Multiscale MAS modeling to simulate complex systems: A case study in soil science

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Abstract. The MicrObEs project is a pluridisciplinary project, which associates computer scientists and biologists. Its main objective is to simulate soil functioning by using an agent-based model. It intends to model earthworms, their physical environment and their impact on soil (soil structure modification, organic matter dynamics and micro-organism activities). Creating a model of an ecosystem leads to complexity problems. A soil is a multi-scale heterogeneous, three dimensional and dynamic environment, which is difficult to model.
An approach based on fractal theory (often used in soil sciences) was chosen to model such a real complex environment; it was integrated into a Multi-Agent System (MAS). MAS allows to simulate situated agents in an virtual world. The originality of this present MAS is that it is based on a dynamic environment which builds itself, on demand, according to an abstract canvas tree and agent motions.
The aim of this paper is to present this approach and its originality. A theoretical view of the approach is given and applied to a case study: the Lamto's soil

Keywords: complex system, fractal, dynamic environment, multi-agent system

1. Introduction

The MicrObEs project aims at understanding biological soil functioning in the context of tropical agro-ecosystem managment. This project considers how changes in microbial diversity affect soil ecosystem services. Different abiotic and biotic factors are known to affect microbial diversity and activity. Among them, earthworms modify soil structure and organic matter dynamics, which strongly impacts microbial communities. We developed a model to simulate the effect of earthworms on soil structure and organic matter dynamics.

In the literature several approaches are proposed to study ecological systems [14]. Some of them are based on analytical theories or simulation techniques such as fluid dynamics, cellular automata and Multi-Agent Systems (MAS). Agent-Based Models (ABM) appear to be interesting ways of solving our problem. This bottom-up approach allows describing a system at a micro level (e.g. earthworms and their local soil environment) in order to observe, during simulation, macroscopic changes (e.g. soil structure evolution and microbial dynamics).

An ABM was developed with an intuitive approach: agents represent earthworms; the virtual environment defines the soil in which earthworms move. Creating this model deals with two major difficulties:

- **The description of earthworm behavior:** many studies in ecology have focused on earthworms. Most of them express general assumptions about earthworm behavior, their attraction (food, humidity) but none has ever determined earthworm behavior detailed rules with accuracy [1,10,16,18].
- **Soil and its complexity:** we wish to create a multi-scale and three dimensional soil model, in which organic matter (e.g. plant debris), mineral matter (e.g. clay, silt and sand) and cavities (e.g. micro- and macropores) are represented as volumes differently organized according to the size scale.

Several approaches have been used to develop ABM of real complex space. They can be divided into two main categories:

- **Continuous approach:** space is considered as a two or three-dimensional environments composed of surfaces or volumes. This type of space is fully used, for example, in the virtual-reality domain to reproduce a scene where agents evolve [11], or in geographical information systems to create maps and execute spatial searches [26].
- **Discrete approach:** space is often represented by a two or three-dimensional regular grid [12]. This technique is often used in the simulation domain because they are efficient and simple.

In the present project, we applied a discrete approach to model the soil. In fact, we conceived an original technique dedicated to the creation of a three-dimensional and multi-scale model of real spaces (e.g. a soil). This technique, called APSF (Agent, Pores, Solid and Fractal), extends the PSF (Pore, Solid and Fractal) approach [3,27]. It is an adaptation of PSF approach to MAS. In addition, it contains some improvements to allow a heterogeneous space description, and some optimization techniques to limit model complexity.

The aim of this paper is to present the APSF approach and its application in the MicrObEs project. This paper is organized as followed: first, we present the basic principles of the PSF approach, then APSF technique is introduced and finally, the case study is presented.

2. Pore Solid-Fractal Approach

The Pore-Solid-Fractal (PSF) approach, originating from the work of Neimark [25] and Perrier [27], is an extension and generalization of the fractal approach to model soil structure. For example, in ecology, it is applied to study soil water retention and water flows [4].

The PSF approach intends to model a real space as an organized, discrete set of cells, which belong to three categories:

- **Pore cells** representing soil cavities;
- **Solid cells** representing compact particles without any cavities, such as sand or organic particles;
- **Fractal cells** representing a subspace that can be decomposed into smaller pore, solid and fractal cells when the resolution increases.

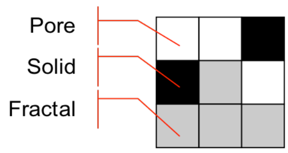


Fig. 1. Soil pattern.

Cells are organized according to a given pattern (figure 1), which defines an abstract architecture of the virtual environment. It is reproduced at each level within the fractal cells (figure 2). For instance, at the first level, cells are organized according to the pattern. At the second stage, fractal cells of the first level are ordered according to the same pattern and so on… It has been shown that the proportions of pore, solid, and fractal cells can be selected to generate a virtual environment that reproduces some given soil characteristics (matter distribution, pore and solid sizes, total porosity, and so on).

A PSF model synthesizes the studied soil architecture by a unique pattern, which is replicated at all levels. Studies have shown that this approach allows making a realistic model of a soil. Indeed, soil characteristics are preserved.

Using this approach needs to make the assumption that the architecture of the studied system is homogenous because a same pattern is replicated at all fractal levels. But a real soil does not follow a fractal architecture. For this reason, this approach cannot be applied in our project. In addition, a PSF model is not suitable for being used in an ABM, because implementing a PSF model in a MAS leads to complexity problems: to be run, a PSF model must be deployed at the smallest size scale, and therefore much memory is needed.

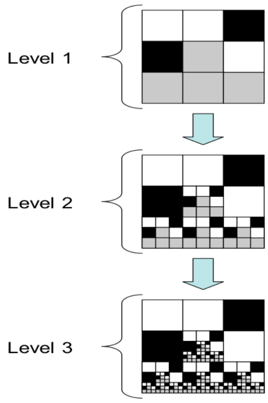


Fig. 2. Fractal decomposition of soil according to the pattern presented in the figure 1.

As a consequence, PSF approach was improved by developing APSF approach, which allows modeling heterogeneous environment and reducing model complexity.

3. APSF: a PSF improvement

The APSF approach adapts PSF technique to agent paradigm. It allows building dynamically a MAS environment according to situated agent evolutions and actions. It models real complex system spaces (e.g. a soil) by an abstract representation composed of organized patterns.

3.1 The approach

The APSF approach uses the same philosophy than the PSF technique. It models a real space as a fractal environment composed of three kinds of cells (pore, solid and fractal cells). In addition, different types of solids can be defined in order to represent various kinds of soil materials: organic debris, sand particles, and so on (figure 3).

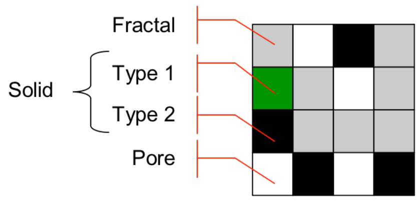


Fig 3. APSF canvas.

Contrary to a PSF description, different patterns, called *canvases*, are determined in an APSF model. Each of them characterizes a spatial organization of cells. All canvases are associated together to define a heterogeneous space whose structure evolves according to the position and the scale.

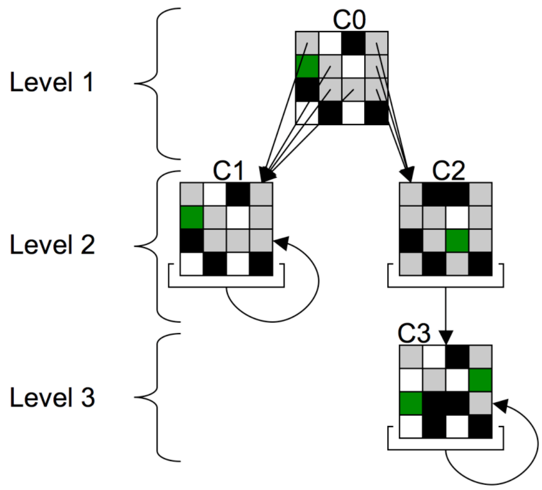


Fig. 4a. Canvas tree example.

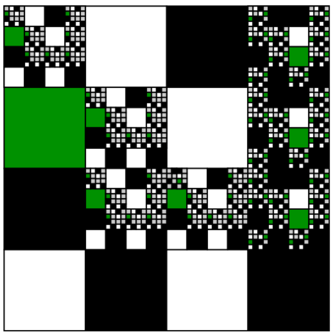


Fig. 4b. Environment created according to the canvas tree presented in figure 4

Canvases are organized in a tree structure (Figure 4a). A canvas is defined at the root of the tree. It models the structure of the space at the highest level (level 1). For each fractal cell of this first canvas, a new canvas is defined. It models a local architecture of a sub-space (at level 2). The same approach is used to each level of the environment. Note that tree leafs are recursive to permit an unlimited fractal decomposition. To illustrate this approach, the canvas tree showed in the figure 4a models the space presented on figure 4b.

3.2 An auto-generated environment for MAS

To reduce the complexity during a simulation, a dynamic MAS environment based on APSF approach was created. It builds up itself, dynamically and on demand, according to the APSF canvas tree model and agent actions.

An agent action affects a very narrow area of the virtual space. Thus, there is no need to load all the space in memory and the only zones of the space explored by the agents are created and stored in memory.

MAS environment contains a dynamic tree to store the explored space. The root of this tree contains all the space; it is composed of sub-spaces, which once-more, include under sub-spaces and so on. This approach is similar to octree [13].

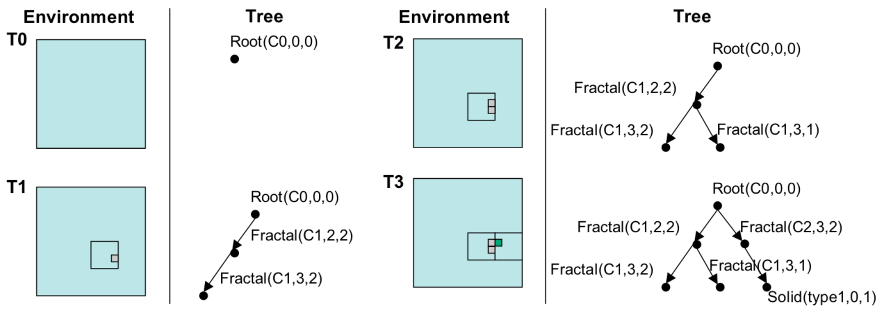
The figure 6a shows how MAS environment tree is modified according to the following agent action sequence:

T0. At the beginning of the simulation, the environment is empty because no action has been done. Only the root of the tree is created.

T1. Then, a second scale-sized agent is located at the first level sub-space A (coordinates 2,2) and at the second level sub-space B (coordinates 3,2) (figure 6b). This agent is then created at the location (11,10) in agent space (figure 6c).

T2. At this step, the agent moves to (11, 9). According to the canvas C1 (figure 4), the agent moves to a new decomposable cell (fractal cell). This cell is created on the environment tree.

T3. At the last step, the agent moves to (12, 9). The decomposable cell located at (3,2 first level sub-space) has not been created yet. It is loaded at this time. According to the APSF tree model, this cell follows the canvas C2 (figure 4). Therefore, a solid cell of type 1 is stored in the tree and located at the position (0,1 second level sub-space).



Legend: CellType(type, X,Y)

- Celltype ➔ kind of cell (pore, solid or fractal cell)
- Type ➔ used canvas or solid type
- X, Y ➔ relative cell coordinate

Fig. 6a. Example of environment evolution in time resulting of agent actions.

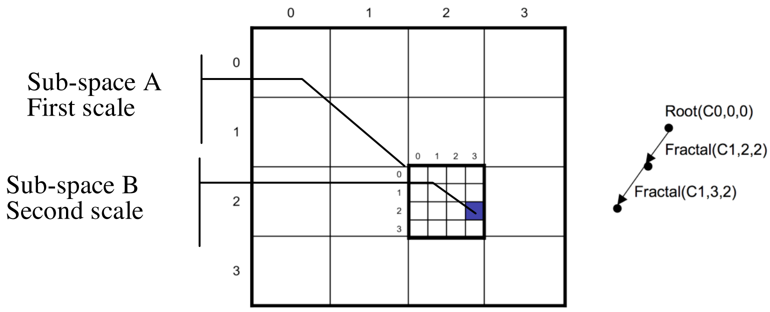


Fig. 6b. Agent location in the environment tree at the date T1.

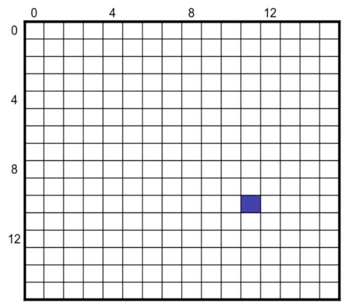


Fig. 6c. Agent location in the virtual world at the date T1 (coordinates 11,10).

Note that the gain of APSF approach is significant. Locating a third scale agent in an environment leaded by a PSF model based on a canvas, which divides a cubic fractal into one thousand sub cells (each side of the cell is divided by 10), needs to create one billion cells (1000*1000*1000 cells). Conversely, locating the same agent in an environment leaded by an APSF model needs to create only 3 cells.

In our modeling approach, the environment could be considered as a complex and autonomous entity, which is created and dynamically modified. It uses a predefined APSF tree model, whose evolution depends on "behavior rules" describing its reaction to other agent actions (e.g. earthworm movements).

4. Case study: the MicrObEs project

In the MicrObEs project, we aim at simulating the effect of earthworms on soil structure and organic matter dynamics. Firstly, an ABM is developed in order to describe the effect of earthworms on soil structure.

The aim of this section is to present the approach used to model then to simulate modification of soil structure. This is based on a case study: the soil of Lamto (Ivory

Coast) for which many studies described the effect of earthworms on soil structure [5,6,7,9,17].

At first, data on Lamto's soil and earthworms are given. Secondly, the developed model is presented. Finally, simulation results are discussed.

4.1 Studied system characteristics

4.1.1 Soil characteristics

As all soils, the soil of Lamto contains mineral and organic particles, and pores. A given volume of Lamto's soil is composed of 53.7% of mineral particles, 1.3% of organic matter, and 45% of pores. Soil bulk density is 1.4 g/cm^3 (with mineral density equal to 2.62 g/cm^3 and organic matter density equal to 0.8 g/cm^3) (table 1).

Table 1 Main properties of Lamto's soil and earthworm casts

	Soil	Earthworm casts
Mineral	53.7%	67.3%
Organic matter	1.3%	1.6%
Porosity	45%	31.1%
Bulk density	**1.4g/cm3**	**1.8 g/cm3**

Mineral particles are divided into three types of particles: sand (0.05-2 mm), silt (0.002-0.05 mm) and clay (<0.002 mm). Lamto's soil contains 83% of sand, 7% of silt and 10% of clay. It is called a sandy soil and does not contain any particles larger than 2 mm.

4.1.2 Earthworm properties

The main earthworm species modifying Lamto's soil structure is *Millsonia anomala* [6,17]. This earthworm is 10 cm long, 2 mm diameter and weighs 4 g at the adult stage.

Earthworm behaviors are partly driven by soil properties where they evolve. Previous studies showed that earthworms are particularly sensitive to soil humidity and soil organic matter content (their food). In general, earthworm behaviors are rather unknown.

Earthworms dig into the soil in order (i) to get their food (organic matter), and (ii) to reach optimal conditions (humidity, temperature, pH and so on). Studies showed that *Millsonia anomala* earthwoms ingest 5 times its own weight of soil at the adult stage [17]. They can assimilate all sizes of organic matter from large debris to clay-sized organic particles [22]. Their assimilation rate ranges from 3 to 7% [17,20]. The gut transit lasts 2-3 hours and the ingested soil is then egested in the form of casts (dejections).

Earthworm casts are composed of organic matter, minerals and pores. Their structure is different from that of the non-ingested soil. Bulk density of casts is higher than that of the soil (table 1) because casts are very compacted [8]. As a consequence, porosity in casts is very low. As earthworms preferentially ingest organic matter, their casts are slightly enriched in it (table 1). Moreover, it has been demonstrated that earthworms do not reingest their casts.

4.2 An ABM to simulate earthworm effects on soil structure

4.2.1 Environment of the MAS

To limit model complexity, the developed model reproduces a reduced sample of soil: 20x20x20 cm. This sample size is enough to describe earthworm activity.

In the soil, the particle size distribution is regular (factor 10): 0.2-2 mm coarse sand, 0.02-0.2 mm coarse silt + fine sand, 0.002- 0.02 mm fine silt, and <0.002 mm clay. We decided to create a canvas tree, which divides recursively a cubic fractal cell into one thousand sub cells (each side of the cell is divided by 10). Therefore, cells measure 20 mm at the first level , 2 mm at the second level, 0.2 mm at the third level, and so on.

As said above, Lamto's soil does not contain any particles larger than 2 mm. For this reason, two fractal canvases are defined (figure 7). The first one is used at the first scale to construct 20 mm side cells. It is only composed of decomposable cells. These cells are organized according to a second canvas used for all the following scales (from the second scale to the infinity).

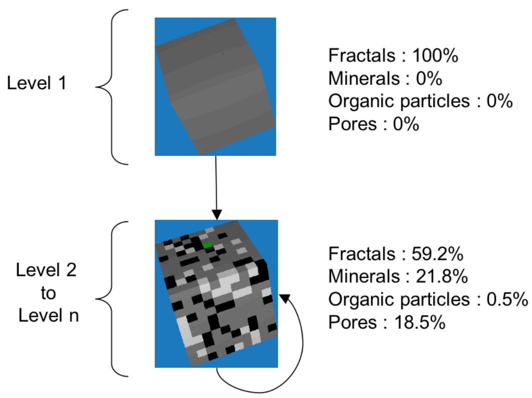


Fig. 7. Defined APSF canvas tree to model Lamto's soil.

The second canvas is defined according to Lamto's soil properties. We created a canvas composed of 21.8% of minerals, 0.5% of organic matter, 18.5% of pores and 59.2% of decomposable cell (fractal cell) where the same canvas will be reproduced at following scales. These proportions have been chosen in order (i) to create a virtual soil with a realistic bulk density of nearly 1.4 g/cm^3, and (ii) to keep the same concentrations of minerals, organic matter and pores measured for Lamto's soil (table 1).

The developed model is rather simple and could be more accurate. In this model, two canvases are defined. It implies that the virtual soil keeps the same structure at each scale level. Nevertheless analyses of Lamto's soil give an accurate particle size distribution: 60% 0.2-2 mm particles, 26% 0.02-0.2 mm particles, 4.5% 0.002-0.02 mm particles and 9.5% <0.002 mm particles. Consequently, additional canvases could be created to describe the soil in a better way. This will be done in a next phase of the model development. We aim first at validating earthworm behaviors.

4.2.2 Agents to represent earthworms

Earthworms are modeled by agents which are characterized by a specific behavior and limited abilities to interact with their environment, the virtual soil. In this section, we present successively agent physical aptitudes and their behavior.

An agent perceives its virtual world as an artificial environment composed of cells. The size of perceived cells depends on the agent scale. For example, an agent evolving at the second scale perceives its environment as a set of second level cells. In this context, an agent moves into its space from a cell to another cell. It takes into account the qualities of nearby cells: category (pore, solid or fractal cells) and amount of organic matter. It also can perceive the number of nearby connected pore cells. Moreover, agents cannot:

- perceive cells that are not located around them;
- move into mineral or organic matter cells larger than them;
- move into cells that contain their dejections;
- egest their casts in solid and fractal cells but only in pores.

In our model, we made the assumption that all casts egested by agents had a unique defined architecture. As a consequence, a cast canvas was defined (figure 8). It is used to create decomposable cells in their environment, when agents egest casts. Characteristics of this canvas are chosen in order to preserve the characteristics of earthworm casts in Lamto's soil (table 1).

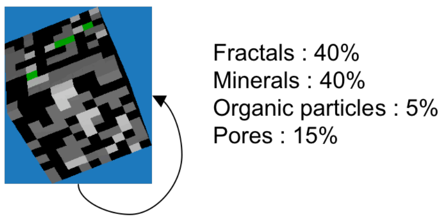


Fig. 8. Agent cast (dejection) canvas.

Agent movements are the results of theirs behavior rules, which take into account the filling rate of their guts and the quality of cells around them (pores, or organic or mineral matter). Two main behaviors drive agent motions:

- **Moving and ingestion behavior:** when they move, agents eat organic debris and bulk soil, and create pores. Thanks to their perception, agents move to the nearby cell containing the highest level of organic matter (organic or fractal cell).
- **Moving and egestion behavior:** when their guts are filled, agents move in pores and egest soil as casts (dejections) as long as their guts are not empty. Thanks to their perception, agents perceive the size of nearby pores and move to the largest one.

These two behaviors change periodically during the day. The period is chosen according to the duration of *Millsonia anomala* digestion and the quantity of bulk soil they have to eat (average 5 g/day). A day is divided into 20 periods (10 ingestion periods alternating with 10 egestion periods).

To summarize, an agent can do three kinds of action on the environment: (i) moving without changing its environment, (ii) moving and creating pores when ingesting soil particles (solid and fractal cells), (iii) moving and filling pores with casts (fractal cells). After each action, agents get a new perception of their environment (figure 9).

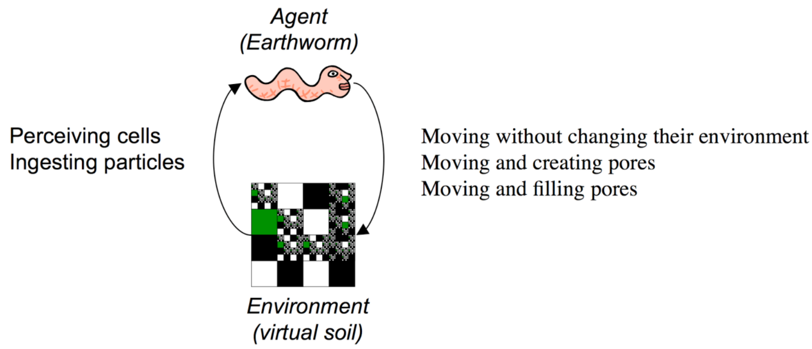


Fig. 9. Interaction between agents and their environment.

4.3 Simulation results

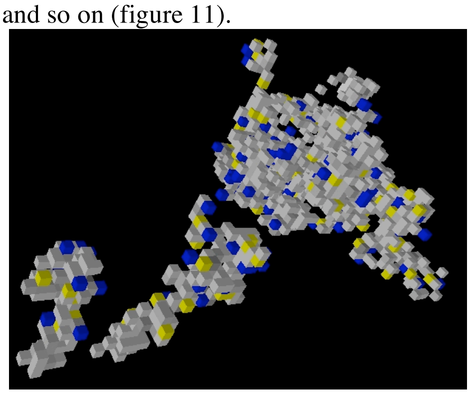
The model was implemented on a multi-agents simulator to obtain results. The simulator extends a MAdKit platform [23,24] plug-in, called RAFALE-SP [19].

At the beginning of this section, simulator outputs are presented. Then, simulation results are analyzed to verify the impact of one or several agents on their environment.

4.3.1 Simulator outputs

This simulator generates several data to measure the impact of earthworms on soil structure. It gives quantitative and graphical outputs of the simulated systems such as:

• **VRML[1] models** to display a 3 dimensional view of the virtual soil state at a chosen time step (figure 10). These models present only soil areas where agents moved, i.e., only environment zones loaded in simulator memory.
• **Images** showing sections of the virtual soil, at a chosen time step (figure 12).
• **Animated images** showing the evolution of the virtual soil structure with time.
• **Graphics and numerical data** to present the evolution of few parameters with time, for example organic matter quantity contained into the soil, food quantity eaten by the agents and so on (figure 11).



Blue➔sand particles
Grey➔fractal particles
Yellow➔cavities

Fig. 10. VRML model presenting an example of MAS environment state after a simulation.

4.3.2 First simulation result: impact of one agent on soil organic matter content

In this first experiment, one agent was simulated in the environment to verify behavior rules. For that purpose, we simulated its impact on soil organic matter content whose results are presented in figure 11.

[1] Virtual Reality Markup Language

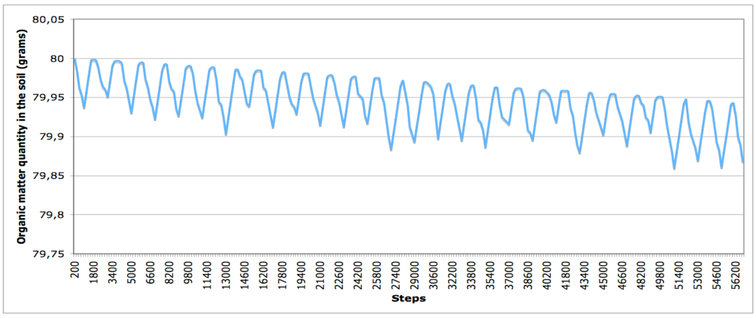


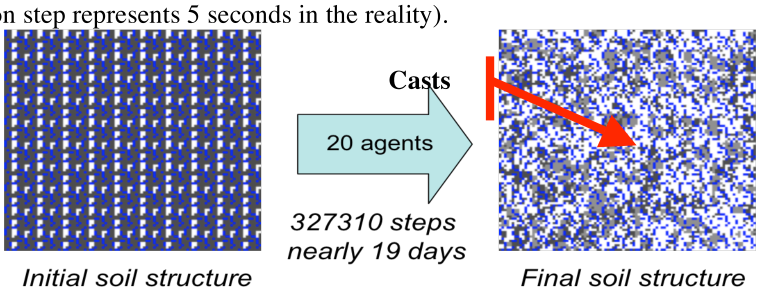
Fig. 11. soil organic matter content evolution.

On this figure, we can observe and analyze agent activity, which is the result of ingestion and egestion behaviors. When the curve goes down, agent is eating the virtual soil and soil organic matter content decreases. When the curve goes up, agent is ejecting casts in the environment and soil organic matter content increases. Figure 11 shows a constant decreasing trend caused by activity of the simulated agent. Indeed, in our model, an earthworm assimilates 3% of organic matter going through its gut.

4.3.3 Second simulation result: compacting effect analysis

In this second simulation, several agents were simulated in the environment to verify agent impact on soil structure. For that, we observe and analyze the evolution of the virtual soil structure, which results of agent actions.

Figure 12 presents the structure evolution of a soil section during a simulation in which 20 agents were placed and moved in the virtual environment. This experiment was executed during about 327 310 steps which simulate 19 days in the reality (1 simulation step represents 5 seconds in the reality).



Blue➔ sand particles
Green➔ organic matters
White➔ pores
Black➔ fractal particles
Grey➔ casts

Fig. 12. earthworm compacting effect on a bulk soil.

This simulation gives realistic results; it reproduces the compacting effect of *Millsonia anomala*. At the beginning of the simulation, the soil is characterized by a homogeneous structure. At the end, this soil structure has changed into a new one in which soil matter is predominantly located in compact zones (earthworm casts). Between casts (grey zones, figure 12), large pores appear (white zones). This architecture is similar to the structure of Lamto's soil explored by *Millsonia anomala*.

Nevertheless, note that sand particles do not move and their organization (localization) do not change. Agents cannot displace sand particles because they do not eat this kind of elements. To solve this problem, modifying agent behavior to allow them to eat few sand particles, would help solving this problem. At last, as gravity is not taken into account in the MAS, particles do not "fall down" and stay in suspension in the environment. This should also be improved in order to get a better representation of the effect of earthworms on soil structure.

5. Conclusion

The Agent-Pore-Solid-Fractal (APSF) approach associates agent paradigm with a fractal approach to model and simulate real and multi-scale complex systems. The efficiency of this approach lies in a simplified, but not too simplistic, description of a real space thanks to an abstract structure, called canvas tree. This tree aggregates the architecture of a heterogeneous space (e.g. a soil) into a set of canvases for which different space architectures (i.e. cell organizations) are determined. Theses canvases are organized in a tree according to the scale and the location of the sub-space they represent.

This model defines the environment of an ABM. It is a virtual world where simulated agents move. This environment is dynamic because it builds up itself, on demand, according to agent moving and action. This strategy allows reducing the memory used by the environment during a simulation.

The APSF approach was applied to a real case study, the Microbes project. We developed an ABM in order to simulate the effect of earthworms (*Millsonia anomala*) on Lamto's soil structure and organic matter dynamics. In this model, agents represent earthworms, and an APSF model describes the soil. Agents are characterized by simple behavior rules (ingested and egested bulk soil). The APSF approach allows creating a simple, but realistic, model of Lamto's soil.

Executing the ABM gives interesting results. It reproduces the earthworm effects on soil structure and organic matter content. These results validate agent behavior rules modeled in our study and verify a few assumption concerning *Millsonia anomala* behavior.

Simulations showed us advantages and limitations of the APSF approach and the model. The APSF approach will be improved in order to incorporate environment optimization features. The aim of these new functionalities is to reduce simulator complexity bt means of algorithms that simplify the simulated environment and minimize used memory.

To achieve the objectives of the project, the model must be improved in few ways:

- Additional canvases should be created to better describe the soil. Analyses of Lamto's soil give an accurate particle size distribution.

- Gravity is not taken into account in the MAS. This should also be improved in order to get a better representation of the effect of earthworms on soil structure
- During agent digestion process, egested mass is nearly the same than egested mass (the difference is the result of earthworm assimilation). In addition, the number of egested mineral particles is the same as ingested ones. Therefore, the fractal structure of cast generated by agents must change according to the ingested matters.

The APSF approach has been developed to describe soil structure. This technique contains a generic structure (canvas tree) that allows describing complex spaces. APSF use can be extended to other fields of agent-based simulation e.g. virtual reality or health.

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