AN EXPERT SYSTEM FOR SATELLITE IMAGE INTERPRETATION

AND G.I.S. BASED PROBLEM SOLVING

DESACHY J., DEBORD P., CASTAN S.

Laboratoire CERFIA
UNIVERSITE PAUL SABATIER
118 route de Narbonne
31062 TOULOUSE CEDEX - FRANCE

ABSTRACT :

This paper describes an expert system for satellite image interpretation and thematic mapping.

The thematician knowledge is kept in a data base as a set of production rules with certainty factors. The facts data base for a given problem is composed of the image to be interpreted and the associated geographic information system.

The system can handle two kinds of reasoning depending on the nature of the given problem :

- data-driven reasoning for classification problems.
- goal-driven reasoning for object possible location mapping.

In addition we plan to include a learning process in our expert system.

1 - INTRODUCTION

Nowadays most cartographic applications manage with satellite imagery, but almost all of them limit themselves to in-image information (spectral or textural features, multitemporal images ...).

In fact when somebody analyzes a satellite image, he takes into account a lot of "a priori", "out-image" knowledge to reach a satisfactory interpretation.

A photointerpreter who wants to produce a vegetation map for example, will manage with three types of information sources.

first : of course the satellite image
second : available cartographic information (topography, soils quality ...)
third : his knowledge of local vegetation types characteristics

So it's quite an evidence that one should "add" to image information, the domain expert "know-how" and the cartographic data in order to "understand" the image.

The expert systems methodology [FAR 3] [VOY 10] is well adapted to solve this kind of approach.

It's not the first time that expert systems technique is used to solve remote sensing problems but they solve as we know quite different problems.

So GOLDBERG deals with this technique to estimate if computed changesin multitemporal images are valid or not [GOL 5].

GOODENOUGH [GOO 6] presents two systems, one of them (MICE) is used to manage with the "registration" of aerial images extracted objects with the corresponding objects in maps ; the other one (LDIAS) is a multiexpert system, which after an analysis of a given image related problem will make an adapted choice of algorithms among an image processing procedures set.

In a synthesis paper, MCKEOWN [MCK 8] presents an analysis of the role of the Artificial intelligence in the joined management of remote sensing data and Geographic Information System.

He submits data bases quite different from classical G.I.S. (MAPS, CONCEPTMAP) but well fitted to model guided object finding and to object spatial context searching (airport scene for example).

He handles object models and abstract descriptions of scenes by spatial relations between objects.

In this domain we got some experience too in scene analysis and understanding systems [DEB 1].

As far as we know other authors have used expert systems in image processing but generally by the mean of model guided research of objects (in most cases in aerial images) (the image is preprocessed and a segmentation is obtained, then the presence of searched objects is decided by the way of match with a model).

In the Edimburgh symposium of C IV ISPRS of september 1986, we presented a paper [DES 2] about an experimental system of automatic remote sensing imagery interpretation.

It allowed us to show on a particular test zone the interest of such an approach to improve a supervised vegetation classification, but the integration in the processing method of the three sources of information (image, geocoded information, expert know-how and knowledge) was quite empirical, just as the uncertainty management in the knowledge representation.

In order to produce a general system we chose the expert system technique as well as a less empirical method of uncertainty management in knowledge handling.

We can solve classification problems (vegetation cartography for example) by using our inference engine in forward tracking ; moreover we can manage with geographic information related problems by using backtracking (for example to determine where it would be optimal to set that or that type of plant knowing that ...).

2 - **THE FIRST STEPS TO THE EXPERT SYSTEM** :

Let's remind of the experimental procedure we applied to a LANDSAT MSS image of Palni hills, India [DES 2] in order to obtain a vegetation map of that region.

We managed then with three different types of knowledge :

1 - The LANDSAT MSS image (and related computed features : spectral and textural features)
2 - Geocoded information (digital terrain model, climates map ...)
3 - Expert knowledge about searched classes of vegetation.

The knowledge of types 1 and 2 is typically a fact data base and knowledge of type 3 is the knowledge data base.

In this experiment the expert knowledge concerning each class of vegetation was coded in the form of logical expressions ($\cap$ and $\cup$ operators) and each basis operand had the general following appearance :

```
( (PTC)    (BTC)    (OTC) ) )
   |         |          └─object characteristic
   |         |
   |         └── belonging (or relational) characteristic
   |
   └── presence characteristic
```

example : ((mainly) (bottom of (valleys)))

the PTC and BTC characteristics permitted to code uncertainty in natural language.

The whole procedure of the experiment is presented in figure 1 (appendix).

First the MSS image was preprocessed (orthogonal transform), then a "preclassification" was made which was a barycentric type supervised classification, managing with spectral and textural features (cooccurrences matrices based features).

For each pixel and for each searched vegetation class we obtained a belonging probability.

Introduction of expert knowledge consisted to modify these computed probabilities taking into account each pixel context in connection with expert knowledge, with relatively empirical methods.

(In fact these methods were quite analogous with the methods used in the medical expert system MYCIN [FAR 3] [VOY 9] to manage with uncertain knowledge and facts).

The expert knowledge stepped in at two levels (pixel or spatial level).

3 - PRESENTATION OF THE EXPERT SYSTEM

First we are going to present our system in a classification problem context.

The general scheme is presented figure 2 (see appendix).let's detail each part :

3.1. What is an elementary fact in our system ?

It is the whole set of available informations for each pixel (some of them may not be immediately available but can be computed). The preclassification is supposed done.

So, one fact appears as follow :

```
(x, y)          pixel coordinates
class   1       certainty factor CF1
class   2       certainty factor CF2
   .                    .
   .                    .
   .                    .
   .                    .
```

PIXEL CONTEXT :

(known or to compute using G.I.S.)
related to D.T.M. : ridges, bottom of valley
E, W, S ... slope,
near a road
related to soils ...

Successive application of knowledge base rules will update the certainty factors CF1, CF2 ... when no more first level rule is eligible a conclusion can be made on the first step of the classification process. Then second level rules can be activated (involving spatial features).

3.2. Knowledge base :

Figures 3 and 4 give the expert knowledge in natural language form, then in the corresponding production rules form.

The number between parenthesis indicates the certainty factor of the rule itself (confidence factor) and is a value from -1. (you are sure it is not ...) to 1. (you are sure it is yes ...).

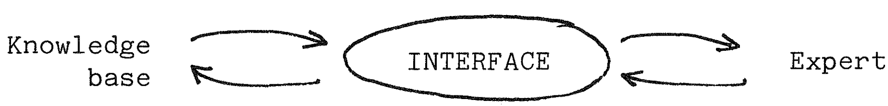
The possible forms of rules are as follow :

$$A \text{ and } B \xrightarrow[(CF)]{} C$$

$$(A \text{ or } B) \text{ and } C \xrightarrow[(CF)]{} D$$

$$A \text{ and } B \longrightarrow \underset{(CF_C)}{C} \text{ or } \underset{(CF_D)}{D}$$

For purpose of knowledge base construction, which is quite variable for each type of region, it is necessary to have an expert-computer interface.



It must be made possible for the expert to express his knowledge in his natural language. However the expert will have to express with predefined keywords related to objects that can be extracted from G.I.S. and to knowledge description.

keywords relating to objects :

valley, versant, ridge, plateau ... (DTM)
road, villages, river ...
clay... (SOILS)

keywords for belonging (relational) characteristics :

far away, near, around ...
upper, bottom ... west, south ...

keywords for presence characteristics

and corresponding certainty factor CF

only (1.)	principally (0.8)	frequently (0.5)
present (0.)	uncommon (- 0.6)	never (- 1.)

.....

keywords for spatial characteristics (level 2)

remains, large surfaces, elongated surfaces ...

The purpose of the interface will be to catch the expert text, to look for keywords and their logical relations and to produce the corresponding production rules and to feedback the expert for corroboration.

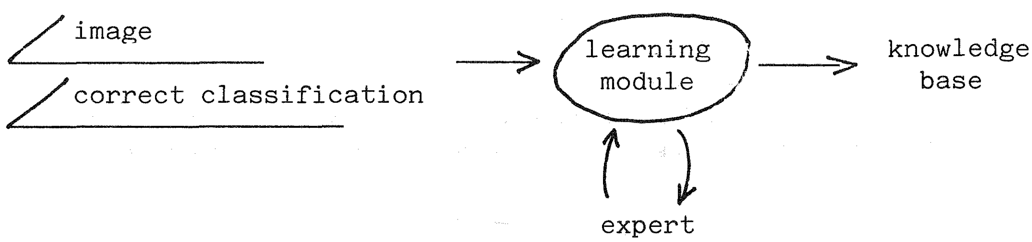
The presence characteristics induce the certainty factor of the corresponding production rule.

On the other hand, the belonging characteristics (NEAR roads, BOTTOM OF valleys, FAR AWAY FROM ...) induce certainty factors for the corresponding premises.

These latter factors can be computed for one pixel on request, or systematically for all pixels at the beginning of the process. This is done by special procedures oftently using fuzzy sets logic [DES 2].

We anticipate to conceave a learning module. Having images and the corresponding correct classifications, the module will extract knowledge in relation with possible objects and belonging, presence and spatial characteristics permitted.

The produced rules will be presented to the expert for confirmation.



3.3. Inference engine :

If the given problem is a classification one, the inference engine will be used in "forward tracking" in the following way :

For each fact of the facts data base (coordinates, certainty factors that it is belonging to each possible class, description of pixel context in terms of G.I.S. objects) all level 1 production rules will be activated since each pixel "belongs to" each possible class with different certainty factors.

(eventually a threshold on certainty factors may be used in order to omit the corresponding searched classes and restrict the number of selectable production rules for each pixel).

For each pixel and for each class we have the following process :

CF_i being the certainty factor that the pixel is belonging to class i, each production rule concerning classi, is applied in order to obtain a new CF.

$CF_i \longrightarrow$ production rules concerning class i $\longrightarrow$ new CF_i

3.4. Dealing with knowledge incertainty :

We saw that each pixel is considered as belonging to each class with a corresponding certainty factor. This factor has a range from -1. (certainty the pixel is not belonging to class) to 1. (certainty the pixel is belonging to class).

Moreover all production rules admit certainty factors for each possible conclusion (range -1. to 1.) which indicates the confidence in that conclusion.

The effect of activation of a production rule admitting certainty factors on conclusions, with uncertain premises will be to modify the corresponding fact (that is to modify the pixel class belonging certainty factors) for that aim we used MYCIN-like uncertainty management [FAR 3].

premises computing examples

if A (CF_A) or B (CF_B) .... $\quad CF_{A\text{ or }B} \longleftarrow \max(CF_A, CF_B)$

if A (CF_A) and B (CF_B) and C (CF_C) ... $\quad CF_{A\text{ and }B\text{ and }C} \longleftarrow \min(CF_A, CF_B, CF_C)$

rules computing examples

if A (CF_A) then class i ($CF_{RULE\ i}$)

let use suppose we have one pixel already belonging to class i with certainty $CF_{class\ i}$ then

$$CF_{class\ i} \longleftarrow \min(CF_{class\ i}, CF_A) * CF_{RULE\ i}$$

If more then one production rule can be activated for identical conclusions (on class i for example), the conclusion will be assigned a combined certainty factor computed by the following commutative and associative operations

ex : $\left\{ \begin{array}{l} \text{application of Rule 1 gives class i } (CF_{1i}) \\ \text{application of Rule 2 gives class i } (CF_{2i}) \end{array} \right.$

then the combined certainty factor CF_i will be :

$$CF_i \longleftarrow CF_{1i} + CF_{2i} - CF_{1i} * CF_{2i} \quad \text{if} \quad CF_{1i},\ CF_{2i} \geqslant 0$$

$$CF_i \longleftarrow CF_{1i} + CF_{2i} + CF_{1i} * CF_{2i} \quad \text{if} \quad CF_{1i},\ CF_{2i} < 0$$

$$CF_i \longleftarrow (CF_{1i} + CF_{2i}) / (1 - \min(|CF_{1i}|,\ |CF_{2i}|)) \quad \text{if} \quad CF_{1i} * CF_{2i} < 0 \quad \text{and} \quad |CF_{1i}| * |CF_{2i}| \neq 1$$

$$CF_i \longleftarrow 1 \quad \text{if} \quad CF_{1i} * CF_{2i} < 0 \quad \text{and} \quad |CF_{1i}| * |CF_{2i}| = 1$$

In a further approach for uncertainty management we plan to take into account the possibility theory to avoid the empiricism of such operations [GRA 7].

3.5. Problem solving context :

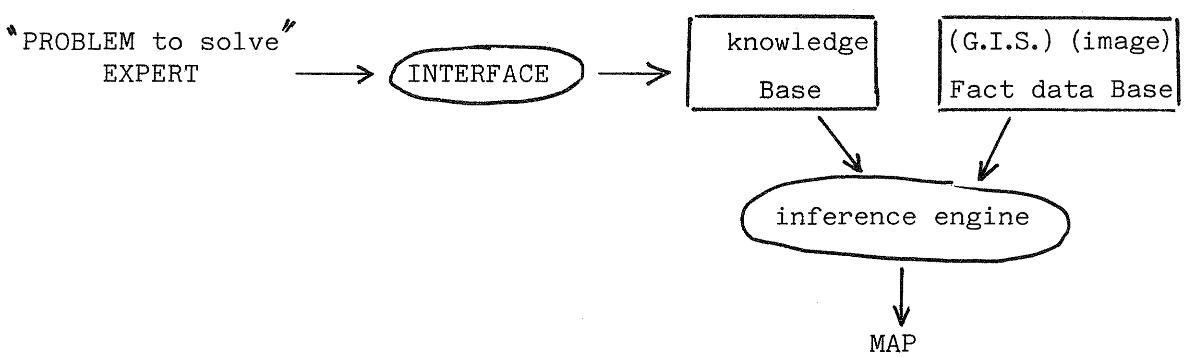
We previously presented our system in a classification, data driven context with the inference engine used in "forward tracking".

The same system can be used in a totally different objective which consists in :

Considering a goal (i.e. a "problem to solve"), connected with the type of informations our system is able to deal with, the geographical zones corresponding to the problem solution can be then determined. In order to do so, the inference engine is used in "back tracking" (in a goal driven context).

The fact data base is G.I.S. information, eventually connected with corresponding images.

The knowledge base will be considered as composed of the sole knowledge on the specific problem to solve



example of problem to solve : "Where to plant rice ?"

connected knowledge (imaginary ... we are not experts !)

"No rice at more then 1500 m of height"
"not too far from villages or roads", "sunny versants"
"no slopes at more than 40 % ...

When the corresponding knowledge base is built, the inference engine is started in "Backward tracking"

(if problem connected rules have premises involving spectral signatures of objects or other image linked characteristics ... then it is possible to use a regional image.

At end the system will produce a map. Each point of the map will be assigned a certainty factor related to its ability to solve the problem

A review of that type of approach can be found in [ROB 9].

4 - CONCLUSION

We propose an expert system able to solve two types of problems :

- classification, cartography problems where accuracy is improved by expert knowledge integration.
- particular problem solving with problem related knowledge integration.

We plan to improve our system in its classification cartography approach by homogenizing the processing techniques :

The preclassification would join the expert system itself ; production rules could be computed concentrating information we have on spectral signature of searched classes (as well as textural features), so the expert system could drive the whole processing.

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APPENDIX

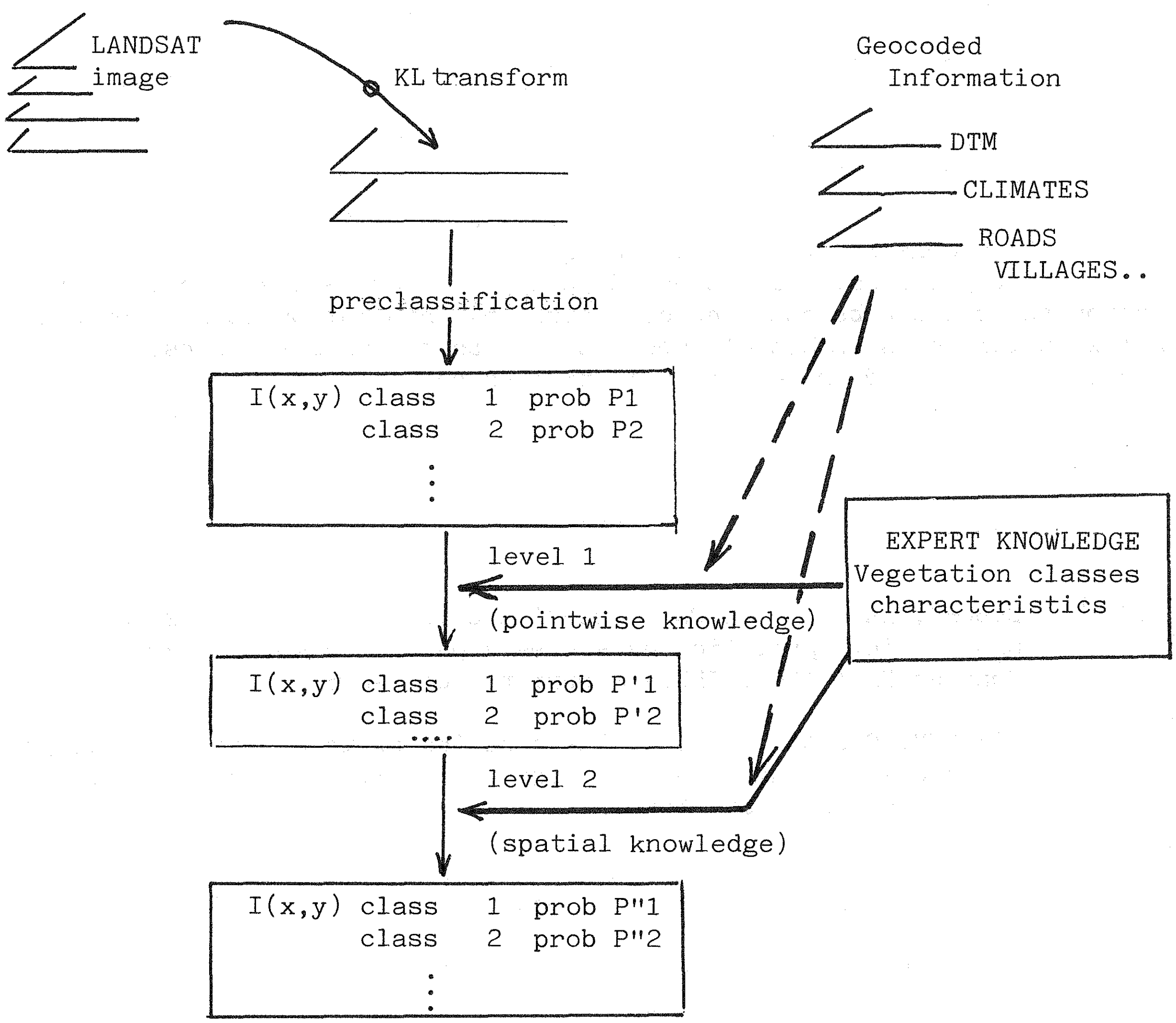

FIG 1 - Experimental classification procedure

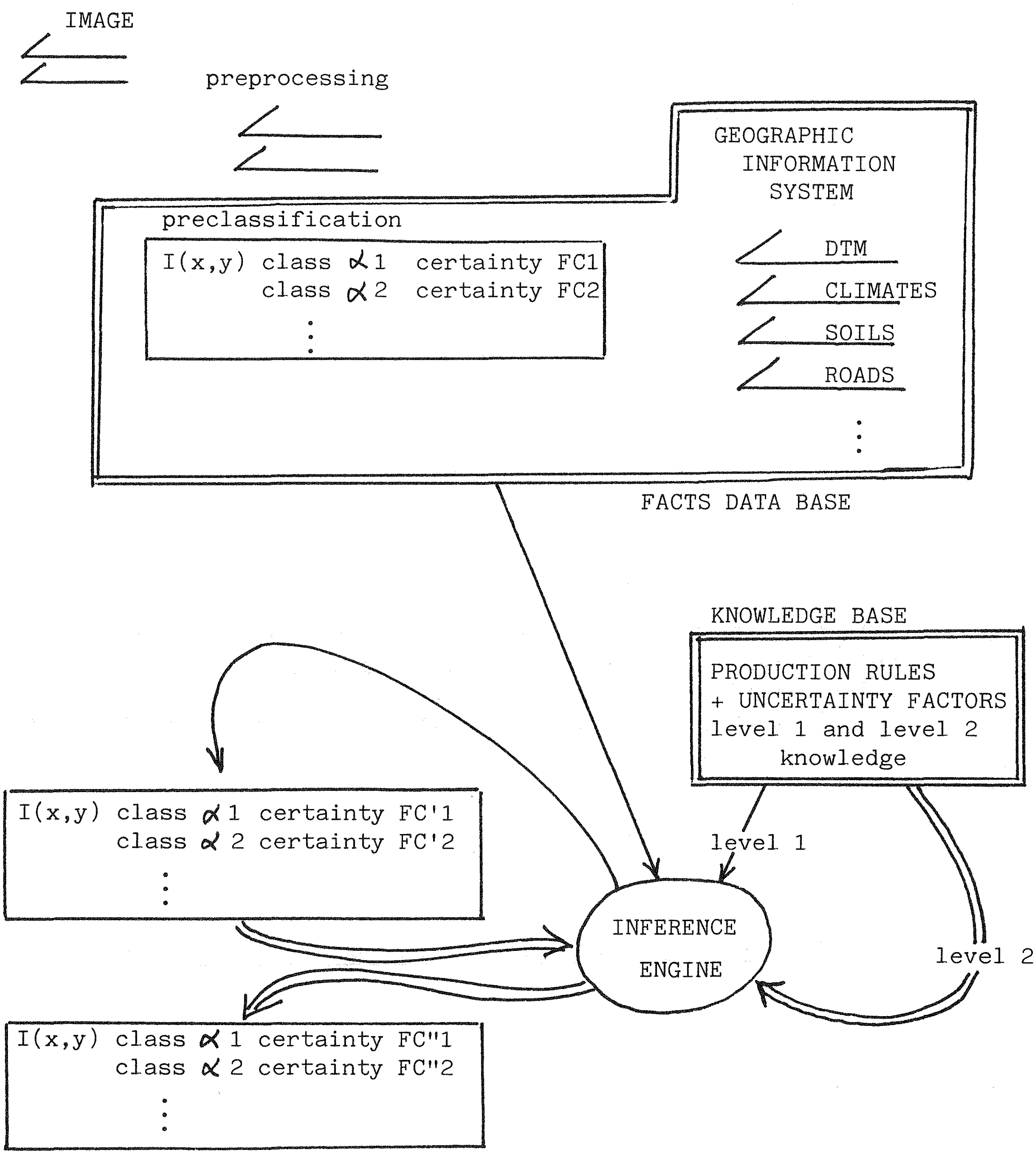

fig. 2 - General schema of the Expert System

class 1 : only (top of ridges or bottom of valleys) and remains
class 2 : only plateau
class 3 : only bottom of valleys and principally east and south versants
class 5 : only near villages
class 6 : only near villages
class 7 : highly predominating on the plateau
class 8 : principally valleys of north global versants
class 9 : only abrupt versants or upper versants
class 10, 11 : no characteristics
class 12 : frequent near villages and roads

class 13 : frequent on all versants
class 14 : principally south and south east versants

fig. 3 - Végetation characteristics for Palni hills (INDIA)

LEVEL 1 RULES

rule 1 : if top of combs then C1 (1.)
rule 2 : if bottom of valleys then C1 (1.)
rule 3 : if plateau then C2 (1.)
rule 4 : if bottom of valleys and (east versants or south versants) then C3 (0.8)
rule 5 : if bottom of valleys and non (east versants or south versants) then C3 (0.3)
rule 6 : if abrupt versants then C4 (1.)
rule 7 : if near villages then C5 (1.) or C6 (1.)
rule 8 : if plateau then C7 (0.9)
rule 9 : if valley and north global versant then C8 (0.8)
rule 10 : if abrupt versants or upper versants then C9 (1.)
rule 11 : if near village or near road then C2 (0.7)
rule 12 : if versant then C13 (0.7)
rule 13 : if south versant or south east versant then C14 (0.8)

LEVEL 2 RULES

rule 1 : if remains then C1 (1.)

fig. 4 - Knowledge base production rules for Palni Hills