A prototype model-based expert system for agricultural landscape analysis

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Abstract

Agronomic experts use satellite imagery (land-use maps) to make frequent diagnoses of the Lorraine region's agriculture. Their diagnoses rely on landscape analysis and involves various knowledge and reasoning methods. Their interest is also in mapping various criteria to validate their field experience at a regional scale. They therefore need AI techniques.

AI techniques attempt to represent domain knowledge by rules or by "domain models". In the current work, the knowledge concerning the relationship between agriculture and landscape has been represented through a "functional model of agricultural landscape": the model components are image regions which have properties and relations whose combination expresses the global functioning of the agricultural system.

This model has been implemented through a multi-agent blackboard based architecture. The prototype has been applied on images of a small part of the Lorraine region, initially to characterize and classify plots and village areas. The first results are very interesting for experts who can then deepen their analysis and improve the model.

Introduction

Remotely sensed data, especially satellite imagery, are useful for agronomic researchers who can use them to more easily study annual modifications or evolution of regional agriculture. However because of the quantity and frequency of these data automatic treatment is needed. To be more efficient such treatment must include the expertise of the researchers concerning agricultural systems. We thus decided to use AI methods to build a knowledge-based system that could help agronomic experts use satellite imagery. This system should perform land-use mapping and also propose tools and methods for the map analysis, in order to provide a diagnosis of both agriculture and the environment.

We have previously built a prototype that is able to recognize land-uses from satellite data of the Lorraine region (Eastern France) [3]. Our interest is now in the way that experts analyse the resulting map and how this expertise can be represented in a knowledge-based system. Their analysis concerns agricultural systems and their effects on the landscape and general environment [1]. They use different kinds of knowledge and different reasoning methods. We have therefore studied knowledge representation in existing expert systems and proposed a particular way of modeling the characteristics of this "living system".

Landscape analysis using satellite data

Remotely sensed data have only recently been used by agronomic experts. Because of this, the way they analyse the resulting maps is based on existing methods of landscape analysis. To achieve such an analysis, experts use different methods and knowledge.

- First they use their own global knowledge concerning a region: what are the factors which structure a landscape (soil, relief, habitat, agricultural system), in what combination patterns do these factors appear, how does the agricultural system function and how it is likely to evolve. This knowledge concerns the regional scale.
- Secondly they have knowledge about land-uses: how is a culture or a pasture managed and under what constraints. These constraints may be due to physical conditions, to the agricultural system or to the techniques employed. Location, form and surface area of plots are important elements to explain how the agricultural system may function. This knowledge concerns the plot scale.
- From their field experience, experts know how some combinations of factors can lead to specific landscape patterns. These patterns exist at various scales and are more or less precise. For instance, figure 1 shows the usual spatial structure of a classical dairy village system in Lorraine.

From a landscape or a land-use map, experts extract information to make a diagnosis of a village or a small region. If the observed situation matches one of the known patterns, they can say that there is a certain agricultural system at this place. If the situation does not match one of the patterns, they have to explain it using deeper knowledge, that is explain how the agricultural system functions at this place. If this case seems interesting, experts will store it and then compare it to other new cases. If there are many similar cases, a new pattern can be built. Comparing the old and new patterns can lead experts to make or confirm hypotheses on the evolution of agricultural systems and their effects on the regional landscape. In this way their knowledge improves. This analysis is achieved at different scales, depending on the local situation.

A functional model of agricultural systems

Agronomic experts use various knowledge and resolution methods to perform image analysis and we have tried to capture and use them with some AI techniques. Two types of knowledge, heuristics and deep knowledge [14], are usually identified in the AI literature.

1. The heuristic level concerns rules associating landscape characterization or situation to a system diagnosis or partial diagnosis. Landscape characterization can be as simple as *surface area or form of a plot* or more complex as described by the *concentric village pattern*. Such knowledge is usually represented in expert systems by production rules.

2. The deep knowledge level concerns the knowledge used when heuristics are not sufficient to solve the problem. In our case, it is used by the expert to explain unknown landscape situations, to compare cases and eventually to define new patterns or heuristic rules. Such knowledge has been used recently in physics and electronic applications [4][5][13]. It is usually represented by domain models (representation of domain elements and relationship) and used for model-based and case-based reasoning.

Both kinds of knowledge are useful for diagnosing agricultural systems. The first is used on known cases or for fast analysis, the second is used on unknown cases or to go deeper into the analysis. Our focus here will be on the second knowledge type because it can capture more complexity than heuristic knowledge and it has rarely been used in expert systems developed for agricultural problems.
We must therefore find first a knowledge representation that enables us to explain the functioning of a farming system from the image data. This can be done thanks to a functional model of the agricultural systems [9]: a system is made of components, which have certain properties and functions. The relationship between components explains the global functioning of the system. The system components

are defined by the available data, that is image regions, and actually plots, or groups of plots, and villages. Systems exist at various geographic scales and one system can be a component for another system. Experts know the functioning of the systems at village and small region levels. Because of this, our model contains four geographic scales [2].

- The first level is the object level, that is the smallest region on the image. An object corresponds to an agricultural plot (or several similar and adjacent plots) and it is characterized by its annual use (crop, forest or pasture).
- The second level is the village territory: it is the union of objects (plots) belonging to the village area (considering distance);
- the third level is the zone, that is the union of related objects that have similar crops or pastures on them.
- The fourth level is the “terroir”: *a terroir* is a small geographic region containing homogenous agricultural system.

Objects have properties and functions: properties include annual land-use and also surface area, form, perimeter, outline form, neighbourhood, production for selling or for herd consumption, *etc.*. Properties can be calculated from the image data or deduced by rules. The functions differ depending on the object land-use: forest forms shadows and thus influences production from adjacent plots, pastures also influence production of neighbouring crops (damage from escaping animals), *etc.*.

The physical constraints on the object (surface or distance constraints, *etc.*) can be deduced from properties and functions. For instance, lack of ploughable area is infered when a forest or a pasture lies near a crop or if the mean surface area of crop plots is small. Distance constraints are evaluated from an optimal location of the various land-uses around the village (see fig. 2).

Properties, functions and constraints of the villages are calculated from the component objects. Farming systems of the villages are explained from their productions, constraints and the general structure of the village territory. Properties of zones and *terroirs* are also deduced from the component objects.

This model can be used in two ways [5][13].

- To analyse and explain a situation: how does the agricultural system work in this village or in this territory. This is what is called model-based reasoning.
- To classify a situation: how can we compare a situation to another one and deduce relationship between global structures and functioning. This can be seen as case-based reasoning.

Implementation of domain models

The second stage of this work is to represent the functional model and the associated reasoning methods in a knowledge-based system. These aspects of expertise representation have been studied in second generation expert systems. Second generation expert systems, indeed, use both deep knowledge and heuristics [14] and therefore contain both a domain model and rules. Such representation of several levels of knowledge has been used for applications in physics and also in medicine to solve diagnosis problems.

In [4] an expert system is described that contains separated surface and deep knowledge bases. Surface knowledge concerns familiar problems. It is structured into three levels: information or facts, hypotheses, and possible solutions. The deep knowledge is a functional model of the device under diagnosis, so its behaviour can be qualitatively simulated. Both surface and deep knowledge are implemented using semantic networks: in particular, the primitives of the functional model are represented by frame-like nodes or arcs. The whole system consists of the two knowledge bases and an executor. Each knowledge base has its own control mechanism so that it constitutes an autonomous expert system; the control of the two is performed by the executor control mechanism. Reasoning about deep knowledge is represented by general rules which then lead to more specific analysis.

A general model-based method called CASNET has been proposed in medicine [15]. A Casnet model uses three levels to represent knowledge: the first level is surface knowledge, in this case observations about the patient, the second level is where patho-physiological states (internal conditions assumed to take place in the patient) are enumerated, and the third level is where the most abstract knowledge is represented, in this case classification of diseases. States are linked together by a causal network, relations between observations and patho-physiological states are represented by association links and relations between states and diseases by classification links. Reasoning is represented by confidence rules that associate observations to states and by rules that classify a given ordered pattern of states as a disease.

Models have also been implemented using blackboard [11][12] or blackboard-like architectures. An exemple is VISIONS [6], a system that uses a static model of the photographic scenes it has to interpret. The model is represented in a *long term memory* through multiple levels of abstraction including **schemas**, **objects**, **volume** and **surface**. Primitive entities are represented by nodes and relations between the various levels are represented by arcs, as in a semantic network. When interpreting a scene the system uses a *short term memory* similar to the *long term memory* to classify the various regions of the scene and then incrementally construct the model scene. Knowledge used to relate image entities to general entities is stored in specific knowledge sources, which operate upon information at one level and produce hypotheses at another.

Computational representation

For the current problem of agricultural classification and analysis, various forms of reasoning (calculation, explanation, comparison, *etc.*) have to be represented that rely on specific knowledge (*e.g.* knowledge about the croping techniques, or about the functioning and the spatial organization of agricultural systems). Furthermore knowledge acquisition phase is an ongoing task and we want to be able to easily modify the system by including other knowledge or reasoning. The multi-agent architecture fulfils these requirements [7] because each component (or agent) contains its own knowledge or reasoning method and cooperates with the others to solve the common problem.

The blackboard architecture has been chosen to represent the functional model of agricultural systems. Its hierarchic structure enables us to easily describe the various model components and their attributes (properties, functions, relations).

We have used the Atome tool which has been developed at CRIN/INRIA Lorraine [8] to implement the system. This tool is a blackboard architecture shell for building multi-expert systems where multiple inter-dependent knowledge sources can cooperate through blackboards to solve a complex problem. It is composed of domain knowledge sources and control knowledge sources: the first type records knowledge about specific sub-problems while the second type records knowledge to organize the problem solving process.

In an Atome-system the domain knowledge is organized with several blackboards and with *specialists* (see fig. 3). Blackboards contain data which describe the solution state, that is static data; specialists are independent modules designed to solve a particular sub-problem according to the blackboard state. *Events* are generated by the specialists, in order to notify important actions to the control expert. The control knowledge is described through *tasks* and *strategy*. A task coordinates a set of specialists according to the events that have been “written” on the blackboards. Strategy works as a meta-level control knowledge source: it chooses a set of sub-problems and the ways to solve them according to a summary of the events.

The Aréopage application

This application has been developed to help the agronomic experts analyse the satellite images. It has to recognize objects and villages on the map, to calculate the various properties of the objects and then to perform a partial analysis of village farming situations.

The previously described functional model of agricultural systems has been implemented through the Atome architecture. A blackboard has been defined with five levels. Each level corresponds to a geographic level of the functional model (see fig. 4), plus the point level which contains the image data. Nodes in the blackboard are linked by composition links. Attributes are defined at each level to represent properties (see fig. 5) and functions (see fig. 6) of the corresponding model element.

Some specialists contain the rules that calculate attribute values from other data: production is evaluated from surface area and land use, constraints are evaluated from surface area or neighbourhood or distance to village, *etc.*. These are *model specialists*. An example of a rule implementation is described in figure 7.

Other specialists are used for reasoning. Specialists have been already written to classify villages according to their production (see fig. 8) and the production of neighbouring zones. In the future, we will write specialists to classify villages from their constraints and their structures. The necessary knowledge has still to be acquired from the experts.

Results and Discussion

ARÉOPAGE has been developed with the C++ language on unix system of HP and SUN workstations. It has been used with G.I.S. data of a part of the Lorraine region. This area contains about 1000 plots and 6 villages. Data describe plot land-use and location.

The system undertakes the following tasks:

- Recognition and labeling of objects, villages and zones. A node is created in the blackboard at the appropriate level for each object (zone or village).
- Calculation of the geometrical properties of each object: surface area, distance to the village, perimeter, form, *etc.*. These values are calculated from the map and then written in the corresponding node and attribute.
- Calculation of derived properties from the geometrical properties and land-use: production, pollution, constraints, particular features.
- Calculation of the properties of villages: surface area, land-uses, production, constraints. These properties are evaluated from those of the component objects.
- Calculation of the properties of zones as surface area, land-uses, production. These properties are evaluated from the component objects.
- First classification of the villages (see rule in fig. 8).
- Analysis of the classification of villages. If the agriculture system is of type *intensifié*, the village structure is compared to the concentric pattern (see figure 1) otherwise the system searches for zones in the village neighbourhood.
- Calculation of the properties of villages from their own area and the area of neighbouring zones. Zones are of meadows or crops and can be used by several neighbouring villages and thus modify their farming system.
- Second classification of the villages.
- Further analysis of particular villages from constraints or other properties.

The calculation time is quite long. The results are written to a file that contains data about the plots or villages, and also on maps of classified plots or villages. Classification are developed from the various attributes, form, surface area, land-use, of plots or agricultural system occuring in the villages (see fig. 9). Even if they are simple these maps are very interesting to the experts and allow them to specify criteria and to deepen the analysis.
Atome's Blackboard seems to be a good architecture to describe static aspects of the functional model (plot geometric properties *etc.*). But, this model also contains dynamic aspects such as the calculation of some properties and relationships and the evaluation of the global functioning of a system from the properties of the components. Calculation and evaluation methods cannot be represented on the blackboard. According to Atome's architecture, they have to be described by rules and implemented in the domain knowledge sources (the specialists).

Consequently several specialists have to read attributes and modify others for each node of the blackboard, that is for each plot of the map or for each village. This means that there are many inputs and outputs to and from the blackboard with undesirable consequences on the efficiency of the system.
A representation where the nodes contain the information for the evaluation or calculation of their own attributes would be better. That could be done with an object blackboard architecture [10], where nodes would have attributes and methods for calculating the values of the attributes. Such an architecture is theoretically interesting because it maintains the "integrity" of the model. Both dynamic and static aspects are represented in a same part of the expert system.

Such an object blackboard would modify the contents of the knowledge sources. In our specific application, many specialists would disappear because their knowledge content is about model functioning and so this would be represented on the blackboard. Remaining specialists would represent surface knowledge, *i.e.* heuristic rules [14]. In the end the architecture of the system would be modified so that deep knowledge and surface knowledge would be separated: deep knowledge would be represented on the object blackboard and surface knowledge with the specialists. Both would be organized by control knowledge sources (tasks and strategy). Such an architecture would be more like the one described in [4].

Conclusion

We have built a prototype expert system to help agricultural system analysts use satellite data. This prototype performs various classifications and some analysis of plots and villages from map data. The expert knowledge has been represented by a functional model of agricultural landscapes. The Atome blackboard-based multi-agent architecture was used to implement this model. The prototype has been applied on some images. Results have proven valuable to the experts but the execution is rather long.

Concerning the agronomic part of this work, the model and the prototype have proven valuable for the experts as a way to obtain new results from the analysis of satellite images. The results will then be used to improve the model.

Concerning the AI part of the future work, we will try to develop an object-based blackboard to represent the static and dynamic parts of the model together. Such a blackboard could constitute an autonomous knowledge source which could be associated with surface knowledge sources and controled by a third module.

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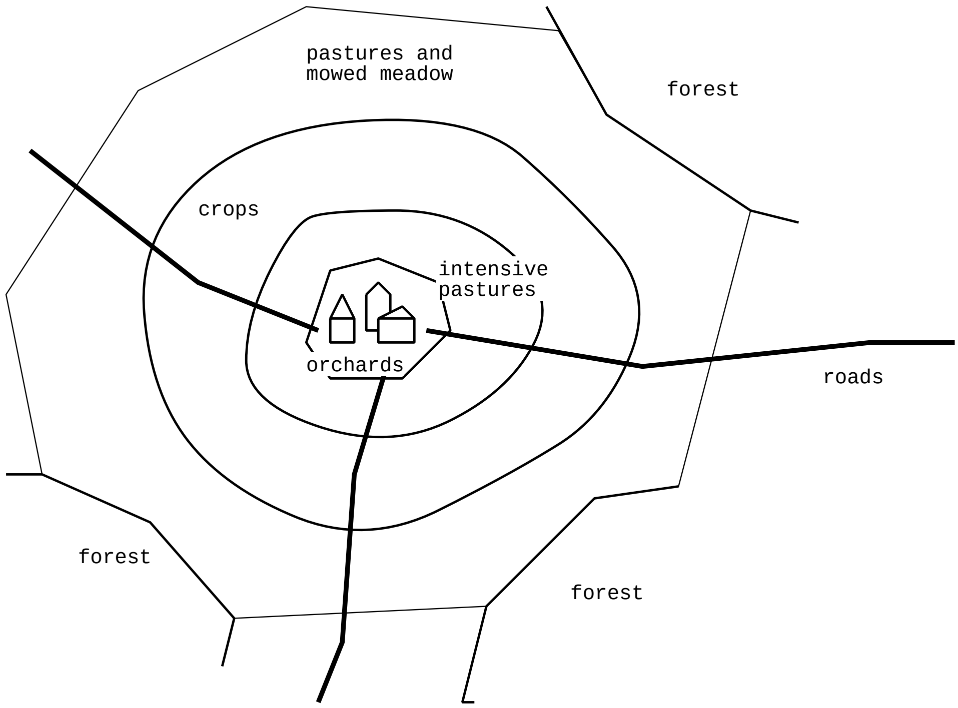

Figure 1: Village concentric pattern.

- constraint is positive if ((land-use = intensive pasture) and (village distance $>$ 1.5 km))
- constraint is negative if ((land-use = intensive pasture) and (village distance $<$ 1.0 km))
- constraint is positive if ((land-use = maize) and (village distance $>$ 4.0 km))
- constraint is negative if ((land-use = maize) and (village distance $<$ 2.0 km))
- constraint is positive if ((land-use = crop except maize) and (village distance $>$ 10.0 km))
- constraint is negative if ((land-use = crop except maize) and (village distance $<$ 5.0 km))

Figure 2: rules for reckoning of distance constraints

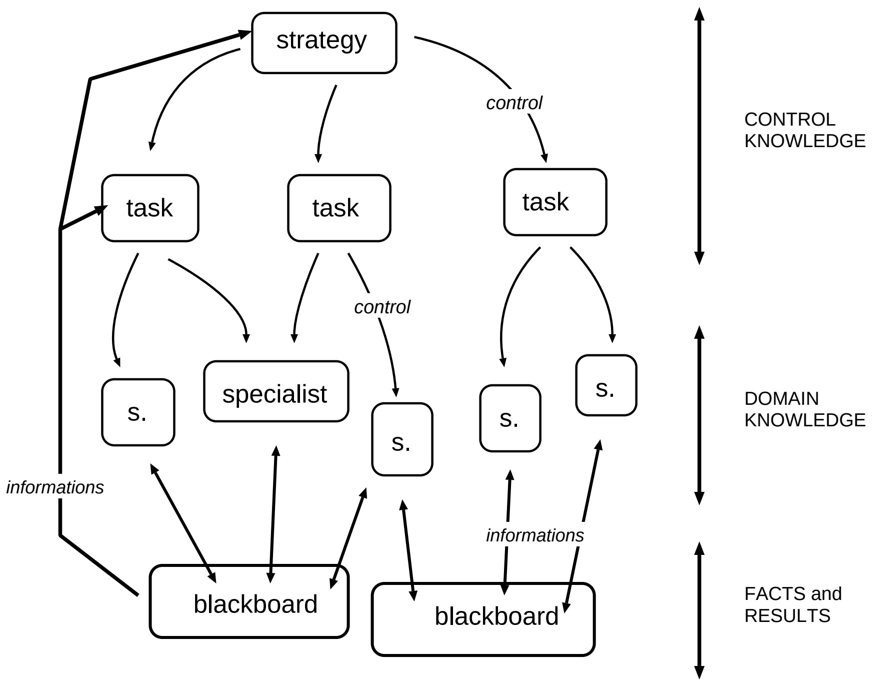

Figure 3: ATOME tool architecture.

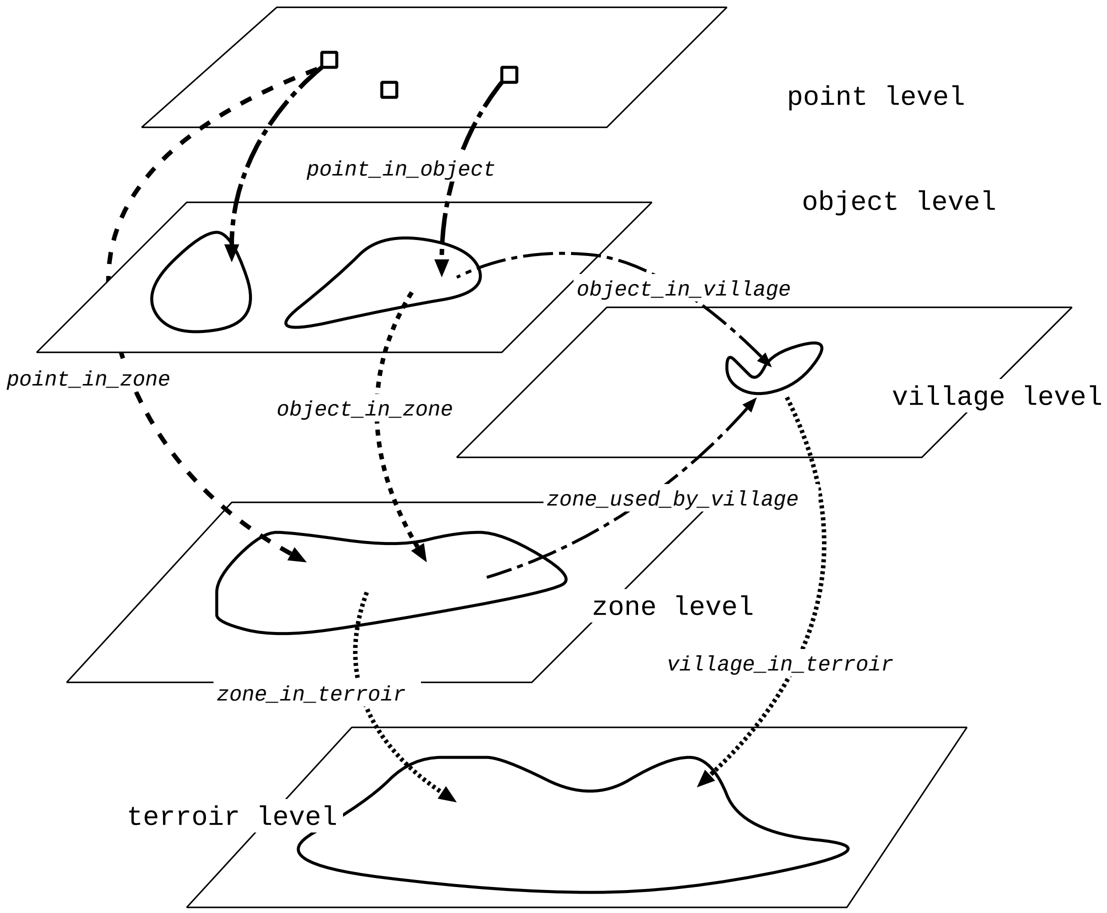

Figure 4: The ARÉOPAGE blackboard: levels and links between levels.

- *numéro*: object's label
- *occupe*: object's land use
- *classedoc*: land use class
- *distance*: object's distance to the nearest village
- *surface*: object's surface area (hectares)
- *périmètre*: object's perimeter (hectometers)
- *découpe*: object's lineout form (qualitative index)
- *forme*: object's form (qualitative index)

Figure 5: Simple attributes of **object level**

- *aliment_étable*: production used to feed the herd in stable (number of animals)
- *aliment_pré*: production used to feed the herd at meadow (number of animals)
- *concentré*: production used as condensed feeding (number of animals)
- *vente*: production sold (quintals)
- *pollution*: nitrogen production (mg/l)

Figure 6: Production attributes of **object level**

```
$defrule distance-pvl
   specialist  -> contraintes
   variable    -> dis of-type int
   selection   -> $select-from unique objet where
            ($get-attribute (occupe) == "pature-int")
  actions        -> {
      cout <<  "calcul des contraintes de distances \n"<< flush;
      $iterate-on ($NODES ()) with noeud {
           ?dis = 0;
            if ($get-attribute (distance, noeud).valeur () > 1.5)  ?dis += 1;
            if ($get-attribute (distance, noeud).valeur () < 1)  ?dis -= 1;
            $modify-nodes (noeud) with
                $c-distance -> ?dis
            endmodify;
                              }
endrule
```

Figure 7: Example of rule implementation. The rule concern the evaluation of distance constraints for an intensive pasture: the constraint is calculated from the distance between village and plot.

```
$defrule système "de production"
   specialist  -> finage
   variable    -> classes of-type relations
   variable    -> sys of-type chaine
   selection   -> $select-from unique village where
            ($get-attribute (territoire).valeur ())
  actions        -> {
      cout <<  "classement des villages \n"<< flush;
      $iterate-on ($NODES ()) with noeud {
           ?classes = $get-attribute (relatif, noeud);
            int prairie = ?classes.nvaleur ("prairie");
            int culture = ?classes.nvaleur ("culture");
            int mais = ?classes.nvaleur ("mais");
            if ((prairie > 0.7) && (mais < 0.1))  ?sys.setval ("simple");
            else {
                if ((prairie > 0.45) && (mais > 0.2)) ?sys.setval ("intensifié");
                else {
                    if ((culture > 0.5) && (prairie > 0.2))  ?sys.setval ("mixte");
                    else  ?sys.setval ("incertain");
                   } } }
            $modify-nodes (noeud) with
                $classement -> ?sys
            endmodify;
                              }
endrule
```

Figure 8: Rules for the first classification of agricultural systems: the agricultural system, *simple*, *intensifié* or *mixte*, is evaluated from percent surface of some particular land-uses (grassland, wheat, barley, maize).

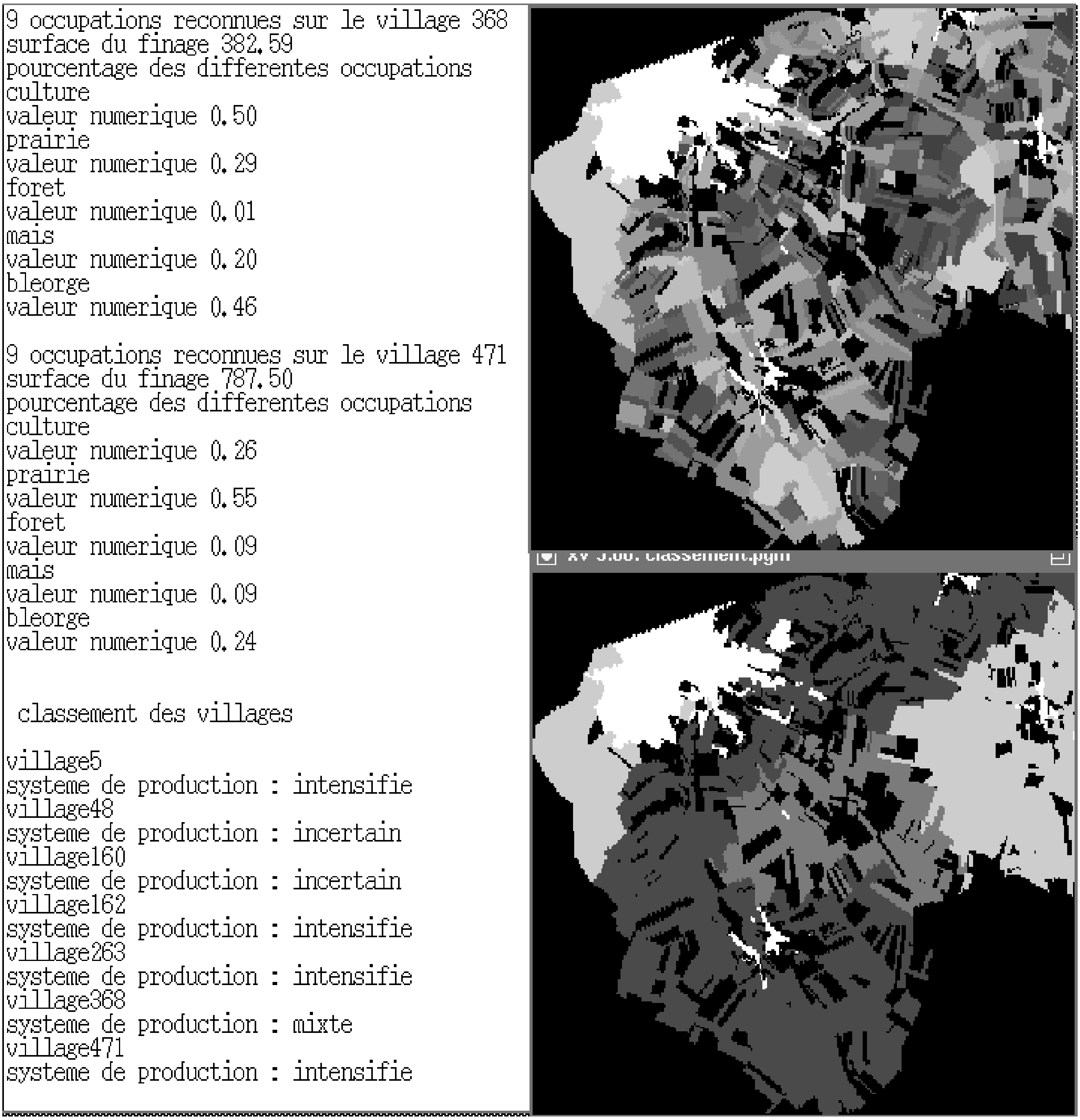

Figure 9: Reasoning steps and results performed by ARÉOPAGE on the Vittel area (screendump). These results concern the classification of village systems (map at the bottom) from the various land-uses of their area (map at the top). Village sites are in white on the map.