the previous goal is kept) a new plan is selected among the ones that can be activated (according to the agent desires and beliefs). The selected plan is the one with the highest priority. Similarly to the goal selection, if several plans have the same priority, the selected plan is chosen randomly among them. At last, the selected plan is executed.

Table 2. Mean results for the percentage absolute deviation (the lowest, the best) and the fuzzy Kappa (the highest, the best) for the three models and for 100 simulations

	Probabilistic model	Multi-criteria model	BDI model
PAD	59.17 %	30.62 %	34 %
Fuzzy kappa	0.46	0.54	0.55

In our model, each parcel agent has the following belief and desire bases:

– *Beliefs*: pieces of knowledge concerning the expected profit for each land-use. Each belief corresponds to a land-use type and a profit associated to it.
– *Desires*: the parcel agents can have two types of desires:
  - define the best possible land-use type (with priority = 2),
  - produce a given land-use type (with priority = 1).
– *Intentions*: the agent can activate two following plans to fulfill its desires:

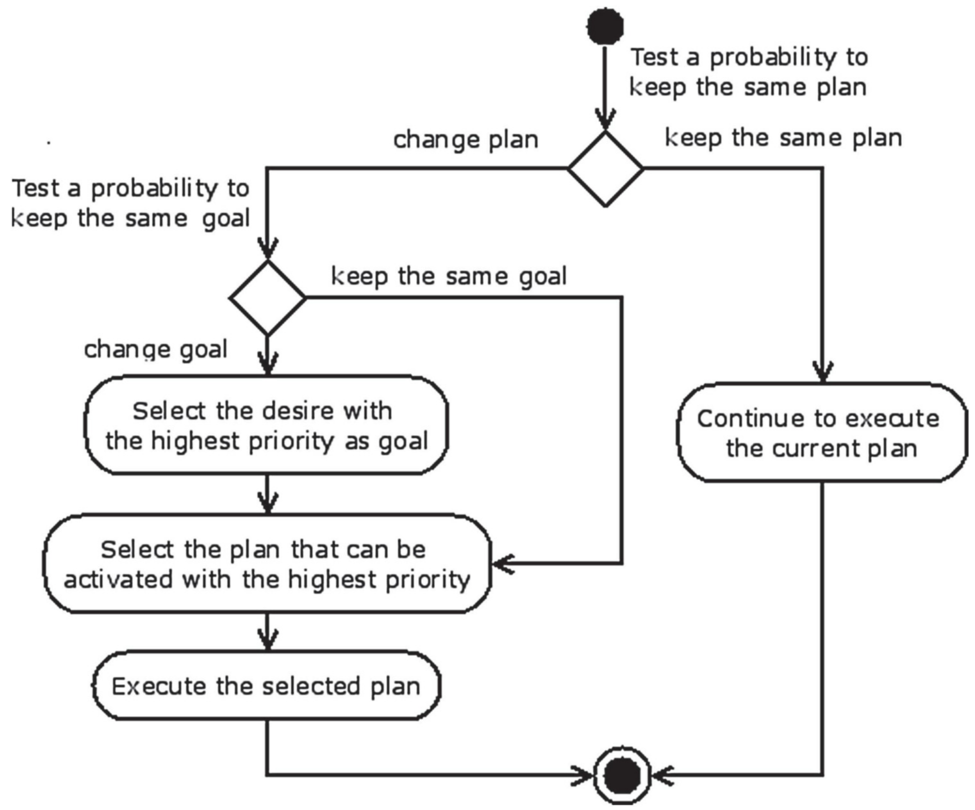

Fig. 2. Activity diagram of the BDI architecture

- *analyze the possible land-use types*: the agent uses the three criteria and its current beliefs to evaluate each possible land-use type and to define the fittest one. Then the value for the probability to change its current plan is set to 1. The plan is activated when the current goal is *define the best possible land-use*,
- *implement a given land-use type*: the agent sets its land-use attribute to the given one and computes the actual profit with this land-use. Then it updates its beliefs and gives this information to its neighborhood. At last, the value for the probability to change its current plan is set to a given parameter value. The plan is activated when the current goal is *produce a given land-use type*.

3.4 Experiments

The three models were implemented on the GAMA platform[1] [6]. GAMA is an open-source agent-based simulation platform that provides modelers with a complete modeling and simulation development environment to build agent-based simulations. It is particularly powerful concerning the management of GIS data and allows to simply manipulate them.

The different parameter values of the models were defined by using a genetic algorithm to find the parameter set that fits the best to the real data. The fitness

[1] http://gama-platform.org.

function is defined using the Kappa coefficient comparing the observed data and the simulation results in 2010. The fuzzy kappa coefficient allows to compare two maps by taking into account the neighborhood of the parcels [21]. This coefficient is between 0 (not similar at all) to 1 (totally similar). In these experiments, we chose a neighborhood size of 100 m.

Figure 3 shows simulation results obtained from the three models and the observed data. As it can be observed, none of the three models allows to reproduce the exact observed land-use. However, the multi-criteria and the BDI architectures provide better results than the probabilistic one.

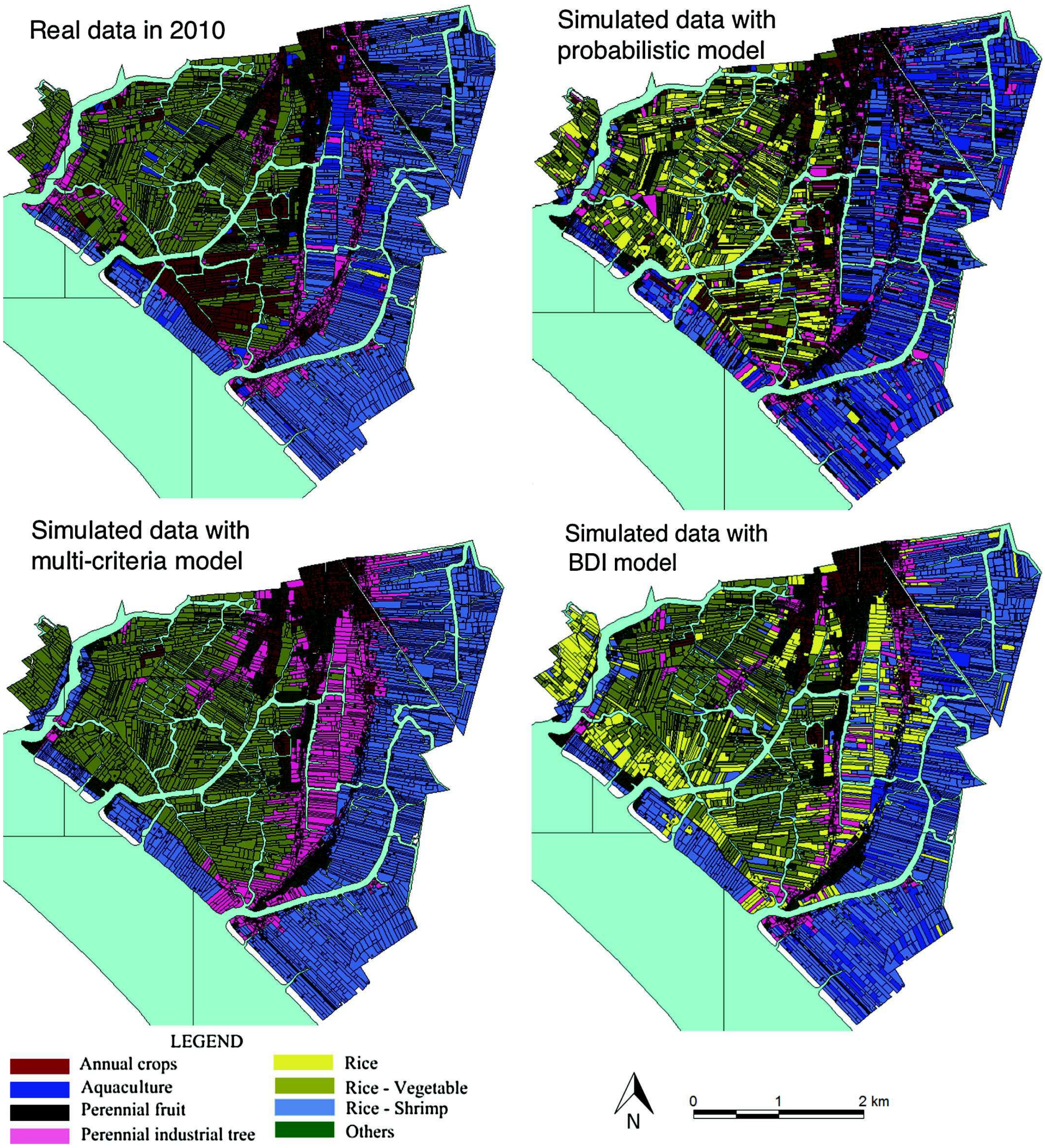

Fig. 3. Observed and simulated land-use map of Binh Thanh in 2010

To quantitatively evaluate the simulation results of the three models, we used two indicators: the fuzzy kappa coefficient (local indicator) and the percent absolute deviation (global indicator).

This second indicator that is often used to evaluate land-use change models is computed by the following formula:

$$PAD(\%) = 100\frac{\sum_{i=1}^{n} |\widehat{X}_i - X_i|}{\sum_{i=1}^{n} \widehat{X}_i} \tag{7}$$

with: $\widehat{X}_i$ the observed quantity of parcels with the land-use i and X_i the simulated quantity of parcels with the land-use i.

As our models (at least two of them) are stochastic, we ran 100 times each model and computed the average fuzzy kappa coefficient (kappa) and percent absolute deviation (PAD). As shown in Table 2, the multi-criteria model allows to get far better results in terms of PAD and kappa indicators than the probabilistic model. Indeed, this model integrates some new pieces of knowledge linked to the economy (profit and cost) and the practices (suitability and transition) that allow to improve the accuracy of the model. Concerning the BDI model, it gives results close to the multi-criteria one (slightly better concerning the kappa coefficient and worst concerning the PAD). However, this model allows to integrate heterogeneity in the model through the influence of the imperfect knowledge and the influence of the neighborhood which make the model more realistic.

4 Conclusion

In this paper, we have compared three architectures to model the land-use change in the Binh Thanh village. The first architecture is based on change probabilities. It gave correct simulation results for reproducing the past events but is limited for predicting the future as it does only allow to reproduce past patterns. The second architecture is based on multi-criteria decision-making. This architecture allowed to get good simulations. However, it does not allow to introduce heterogeneities between agents. The last architecture, which shows the highest fuzzy kappa coefficient, is based on a BDI architecture. This architecture allows to take into account the imperfection of knowledge of farmers and the relations between them. If the three models gave good results, we plan to improve them, and more particularly the third model, by integrating more domain-specific knowledge inside.

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