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## A METHODOLOGY FOR URBAN AND LAND-USE MANAGEMENT SIMULATION USING SPATIAL SELF-ORGANIZATION PROCESSES

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**Abstract.** In this study, we develop a methodology based on computational intelligence concepts, for decision making tools using simulation of self-organized complex systems. Land-use management is considered here as the output of sustainable development strategies, dealing with the achievement of many objectives, interacting in a complex way, like environmental, economical and social objectives. The methodology presented here can be considered as a conceptual evolution in simulation processes from the simulations based on rule systems over geographical cellular automata toward the simulations involving self-organized agent-based systems over geographical information systems (GIS). Our methodology is based on self-organization patterns detection which emerge from spatial and behavioral systems. According to the complex systems modelling principles, we let the system evolve by itself with only partial control implemented here by an evolutive and selective process based on a fitness function over the whole system.

**Keywords.** Land-use, self-organization, geographical information systems, agent-based modeling, automata with multiplicities, community detection, territorial intelligence.

## 1 Introduction: Complexity Concept Approach for Land-Use Management

Land-use management, in regional or urban development, deals with *Territorial Intelligence* concepts. The word “Intelligence” has to be considered from its latin root, “Intelligere”, which means understanding. So, our purpose is to understand the territorial management by the complex interaction of many kinds of phenomena. The description proposed here for territorial management is based on the *Sustainable Development* strategies which try to avoid naive solutions which may appear at first efficient to solve specific problems

in short a term vision. Without understanding the complex implication of some naive solutions, the whole system can lead to irreversible evolutions, making it fail on long term development for social or environmental features. Sustainable development has mainly three objectives which are environmental, economical and social ones. The complexity of the interaction network between these objectives leads to the necessity to develop decision making tools based on simulation to help understand the system evolution on a spatial and a temporal multi-scale description.

The complexity analysis on which we focus our attention to develop the methodology is based on multi-description approaches : (i) the multi-scale modelling is here essential and an example of this need can be illustrated by the climatic change problem as a global Earth phenomenon which can induce modifications on urban management. (ii) The multi-actors modelling is also needed for resources management which is affected or concerned by farmers, economists and politicians. (iii) A Multi-disciplinary approach is also needed to take into account environment, economy and social dynamics, using multi-modelling methods, to mix differential and individual-based models. To conclude, we finally deal with an integrative description simulation which is based on very specific features related to complex systems modelling.

The complexity analysis that we have to integrate in our way of modelling must contain some conceptual functions based on emergent self-organized systems and their associated dynamical morphologies. We have to implement micro-macro interactions in multi-scale description which are generally the basis of the dynamic of the emergent organizations. By these functions, we must be able to understand evolution and adaptation properties of these organizations. These evolutions generally lead to hierarchical structures of the organizations themselves, like in geographical systems where simulations may need descriptions from urban districts to regional or international area. Organization feed-back of these herarchical structures on the entities are also essential to understand the organization evolution (in multi-scale approaches) like, for example, how country laws can feed-back on the cities management.

## 2 Modelling and Simulation Approaches

We will present, in the first section, a short review of the main features concerning land-use management modelling. Then, in the following sections, we will develop our own approach, based on agent-based modelling for complex systems using automata with multiplicities.

### 2.1 Land-use systems modelling

Following the review proposed by Itzhak Benenson [2], we can classify the different approaches of territorial systems modelling in two main classes: the

“Black-box” macro-modeling and the individual-based micro-modeling.

The first category of approaches concerns mainly “stock and flow” descriptions of socio-economic indicators. The main first contributors generally mentioned, are I.S.Lowry [20] and J.W. Forrester [10]. Lowry’s model of urban system, applied to the city of Pittsburg, proposed some “integrated” model, defining a flow chart between the three main indicator classes: (i) the basic sector of industrial and business activities, (ii) the householder sector and (iii) the retail sector concerning the local population. This flow chart model already deals with a mile-square decomposition similar to spatial decomposition used later as an adaptation of cellular automata grid to geographical real space. The final output of the modeling process leads to a kind of socio-economic equilibrium state. This approach finds its limit because of its static description and dynamical models are essential to understand the city evolution. Forrester proposed a dynamical modeling based on the application of industrial dynamics on urban dynamics. His model is based on non spatial stock and flow models. Stocks are exchanged within a three income levels decomposition over housing, jobs and population. This model based on simple urban description was aimed at generating simulation and Forrester claims the benefit of computer simulation to understand the city evolution and how we can predict its evolution by the modification of guiding policies within the system.

The stock and flow models continue to be improved and to propose more and more details, including transportation subsystem or land market, for example. One of the most complete, called Integrated Urban Model (IUM) was proposed by Bertuglia et al. [4]. The computational complexity increases with the accuracy of the description and finally avoids to obtain reasonable estimates of the parameters. These models are more representational tools than simulation tools [2].

To build efficient simulation models, the idea was to simplify the description, using a more global one facilitating the analytical description. From the inspiration of dynamics of population theory, some researchers proposed to build urban dynamic models from ecological modeling. The paradigm of prey-predators systems is then used to give efficient simulation tools to investigate the main feature allowing then to understand the global dynamics. For example, Dendinos and Mulally [8] use a prey-predator model, assuming that the increase of city population make decrease the economic status. The predator represents the urban population and the preys, the per capita income.

All the previous described models are based on top-down approaches to model the system dynamics. We first consider the whole phenomenon and we propose a way of how to split it in many sub-problems and then in stocks and flows or in different terms constituting the equational system. Another

class of modeling is based on micro-modeling and bottom-up representation of the city as a collection of individual-based descriptions, behavioral rule-based descriptions and interaction systems. From this constructive approach, we want to obtain an emergent description of the whole system or of some sub-systems included in a hierarchical process. Two complementary methodologies can be used for that and we detail them in the following paragraphs.

The first methodology consists in generating a simulation where all the components, behaviors and rule-based, interact over a environment, perceiving and acting on it. The environment evolving is the support of emergent properties. The cellular automata modeling deals with this kind of simulations. The basic definition of cellular automata for urban or regional modeling, for exemple, consists in the decomposition of the city, region or any geographical area in a lattice of cells. Each cell is in some state which belongs to a finite set  $S$ . At each time step, the cells change their own state according to some transition rule based on their previous state and their neighbor cells. Many works based on cellular automata, have been developped for geographical systems and urban dynamics [1,9]. Extensions on environmental problems like water streaming are using these medels as efficient tools [19]. Cellular automata can be seen mainly as distributed tools to model diffusive penomena using rule-based systems. One of the first researchers in human sciences who proposed models based on diffusive rule-based systems is T. Hägerstrand in a very early period, during 50' [17] but his work itself started to be diffused over the science community more than 15 years later, when the computer development became able to implement its model in realistic studies. One of the most famous cellular-based model for social modeling is du to T. Schelling [21], describing the segregation process. But with the implementation of this model, we face an important extension to cellular automata where we need to represent individuals moving after a simple deliberative process. The mixing of spatial data and cellular automata with autonomous entities, like agents, is here needed [7].

The second methodology to deal with emergent description in micro-modelling, consists in completing the previous approach based on simulation, by introducing some computational processes which are able to detect emergent systems or organizations. The final goal of this method is then to be able to re-introduce these emergent systems or organizations inside the simulation and manage their evolutions and their interactions with the components of the system. The re-integration of the emergent systems, during the simulation, can be explicitly expressed like in the multiscale fluid flow simulation proposed by P. Tranouez [23] or it can be implicitly expressed using a self-controlled process as we describe in the following, using genetic algorithms.

## 2.2 Basic agent-based concepts and complex systems modelling

In this section, we give the basis of the conceptual tools which allow to extend the reactive and diffusive grid cases behavior to more sophisticated entities, using agent-based models. We propose to model the agent behavior with automata with multiplicities which are powerful algebraic structures.

According to General System Theory [18], a complex system is composed of entities in mutual interaction and interacting with the outside environment. A system has some characteristic properties which confer its structural aspects, as schematically described in part (a) of Figure 1:

- The set elements or entities are in interactive dependance. The alteration of only one entity or one interaction reverberates on the whole system.
- A global organization emerges from interacting constitutive elements. This organization can be identified and carries its own autonomous behavior while it is in relation and dependance with its environment. The emergent organization possesses new properties that its own constitutive entities do not have.
- The global organization retro-acts over its constitutive components.

The interacting entities network as described in part (b) of Figure 1 leads each entity to perceive informations or actions from other entities or from the whole system. Each entity also acts on the interaction network or on the environment.

A well-adapted modeling consists in using an agent-based system representation which is composed of a set of entities called agent. Each entity perceives and acts on an environment, using an autonomous behaviour as described in part (c) of Figure 1.

To compute a simulation composed of such entities, we need to describe the behaviour of each agent. This one can be schematically described using internal states and transition processes between these states, as described in part (d) of Figure 1. So an automaton with multiplicities as described in the following section is well-adapted for the agent behavior modelling. Each transition is labelled by an input as the agent perception and an output as the agent action.

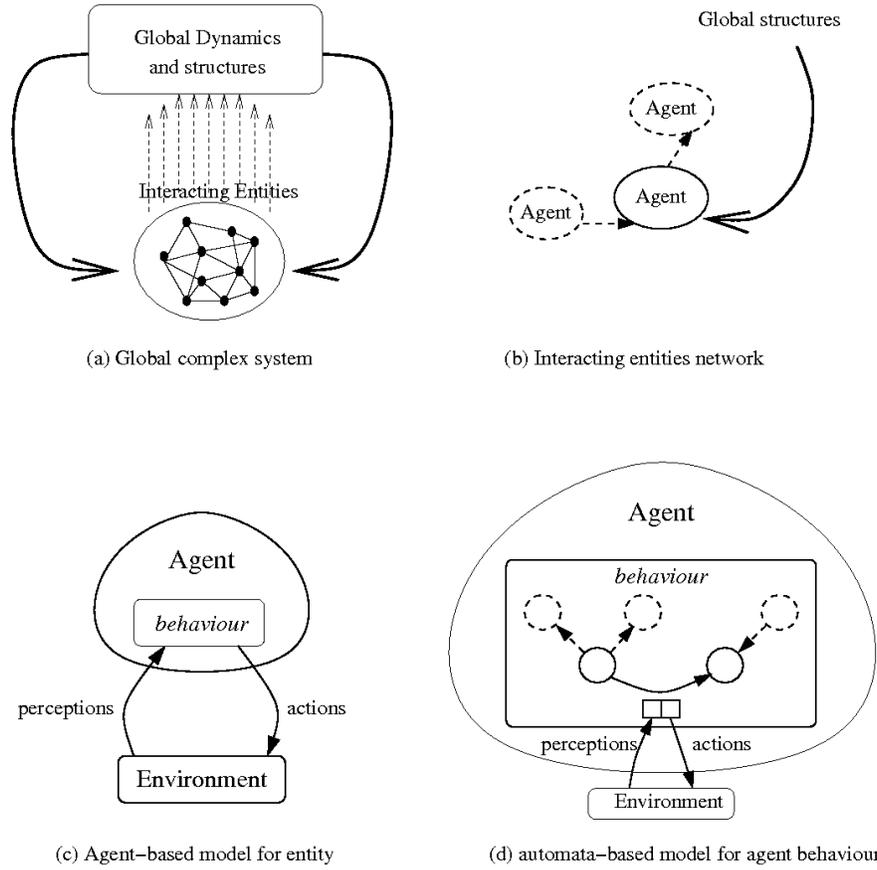


Figure 1: Multi-scale complex system description: from global to individual models

### 2.3 Automata-based modelling for agent behavior

An automaton with multiplicities is based on the fact that the output data of the automata belongs to a specific algebraic structure, a semiring, including real, complex, probabilistic, non commutative semantic outputs (transducers) [15,22]. In that way, we will be able to build effective operations on such automata, using the power of the algebraic structures of the output data. We are specifically able to describe automata by means of a matrix representation with all the power of the new (i.e. with semirings) linear algebra.

#### Definition 2.1 (Automaton with multiplicities)

*An automaton with multiplicities over an alphabet  $\Sigma$  and a semiring  $K$  is the*

5-uple  $(\Sigma, Q, I, T, F)$  where

- $Q = \{S_1, S_2 \dots S_n\}$  is the finite set of state;
- $I : Q \mapsto K$  is a function over the set of states, which associates to each initial state a value of  $K$ , called entry cost, and to non- initial state a zero value ;
- $F : Q \mapsto K$  is a function over the set states, which associates to each final state a value of  $K$ , called final cost, and to non-final state a zero value;
- $T$  is the transition function, that is  $T : Q \times \Sigma \times Q \mapsto K$  which to a state  $S_i$ , a letter  $a$  and a state  $S_j$  associates a value  $z$  of  $K$  (the cost of the transition) if it exist a transition labelled with  $a$  from the state  $S_i$  to the state  $S_j$  and and zero otherwise.

**Remark 2.2** We have not yet, on purpose, defined what a semiring was. Roughly it is the least structure which allows the matrix “calculus” with unit (one can think of a ring without the ”minus” operation). The previous automata with multiplicities can be, equivalently, expressed by a matrix representation which is a triplet

- $\lambda \in K^{1 \times Q}$  which is a row-vector which coefficients are  $\lambda_i = I(S_i)$ ,
- $\gamma \in K^{Q \times 1}$  is a column-vector which coefficients are  $\gamma_i = F(S_i)$ ,
- $\mu : \Sigma^* \mapsto K^{Q \times Q}$  is a morphism of monoids (indeed  $K^{Q \times Q}$  is endowed with the product of matrices) such that the coefficient on the  $q_i$ th row and  $q_j$ th column of  $\mu(a)$  is  $T(q_i, a, q_j)$

### Definition 2.3 (Automata-Based Agent Behavior)

We represent the agent behavior by automata with multiplicities  $(\Sigma, Q, I, T, F)$  over a semiring  $K$ :

- The agent behavior is composed of a states set  $Q$  and of rule-based transitions between them. These transitions are represented by  $T$ ;  $I$  and  $F$  represent the initial and final transitions;
- Alphabet  $\Sigma$  corresponds to the agent perceptions set;
- The semiring  $K$  is the set of agent actions, sometimes associated to a probabilistic value which is the action realization probability (as defined in [12]).

## 2.4 Agent Behavior Metric Space

The main advantage of automata-based agent modelling is their efficient operators. We deal in this paragraph with an innovative way to define a behavioral semi-distance as the essential key of self-organization processes proposed later.

**Definition 2.4 (Evaluation function for automata-based behavior)**

Let  $x$  be an agent whose behavior is defined by  $A$ , an automaton with multiplicities over the semiring  $K$ , we define the evaluation function  $e(x)$  by:

$$e(x) = V(A)$$

where  $V(A)$  stands for the stringing-up of all coefficients of  $(\lambda, \mu, \gamma)$ , the linear representation of  $A$ , defined in remark 2.2.

**Definition 2.5 (Behavioral semi-distance)**

Let  $x$  and  $y$  two agents and  $e(x)$  and  $e(y)$  their respective evaluations as described in the previous definition 2.4. We define  $d(x, y)$  a semi-distance or pseudometrics<sup>1</sup> between the two agents  $x$  and  $y$  as

$$d(x, y) = \|e(x) - e(y)\|.$$

The notation  $\|\cdot\|$  standing for any vector norm.

## 3 Spatial and Behavioral Modeling Based on Community Detection

In this section, we give an operational definition of a community in terms of functional concepts dealing with complex and social modelling. To model such communities, we have to complete the concept of automata behavior with some spatial aspects and with some adaptive capabilities that genetic operators can allow to implement. With these concepts, we can model communities by evolutive population of these genetic spatial automata.

**Definition 3.1 (Community operational definition)**

A community is a system or an organization which is characterized by a spatial property, a behavior property and the interaction between both.

**Example 3.2** In ecology, a community is a group of plants or animals living in a specific region, each interacting with the others.

The spatial patterns generated by Schelling models are some examples of communities and these spatial patterns are linked with the very specific behavioral rules implemented for each grid case. Our purpose here is to

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<sup>1</sup>see [6] ch IX

give a more generic processus which can be mixed with sophisticated agent behaviors. Using agent communication protocol, we can extend the diffusion process linked with cellular automata to more distant communications and interaction between spatial agents. In the following, we define this notion of spatial automata-based agents and then we develop the genetic operators allowing to transform automata with multiplicities to genetic automata. We will explain how the definition of adapted fitness will generate the detection processus.

**Definition 3.3 (Spatial Automata-Based Agent)**

*A spatial automata-based agent is defined by its structural representation:*

- *An automaton with multiplicities corresponding to its behavior as a whole processus managing its perceptions and its actions over its environment. They include its communication capabilities and so its social behavior;*
- *A spatial location defined on some specific metric space.*

### 3.1 Genetic operators on automata population

We consider, in the following, a population of automata with multiplicities which are each represented by a chromosome, following the genetic algorithm principles. We define the chromosome for each automata with multiplicities as the sequence of all matrices associated to each letter from the (linearly ordered) alphabet. The chromosomes are composed with alleles which are here the lines of the matrix [5].

In the following, genetic algorithms are going to generate new automata containing possibly new transitions from the ones included in the initial automata.

The genetic algorithm over the population of automata with multiplicities follows a reproduction iteration dividing in three steps [16]:

- *Duplication:* each automaton generates a clone of itself;
- *Crossing-over:* for each couple of automata, we consider a sequence of lines of their matrix. A permutation on the lines of this sequence is made between the analogue matrices of this couple of automata;
- *Mutation:* a line of each matrix is choosen at random and a sequence of new values is given for this line.

Finally, the whole genetic algorithm scheduling for a full process of reproduction over all the population of agents is the evolutionary algorithm:

1. For all couple of agents, two children are created by duplication, crossover and mutation mechanisms over their behavioral automata. The location of the children can be choosen in many ways: on the linear segment defined by the parents location or as the node of a square described by them and their parents (more details are given in [14]);
2. The fitness for each automaton is computed;
3. For all 4-uple composed of parents and children, the performless agents, in term of fitness computed in the previous step, are suppressed. The two agents, still living, result from the evolution of the two initial parents.

**Remark 3.4** *The fitness is not defined at this level of abstract formulation, but it is defined corresponding to the context for which the automaton is a model, as we will do in the next section.*

### 3.2 Adaptive processus to implement community detection

The community detection is based on a genetic algorithm over a population of spatial automata-based agents. The formation of the community is the result of the population evolution crossing by a selection process computed with the fitness function defined in the following.

For this computation, we deal with two distances defined on the set of agents. The first is the spatial distance associated to the agent spatial location and the second is the behavioral semi-distance defined in the definition 2.5.

#### Definition 3.5 Community clustering and detection fitness

Let  $V_x$  a neighbourhood of the agent  $x$ , relatively to its spatial location. We define  $f(x)$  the agent fitness of the agent  $x$  as :

$$f(x) = \begin{cases} \frac{\text{card}(V_x)}{\sum_{y_i \in V_x} d(x, y_i)^2} & \text{if } \sum_{y_i \in V_x} d(x, y_i)^2 \neq 0 \\ \infty & \text{otherwise} \end{cases}$$

where  $d(x, y)$  is the behavioral semi-distance between the two agents  $x$  and  $y$ .

As such, the agent fitness  $f(x)$ , increases when the automaton finds similar behaviors within its neighbourhood.

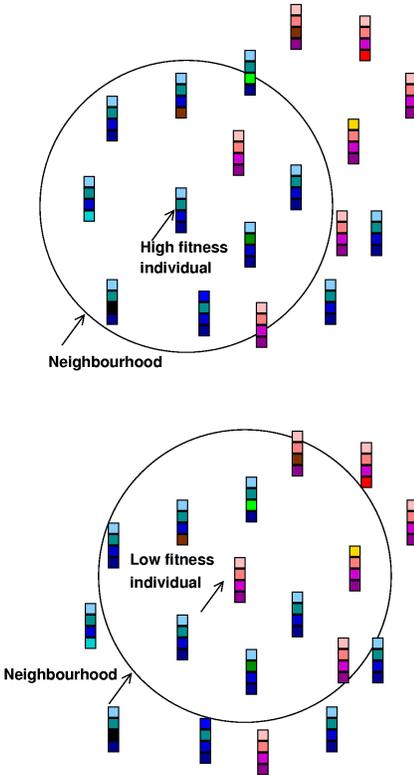


Figure 2: Fitness evaluation for community detection

On figure 2, we represent a population of automata where each automaton is a colored chain representing its chromosom. Automata with similar colored chain must be understood as similar behavioral automata. In the left part of the figure, we focus on one high fitness individual after computing its spatial neighbourhood and observing the behavioral similarity of all automata included in this neighbourhood. In the right part of the figure, composed of the same population, we focus on a low fitness individual, showing a behavior dissimilar to the other automata of its neighbourhood.

The genetic evolution of the spatial automata-based agents leads to a self-organization which creates a clustering of the agents set in such way that each cluster contains agents of similar behavior. During the evaluation process, genetic algorithms can be tuned such that individuals *outside their*

*communities* be attracted by them. The center of the clusters, the size of the clusters and the behavior of the agents within the center of each cluster are the result of the overall genetic process which generates self-organization communities.

## 4 Conclusion and Perspective : Integrating Self-Organization Simulations within Geographical Information Systems

As explained in the end of the section 2.1, social and environmental simulations can need to mix spatial data with autonomous entities, like agents. Both the agent programming and the spatial data available have been increased since the last decade. On the one hand, we present in the previous section some innovative approaches to deal with agent programming, fusing artificial intelligence, automata modelling, distributed computing, swarm intelligence and genetic algorithms to solve complex systems based phenomena. On the other hand, geographical information becomes a very wide and huge database following the impressive development of Geographical Information Systems (GIS). Land-use management has now to deal with a very huge amount of heterogeneous geographical, economical and social data which are expected to be used for relevant analysis allowing efficient decision making. The goal of our new methodology based on the community swarm optimization is to include the community detection as a agent-based self-organization process inside GIS, including spatial adaptation. It is an open way to implement intelligent tools inside decision making systems for urban or territorial management, respecting their complexity.

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