

**Multisensor data fusion using fuzzy concepts : Application to
land-cover classification using ERS-1/JERS-1 SAR composites**

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Abstract

In this study, a fuzzy-based multisensor data fusion classifier is developed and applied to land cover classification using ERS-1/JERS-1 SAR composites. This classifier aims at the integration of multisensor and contextual information in a single and a homogeneous framework. Initial Fuzzy Membership Maps (FMM) to different thematic classes are first calculated using classes and sensors *a priori* knowledge. These FMM are then iteratively updated using spatial contextual information. A classification rule is associated to different iterations. This classifier has the following advantages: first, due to the use of fuzzy concepts, it has the flexibility of integrating multisensor/contextual and *a priori* information. Secondly, the classification results consist of thematic as well as confidence maps. The confidence map (a classification certainty map representing the degree of certainty in the thematic map) constitutes an important issue in order to evaluate the classification process complexity and the validity of the assumptions. The application of this classifier using ERS-1/JERS-1 SAR composites is shown to be promising.

Key words : Multisensor data fusion, fuzzy sets, classification, confidence maps

I. Introduction

Multisensor image interpretation is one of the most important tasks in the analysis of remotely sensed satellite imagery. Two approaches are generally used : the analyst's visual and the computer-based interpretation approaches.

The analyst's visual interpretation consists in using one specific sensor (visible, for example), or a color composite of three sensors, as a visual input to which the theoretical knowledge and expertise of the analyst are applied. This method suffers from subjectivity and speed. Nevertheless, it has the main advantage of being capable of using several knowledge sources simultaneously during the interpretation process.

Computer-based interpretation methods consider the reflected radiation, or emission, from different sensors as a numerical feature vector in the feature space. Thus, the multisensor image interpretation problem is considered as one of classification (or a pattern recognition). Mathematical models, generally based on a range of assumptions about the data, are then applied in discriminating land covers. The validity of the assumptions (due to the natural variability of the landscape) governs the success of computer-based methods.

Recall that the aim of the classification process is to assign each pixel from the analyzed scene to a particular class of interest, such as water, dry soil, wet soil, forest, etc. The image resulting from the labeling of individual pixels is henceforth referred to as a thematic (or class) map. Such maps have much potential for applications concerned with topographic mapping, agricultural production monitoring, or environmental protection. Since land use usually occurs in patches larger than the pixel footprint and since remotely sensed data is affected by noise (a multiplicative speckle noise in the case of radar data), it seems clear that information from neighboring pixels should increase the discrimination capabilities of the pixel-based measured data and, thus, improve the interpretation accuracy. This information is referred to as the spatial contextual information.

Methods integrating spatial contextual information in multisensor images classification have for a large part been of two main types according to their level of application:

1) Contextual input data fusion, where, spatial correlation between adjacent pixels in the feature space is used. Several methods have already been proposed: Szu [1], has proposed the concatenation of the features of neighboring pixels, to those of the pixel to be classified, before being fed into a neural network classifier. Rosenfeld [2], used probabilistic and fuzzy relaxation algorithms. Landgrebe [3] has proposed one of the most known pre-classification contextual level classifier, the Supervised Extraction and Classification of Homogeneous Objects (SECHO) classifier. This classifier starts first by dividing the analyzed scene into homogeneous "objects". These objects are identified based on an analyst-specified threshold, below which adjacent pixels are grouped together. Statistics for these homogeneous objects are computed, and then, compared to the statistics of the trained classes. Each object is then assigned into the class which it most closely resembles.

2) Contextual output decision fusion, where spatial correlation between adjacent pixels in the decision, or thematic, space is used. These methods are generally referred to as smoothing methods. They consist in modifying the label of each individual pixel on the basis of its immediate neighborhood labels. The simplest method is the logical smoothing algorithm [4], which consists in assigning to each pixel the label of its 8 neighbors if all of them are similarly labeled. A slight modification of this method is the majority filter [5] assigning every pixel to the majority class within a window surrounding the pixel.

One common limitation of these two contextual information fusion approaches is due to the fact that no interaction (or feedback) exists between input features and classification results. In fact, the first approach concentrates all the efforts on processing multisensor data

before its injection into the classification process. On the other hand, the second approach concentrates its efforts on the improvement of thematic results.

In this study, we propose a fuzzy based classifier introducing a "conceptual" level between the information issued from the multisensor data and the decision level : it is the thematic class membership level. Multisensor data, on a pixel-based level, is first "transformed" into membership values to different thematic classes. This space transformation allows the application of fuzzy combination rules in order to summarize, for each observed pixel and each considered class, the multisensor data in a single membership value. This value reflects the "global" degree of belief that the observed pixel belongs to the considered class.

An iterative class membership values updating process using contextual information is then conducted. The decision making is only realized when the expert's predefined decision conditions are satisfied. This information processing organization is similar to the expert's decision making reasoning. On a pixel-based level, only few "individual" pixels can be labeled by the expert. Remaining unlabelled pixels are classified based on the information available from their local contextual information or even, similarly to the SECHO classifier proposed by Landgrebe [3], based on the region to which they belong. In some sense, the proposed classifier realizes a graduate classification process starting from individual pixels level and ending at the region based classification level.

The next section gives a brief introduction to fuzzy concepts and to the development of the proposed classifier. Section III, explores the application of the proposed classifier using ERS-1/JERS-1 SAR composites. Conclusions and further comments are given in section IV.

II. Multisensor fuzzy classifier design

As previously mentioned, the expert decision making process is based on the coupled use of multisensor and contextual knowledge information sources. In this study, we propose a fuzzy classifier which is strongly inspired by expert reasoning approach. An important issue is also addressed through this classifier. It concerns the fact that the classification results (given as a thematic map) lack additional information related to the degree of certainty, and/or complexity, associated with each thematic decision. The fuzzy set theory pioneered by L. Zadeh [6] provides us with a powerful mathematical tool for modeling the human ability to reach conclusions when the information available is imprecise, incomplete, and not totally reliable. In conventional crisp set theory, one element either belongs to a set or it does not. The major characteristic that distinguishes fuzzy set theory from traditional crisp set theory is

that it allows intermediate grades of membership. Let Ω denote the universal set. A fuzzy set A over Ω is defined as the set of ordered pairs

$$A = \{ (X, \mu_A(X)), X \in \Omega \}, \quad (1)$$

where $\mu_A(X) (\in [0,1])$ is termed the grade of membership, or simply the membership function, of the element X to the fuzzy set A . It is important to notice that all elements X in Ω belong to A with different grades of membership.

In a multisensor classification problem, a pattern X is described as a vector in an N -dimensional space, $X=[x_1, x_2, \dots, x_N]$, $x_n \in \Omega_n$, $n = 1, 2, \dots, N$, where Ω_n denotes the n^{th} sensor data observation space (i.e; the source universe), and N the number of sensors. Using this formulation, the universal set Ω is the Cartesian product $\Omega_1 \times \Omega_2 \times \dots \times \Omega_N$ representing the multisensor observation space. If $\mathcal{C} = \{C_1, C_2, \dots, C_M\}$ is the set of " M " predefined classes, then, each class C_m is defined as a fuzzy set over Ω . Thus, $\mu_{C_m}(X)$ conveys information on the degree to which the pattern $X \in \Omega$ may be treated as belonging to the class C_m .

Fuzzy concepts application to multisensor data classification can be decomposed into the three following steps :

a) Fuzzification in source universe

This step aims at the determination of the membership value of each pattern X over the n^{th} source universe (Ω_n) to different classes: $\mu_{C_m,n}(X)$, $m=1, \dots, M$, $n=1, \dots, N$. These membership functions, $\mu_{C_m,n}(\cdot)$, will be referred to as the *Source Related (SR) membership functions*.

b) Fuzzy reasoning

The fuzzification in the source universes operates on the different sources of data "separately" in order to obtain the SR membership functions $\mu_{C_m,n}(X)$. Based on these SR membership functions, the fuzzy reasoning step aims at using the expert's as well as *a priori* knowledge in order to compute the membership functions $\mu_{C_m}(X)$, $m = 1, \dots, M$, of the pattern X to different classes :

$$\mu_{C_m}(X) = \mathcal{F} (\mu_{C_m',n}(X)) , n = 1, \dots, N; m' = 1, \dots, M; \quad (2)$$

where $\mathcal{F} (\cdot)$ denotes a fuzzy combination operator. A first simplification to (2), generally used in fuzzy multisensor classification, is to consider the SR membership functions concerning the same class of interest (i.e; $m'=m$). Equation (2) is thus reduced to :

$$\mu_{C_m}(X) = \mathcal{F}(\mu_{C_m,n}(X)), n = 1, \dots, N; \quad (3)$$

This equation means that $\mu_{C_m}(X)$ is computed as a function of the SR membership functions for the same class C_m . The wide range of combination operators proposed in fuzzy set literature (see, for instance, [7-8]) reflects the powerful as well as the flexibility of the use of fuzzy concepts. In this study, the simple fuzzy intersection operator (i.e; a "conjunctive-type" combination operator [7]) is used:

$$\mu_{C_m}(X) = \text{Min}_{n = 1, \dots, N}(\mu_{C_m,n}(X)) \quad (4)$$

Notice that this operator considers the N sensors as "equivalently" informative about the considered class C_m . A null membership degree for a given sensor (for instance $\mu_{C_m,n_0}(X)=0$) produces a null global membership degree (i.e; $\mu_{C_m}(X) = 0$) regardless of the importance of sensor n_0 in characterizing the class C_m .

c) Defuzzification and Decision making

The defuzzification step aims at obtaining a 'hard' membership decision by attributing the pattern X to only one of the predefined classes. Similarly to the maximum likelihood decision approach, the defuzzification step uses, generally, the *maximum membership decision rule*: X is labeled as belonging to C_{m_0} if and only if ,

$$\mu_{C_{m_0}}(X) = \text{Max}_{m = 1, \dots, M} \{ \mu_{C_m}(X) \} \quad (5)$$

In this study, the following assumptions are made for the development of the proposed fuzzy classifier :

- 1- The observed scene contains M thematic classes denoted as $C_1, \dots, C_m, \dots, C_M$.
- 2- Each pixel in the observed scene is characterized by a feature vector :
 $X=[x_1, \dots, x_n, \dots, x_N]$, $x_n \in \Omega_n$, $n = 1, 2, \dots, N$, where x_n is the observed, measured or computed data from the n^{th} sensor at the pixel's location, Ω_n denotes the n^{th} sensor data observation space and N the number of sensors.
- 3- Each thematic class C_m , $m = 1, \dots, M$, is "described" by a learning set B_m of samples extracted, by the expert, from the analyzed scene.

Notice that these assumptions are simple and very general in terms of their applicability to most remotely sensed data classification situations. In fact, no particular knowledge is needed concerning the relative relationship between different sensors neither potential correlation between each sensor and each thematic class. The architecture of the proposed classifier is

illustrated on figure 1. This classifier is composed of three systems: 1) a fuzzy membership determination, 2) a contextual processing, and, 3) a decision systems.

The fuzzy membership determination system aims at realizing the multisensor data fusion by computing the membership values, $\mu_{C_m}(\cdot)$, of different pixels to the M predefined thematic classes. The contextual processing system is devoted to the use of the contextual information in order to compute a contextual-based membership values, denoted $\eta_{C_m}(\cdot)$. Finally, the decision system is in charge of making classification decisions, when possible, based of the contextual membership values. In the case where a decision is made, this information is back-propagated in order to update the initial fuzzy membership values. In the following sub-sections, these systems are described in detail.

II. 1 Fuzzy membership data fusion

The fuzzy membership determination constitutes the only processing step at the pixel level. It aims at assigning, to each pixel of the observed scene, membership values to the M predefined thematic classes. This determination process can be intuitive (i.e.; empirical representing the expert's knowledge) or it can be based on some algorithmic, probabilistic or logical operations. In this study, this process is conducted based on the use of probability density functions, p.d.f.

Consider a thematic class C_m and let $p_{C_m}(x_n)$ denotes its p.d.f defined over the set Ω_n , the observation space associated with the n^{th} sensor. Dubois and Prade [9] have proposed to compute the membership function $\mu_{C_m}(x_n)$ from this p.d.f by :

$$\mu_{C_m,n}(X) = \sum_{x_n' \in \Omega_n} \min(p_{C_m}(x_n), p_{C_m}(x_n')) \quad (6)$$

The probability density functions are computed using the histograms estimated from the learning set B_m . Therefore, a pixel observed through different sensors, in terms of a feature vector $[x_1, \dots, x_n, \dots, x_N]$, is expressed in terms of a $M \times N$ membership matrix

$$\mu(X) = \{\mu_{C_m,n}(X)\}, m = 1, \dots, M; n = 1, \dots, N. \quad (7)$$

The m^{th} line of this matrix contains the membership values of the observed pixel to the class C_m through different sensors. On the other hand, the n^{th} column represents the membership values of the feature vector issued from the n^{th} sensor (x_n) to different classes.

In the framework of fuzzy set theory, multisensor information fusion aims at "combining" the membership values of this matrix in order to obtain a single membership value $\mu_{C_m}(\cdot)$ of

the observed pixel to the class C_m . This value is assumed to summarize all the knowledge concerning the observed pixel, in terms of its grade of membership to the class C_m .

Combining (or aggregation) operators are generally of three main categories [7]-[10] : 1) Conjunctive-type operators (searching for the most reliable information among the set of agreeing sensors, 2) Disjunctive-type operators (trying to find reliable information among a set of disagreeing sensors), and, 3) Trade-off -type operators (assumed to deal with partially agreeing and partially disagreeing sensors). In this study, the fuzzy intersection operator (i.e; a "conjunctive-type" combination operator [7]) is used, eq.4. This operator assumes that different sensors to be merged are reliable, meaning that they should be agreeing. There is no doubt that this is the simplest combining operator in the sense that it is sensor and class independent. Nevertheless, in case of conflicting sensors or an unreliable sensor, the membership value obtained through this operator is worthless. It is important to notice that specific knowledge related to different sensors and to their thematic classes discrimination capacities can be introduced through the use of more sophisticated aggregation operators.

II. 2 Contextual membership data fusion

The aim of the contextual processing system is to integrate the spatial correlation between adjacent pixels in order to improve the classification results. When analyzing the expert's decision making reasoning process, we notice that if a pixel-based multisensor data decision is difficult to make, then, the expert's decision is based on the "homogeneous region" surrounding the considered pixel. This region-based classification approach has been successfully proposed by Landgrebe [3] (the SECHO classifier). An important difficulty when applying this approach concerns the application of a robust preprocessing segmentation step in order to obtain homogeneous regions (i.e; objects [3]). This task is particularly difficult when dealing with data affected by speckle noise (radar images, for instance).

In this study, the proposed classifier introduces an intermediate contextual level : a restricted spatial neighborhood of each pixel. This local neighborhood is exploited in order to "update" the membership values to different thematic classes, see figure 2. This restricted neighborhood contextual membership values updating is iteratively repeated in order to "propagate" (or to diffuse) the validated decisions to their surrounding regions. In fact, the input to this processing system is a set of M fuzzy membership maps $\mu_m = \{ \mu_{C_m}^t(P) \}$,

where "t" denote the processing iteration number (initially equals to zero), and, $\mu_{C_m}^t(P)$ the membership value of the observed pixel P in the analyzed scene to the class C_m , $m=1, \dots, M$.

The pixel's P_0 restricted neighborhood considered in this study is a 3x3 window centered on P_0 . Only the membership values, in the restricted neighborhood, to one class of interest are considered in order to update the membership values (i.e; cross membership values are not considered). The contextual data fusion algorithm used in this study is as follows:

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for ( m = 1, ..., M) do                                // a loop over all the considered classes
    if ( $\mu_{C_m}^t(P_0) = 0$ ) Then  $\eta_{C_m}^t(P_0) = 0$ ;
    if ( $\mu_{C_m}^t(P_0) \neq 0$ ) Then  $\eta_{C_m}^t(P_0) = \frac{1}{9} \sum_{j=0}^8 \mu_{C_m}^t(P_j)$ ;
End for;

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The contextual membership determination process for each class C_m ($m=1, \dots, M$) affects pixels for which $\mu_{C_m}^t(P_0) \neq 0$, meaning that P_0 possibly belongs to the thematic class. In this case, the contextual membership value is computed using the multisensor membership assignments, to the same class, in the restricted neighborhood of this pixel. The mean value of the membership degree is used here. Notice that this contextual process does not use any particular knowledge concerning existing structures in the analyzed scene. Thus, linear structures (roads, ..) will not be necessarily preserved as will be shown in simulation results.

II. 3 Decision and confidence map computing

The decision making system aims at attributing, based on the contextual membership values, of a classification decision label for each pixel in the analyzed scene. A decision rule is applied in order to determine whether a decision can be justified, and thus made, or not. Based on the initial fuzzy membership values (i.e. $t = 0$; and $\eta_{C_m}^t(P) = \mu_{C_m}^t(P)$, for all the pixels P), the decision making rule attributing the pixel P_0 to the class m_0 is as follows :

$$\begin{aligned}
 & \text{if} ((\eta_{C_{m_0}}^t(P_0) \approx 1) \text{.AND.} (\eta_{C_m}^t(P_0) \approx 0 \ \forall m \neq m_0)) \\
 & \qquad \qquad \qquad \text{Then} \quad (\text{decide class } m_0) \qquad \qquad \qquad (8)
 \end{aligned}$$

This rule means that if the pixel-based membership degree to a given class m_0 is the highest (unity) and is null to all the other classes, then, a decision can be made. Such a decision is associated with the highest certainty value (unity).

If $t > 0$ (contextual membership values are used), the decision making rule is given by :

$$if ((\eta_{C_{m_0}}^t(P_0) \geq 0.5) .AND. (\eta_{C_m}^t(P_0) < 0.5 \forall m \neq m_0))$$

$$Then \text{ (decide class } m_0) \quad (9)$$

The reason for which this decision rule is less "severe" than the pixel-based rule is that the contextual membership values at the iteration "t" are obtained by averaging those of the iteration "t-1" over the restricted pixel's neighborhood. Therefore, the existence of pixels belonging to other classes in this neighborhood will not « disturb » significantly the decision making process. Recall that an important issue of the proposed approach is to establish a confidence map (a classification certainty map representing the degree of certainty in the thematic map). Several approaches can be used in defining such a certainty factor.

In this study, the Certainty Factor (CF) concept is associated with the degree of “complexity” encountered while labeling each considered pixel. The method proposed in evaluating this complexity is considered as related to the iteration number through which a pixel is labeled. Therefore, the maximum certainty factor (i.e. CF=1) will be attributed to pixels labeled on the pixel-based multisensor information. Let “K” denote the last contextual labeling iteration number, then, the certainty factor can be estimated using a decreasing function of the iteration "t". For instance, in this study a simple linear function (CF(t=0)=1 and CF(t=K)=0) is considered, figure 3.

Finally, the global contextual fusion and decision making algorithm is illustrated on figure 4. In order to « control » this knowledge revision procedure, a logical condition permitting to decide when to stop the revision iterations is integrated. The stopping condition used in this algorithm corresponds to the expert’s reasoning approach in a similar situation. In fact, if the number of newly labeled pixels through the current iteration is “judged” by the expert as “non significant” compared to the total number of pixels in the analyzed scene, then, the expert will consider that further iterations will not improve the obtained results. Notice that when a pixel P_0 is labeled as belonging to the class m_0 , then, this decision is "diffused" to its surrounding pixels by setting the membership value of P_0 to the class m_0 to unity ($\mu_{C_{m_0}}^t(P_0) = 1$) and,

its membership value to other classes as equal to zero ($\mu_{C_m}^t(P_0) = 0, \forall m \neq m_0$). As a result of the application of this algorithm, thematic as well as confidence maps are obtained.

III. Simulation results

In this section, the proposed classifier is applied to land-cover classification using ERS-1/JERS-1 SAR composites of the Raco test site (northern Michigan), figure 5.

The European ERS-1 SAR has been in orbit since July 1991. Since launch it has imaged most of the continental land masses at least once. The Japanese JERS-1 has been operating since April 1992 and operates at a longer wavelength than the ERS-1 SAR. Taken alone, either instrument has demonstrated deficiencies for classification of land-cover. When used together, the two instruments are found to be very potent tools for this purpose [11]. The main reason for this is that the difference in wavelength of the two SARs yields spectral information that can be exploited to differentiate structural properties of surfaces and vegetation covers [12].

The ERS-1 SAR operates at C-band (5.3 GHz, 5.656 cm), *vv*-polarization and with a 23° look angle at boresight. The JERS-1 SAR operates at L-band (1.25 GHz, 23.5 cm), *hh*-polarization and with a 35° look angle at boresight.

In this study, the ERS-1 SAR image was acquired August 12, 1991, and the corresponding JERS-1 SAR image was acquired August 7, 1992. Each image was orthorectified using ground control points that were manually determined. During orthorectification the calibration was applied, if not already, and the correction due to the actual area on the ground was applied. The data came as 3-look for ERS-1 and 6-look for JERS-1 and this was not changed : no despeckling or averaging was performed on the data.

A power ratio channel was then calculated pixel-by-pixel by subtracting the C-band data from the L-band data. Hence, three separate channels are used by the proposed classifier as input sensor features.

Each pixel pattern is characterized using the feature vector $X = [x_1, x_2, x_3]$, where, x_1 : is the ERS-1 C-band data (C-*vv* : σ_C^0), x_2 : is the JERS-1 L-band data (L-*hh* : σ_L^0) and x_3 : is the spectral gradient data (L-*hh*/C-*vv* : $\sigma_L^0 - \sigma_C^0$).

The analyzed region contains numerous lakes, scattered grass-lands, marsh, agricultural areas, and is dominated by forests : northern hardwoods, aspen, upland conifers, and lowland

conifers. In this study, five land-cover thematic classes are distinguished: C_1 : Flat Surfaces (non-vegetated), C_2 : Short Vegetation, and three structural tall vegetation classes chosen for the Raco test site, C_3 : Excurrent Upland Conifer, C_4 : Decurrent Broadleaf and C_5 : Excurrent Low land Conifer. Each class C_m , $m = 1, \dots, 5$, is characterized by a set of independent training (B_m , $m=1, \dots, 5$) and testing (T_m , $m = 1, \dots, 5$) populations of 1000 pixels each. The location of these populations, depicted in figure 5, is manually selected by an expert.

The first step in the application of the proposed classifier consists in the determination of the fuzzy membership functions, figure 6, using the training sets B_m , $m = 1, \dots, 5$, and, the multisensor membership data fusion approach. The use of a histogram-based membership functions determination (i.e ; a statistical-based approach), detailed in section II.1, is mainly used in order to satisfy the basic assumption of not using any particular knowledge. In the case where the expert's knowledge (even empirical) is available, then, classical fuzzy membership determination methods can be used. Pixel-based classification results, using the membership functions, is given on figure 7. Notice that less than 10 % of the pixels in the analyzed scene are successfully labeled when using the decision rule (8). The Flat surfaces and the Short Vegetation classes are completely absent from this classification. This clearly confirms the discrimination complexity of these two thematic classes when the classification rule is based only on the pixel-level information.

The second step in the application of the proposed fuzzy classifier consists on the iterative application of the contextual membership data fusion discussed in section II.2. The logical condition used in order to stop the updating iteration is based on the percentage of newly labeled pixels. In this study, this condition is simply to have less than 0.1% of new pixels labeling. The newly labeled pixels percentage is given on figure 8.

Thirty five iterations were necessary in order to satisfy this empirical stopping condition. Notice that most of the pixels are mainly labeled through the first ten iterations. Several intermediate thematic maps are given on figure 9 as a function of the fuzzy contextual membership functions updating iteration. Starting the first contextual iteration, thematic classes Flat Surfaces and Short Vegetation appear. This indicates the great importance of the use of contextual information when classifying radar images. Notice also that the famous « salt and pepper » noise is highly reduced through the ongoing contextual iterations. Nevertheless, an important drawback of the proposed classifier is that the linear structures (roads, ...) are not preserved. This is mainly due to the use of a 3x3 rectangular window centered on each pixel (as a restricted neighborhood) in computing the contextual membership

functions. This particular problem can be resolved by considering an adaptive restricted neighborhood. For instance, Nagao [13] and Solaiman [14] have proposed the use of nine cliques (four diagonal, two vertical, two horizontal and one centered cliques) surrounding each pixel. The form of these cliques is determined in such a way that, if the pixel considered is adjacent to an edge pixel, then at least one of the cliques covers a small-size homogeneous region containing the pixel.

On the other hand, homogeneous regions are obtained and refined through the successive iterations. The fuzzy membership functions revision based on contextual information, can thus be considered as an efficient mean for the knowledge « *diffusion* » in order to obtain the final thematic map. The final thematic as well as the confidence maps are given on figure 10.

Notice that pixels corresponding to region boundaries, even when labeled, assume low certainty values, see figure 10-b. Similarly to the case of linear structures, this is due to the main drawback of using a 3x3 rectangular window centered on each in computing the contextual membership functions.

Homogeneous regions that remain as unlabeled can be simply labeled using the classical maximum membership approach. Nevertheless, we have kept these regions as unlabeled in order to indicate that, based on the available evidences (training data bases, the predefined thematic classes, ..), a particular attention should be paid by the experts when dealing with these regions. In fact, these regions may contain a kind of mixture of the predefined classes, while in this case the use of the maximum membership classification rule can be justified, or, that these regions may contain other thematic classes that are not considered by the experts while the available evidences are defined. Figure 11 shows several of these regions, where, some of them are clearly composed of mixtures of the predefined classes (region A), while others mainly contain « pure » thematic classes that are not considered through these simulations (regions B and C).

Finally, the training and the test areas (depicted on figure 5) are used in order to analyze the classification accuracy of the proposed classifier. Obtained results are summarized in Table I, where unlabeled pixels from the training (B_m , $m = 1, \dots, 5$) and the test (T_m , $m = 1, \dots, 5$) sets are not attributed to any of the five initial classes. From Table I, it is clearly seen that discriminating the flat surfaces and the short vegetation classes remains a difficult task even when using the multisensor and the spatial contextual information. On the other hand, if these two classes are grouped into a single class, and by attributing a label to unlabeled pixels for which, and after this classes grouping, there is no classification "confusion", then, the

classification accuracy for the newly formed class is close to 99%. Concerning the three remaining classes (i.e; decurrent broadleaf, excurrent upland conifer and excurrent lowland conifer) the classification accuracy (over 90% for all the training and the test areas) is of great interest and shows the promising capacity of the proposed classifier in combining multisensor and contextual information.

IV. Conclusions and further comments

In this study, a fuzzy-based multisensor data fusion classifier is developed and applied to land cover classification using ERS-1/JERS-1 SAR composites. This classifier aims at the integration of multisensor, contextual and *a priori* information in a single and a homogeneous framework. Multisensor data fusion is realized by means of computing fuzzy membership functions to different classes. Contextual information fusion is conducted through an iterative contextual-based membership functions updating. Three main advantages of the proposed classifier are to be stressed :

- a) the *a priori* knowledge assumptions used by the classifier are restricted to the knowledge of a set of predefined classes and a learning base associated with each class. These assumptions are simple and very general in terms of their applicability to most remotely sensed data classification situations. No particular assumptions are used concerning the correlation between different sensors and the predefined classes. Nevertheless, if such information is available, it can be easily integrated to the proposed classifier by using the appropriate combination rule in order to obtain the pixel-based fuzzy membership functions.
- b) the knowledge diffusion through the contextual membership functions updating seems to be very promising in terms of scene segmentation into homogeneous regions. It is clearly shown that the selection of a 3x3 window surrounding each pixel is an efficient support for this knowledge diffusion. The main drawback of this approach concerns the linear structures «destruction». They can be avoided by using adaptive restricted neighborhood support.
- c) classification results given as thematic as well as confidence maps are of great interest for the expert. In fact, on a pixel level, each classification decision is associated with a degree of confidence representing the complexity encountered by the classifier. On a region level, this type of information permits the expert's attention focusing on unreliable regions. This information is particularly interesting in temporal change analysis.

Finally, actual studied are conducted in order to integrate other « sources of knowledge » like symbolic information concerning the analyzed scene.

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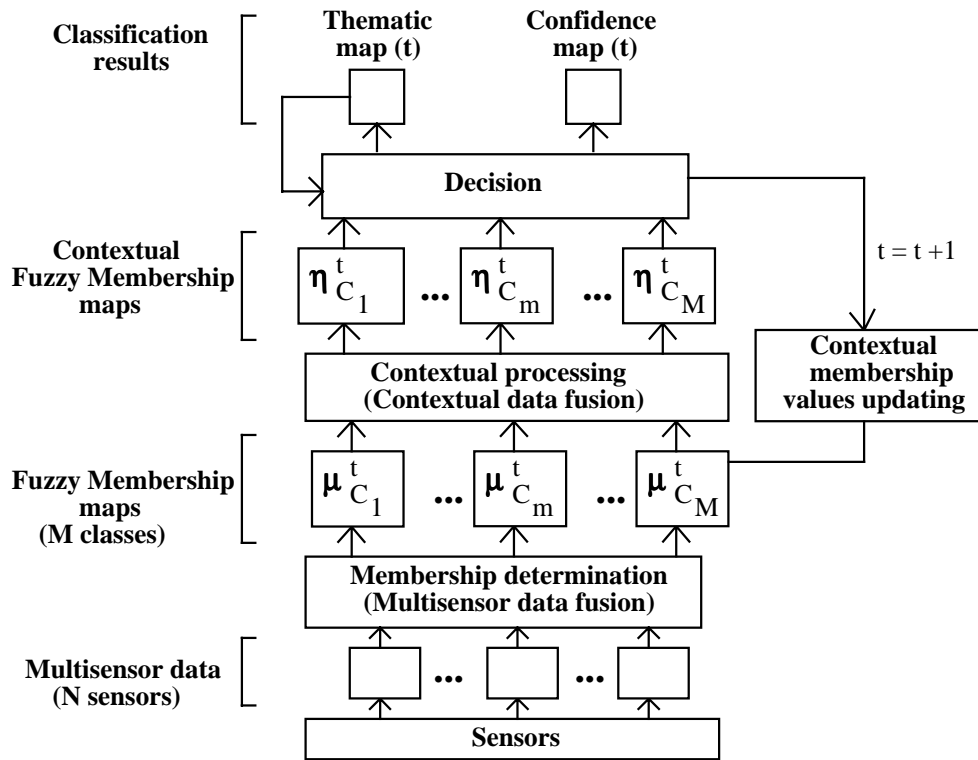


Figure 1, Fuzzy classifier integrating multisensor and contextual information sources

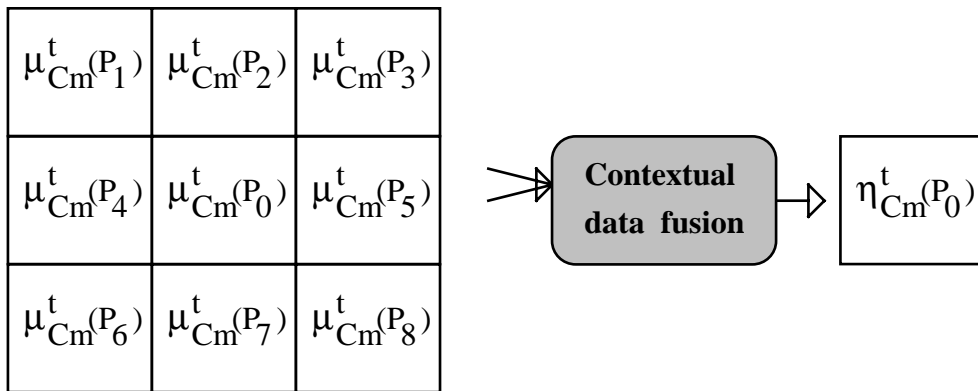


Figure 2, Contextual membership data fusion based on the use of a restricted pixel neighborhood

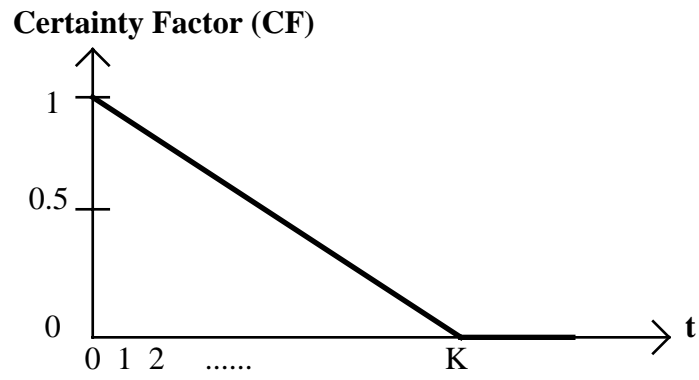


Figure 3, Decision certainty factor as a function of the labeling iteration number

```

// initializing the decision process
t ← 0;
Stopping Condition ← False;
//iterative decision and decision confidence computing
While (Stopping Condition ≡ False) do
  for every (Pixel P0 in the scene ) do
    if (t=0) do
      //Decision & membership updating
      if ( (  $\eta_{C_{m0}}^t(P_0) \approx 1$  ) . AND . (  $\eta_{C_m}^t(P_0) \approx 0$  for all  $m \neq m_0$  ) ) do
         $\mu_{C_{m0}}^{t+1}(P_0) \leftarrow 1$ ;
         $\mu_{C_m}^{t+1}(P_0) \leftarrow 0$ , for all  $m \neq m_0$ ;
        Thematic decision ← m0;
        Decision Confidence (P0) ← 1;
      End if ;
    Else Thematic decision ← Null;
  End if;
  if (t≠0) do
    //Decision & membership updating
    if ( (  $\eta_{C_{m0}}^t(P_0) \geq 0.5$  ) . AND . (  $\eta_{C_m}^t(P_0) < 0.5$  for all  $m \neq m_0$  ) ) do
       $\mu_{C_{m0}}^{t+1}(P_0) \leftarrow 1$ ;
       $\mu_{C_m}^{t+1}(P_0) \leftarrow 0$ , for all  $m \neq m_0$ ;
      Thematic decision ← m0;
      Decision Confidence (P0) ← CF(t);
    End if;
  Else Thematic decision ← Null,
End if;
End for;
t ← t + 1;
Stopping Condition evaluation
End while;

```

Figure 4, Contextual fusion and decision making algorithm

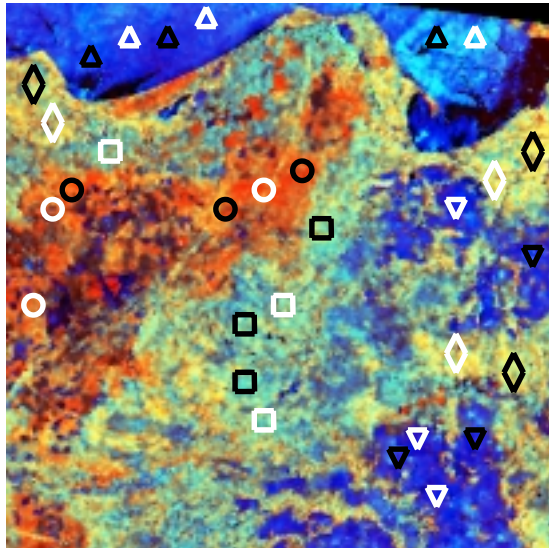


Figure 5 : False color composite of the Raco test site in northern Michigan annotated with positions of training (white symbols) and testing (black symbols) areas used by the proposed classifier : flat surfaces (\blacktriangle), short vegetation (\blacktriangledown), decurrent broadleaf (\blacksquare), excurrent upland conifer (\bigcirc) and excurrent lowland conifer (\blacklozenge).

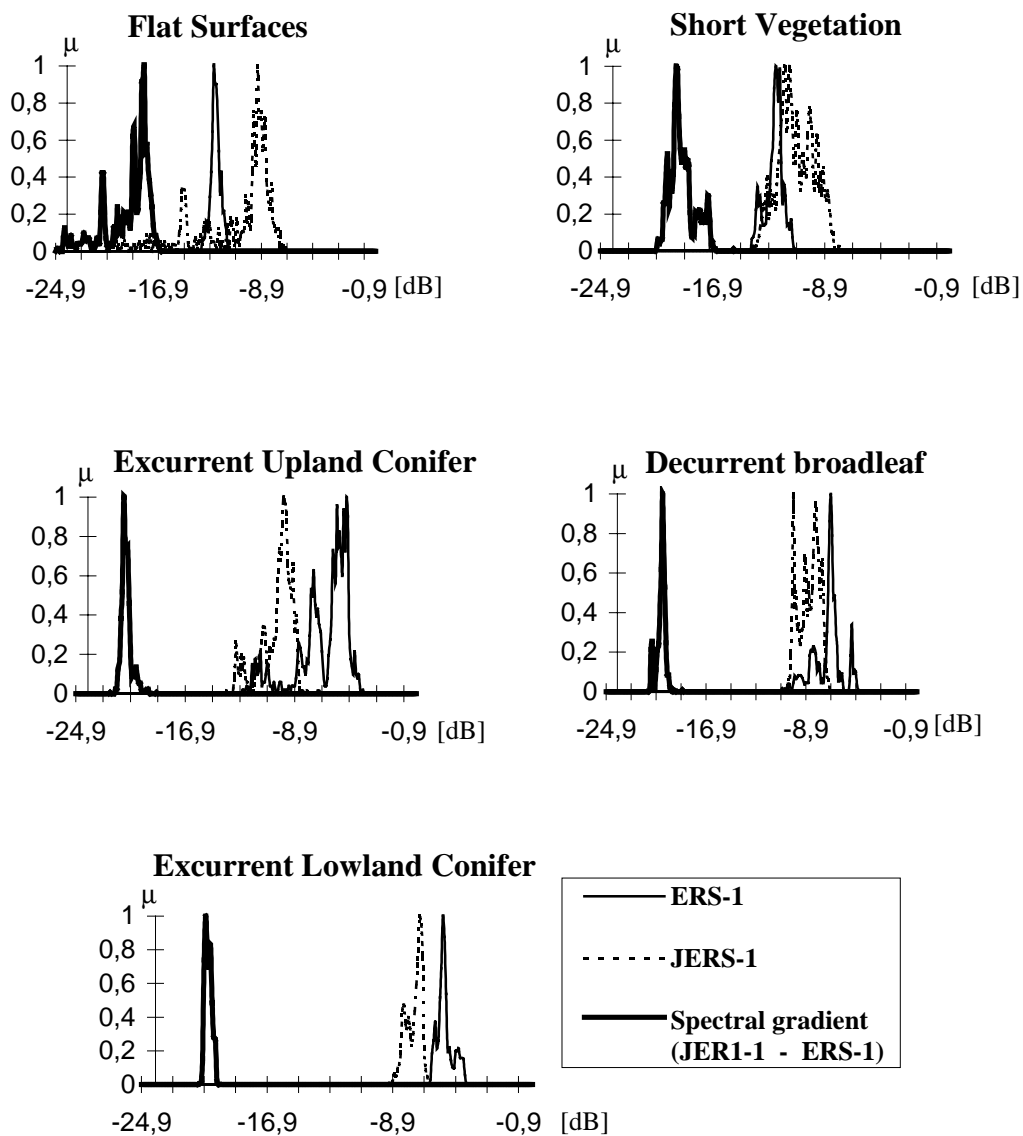


Figure 6, Fuzzy membership functions of backscattering values, expressed in dB, for the five land-cover thematic classes

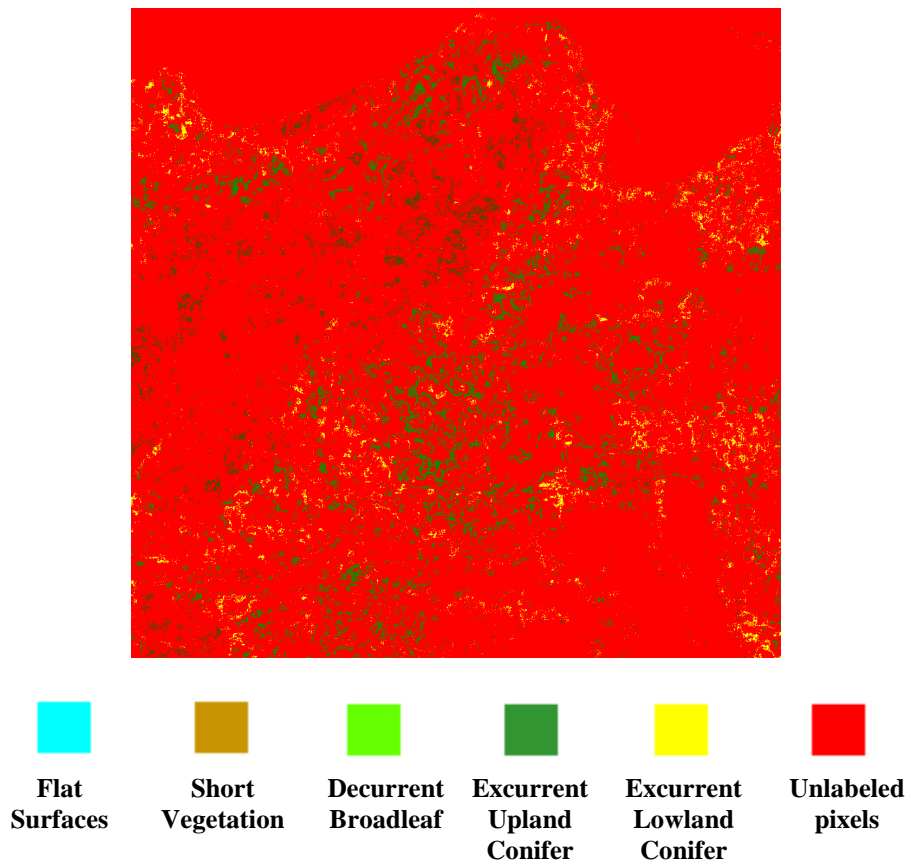


Figure 7, Thematic map using initial membership functions and the pixel-based decision rule (eq. 8)

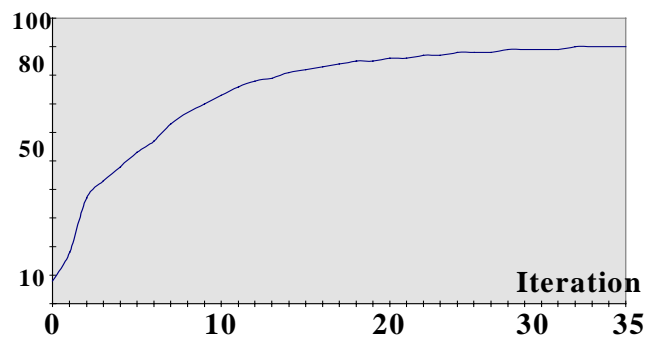


Figure 8, Percentage of newly labeled pixels as a function of the contextual membership functions updating iteration

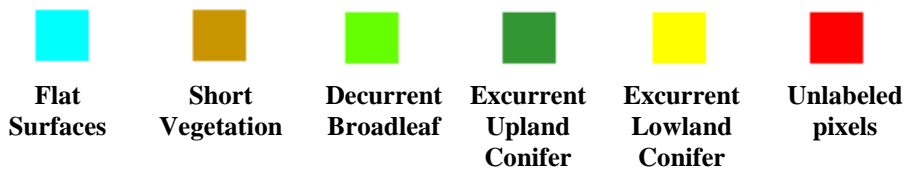
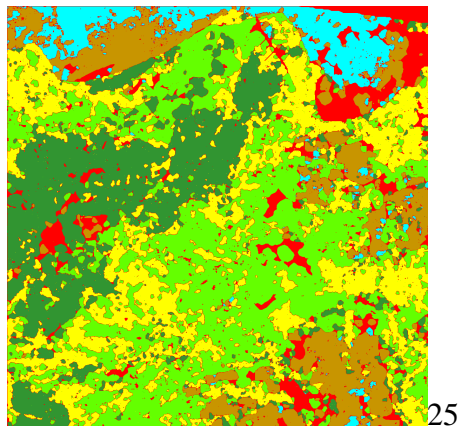
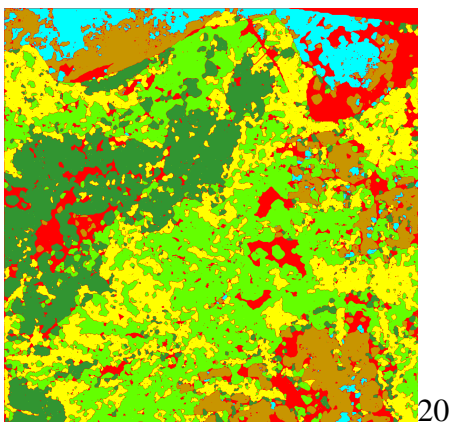
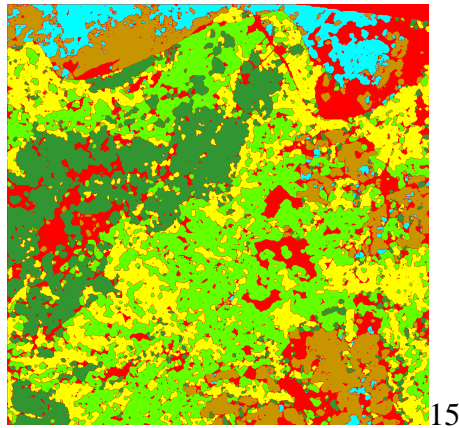
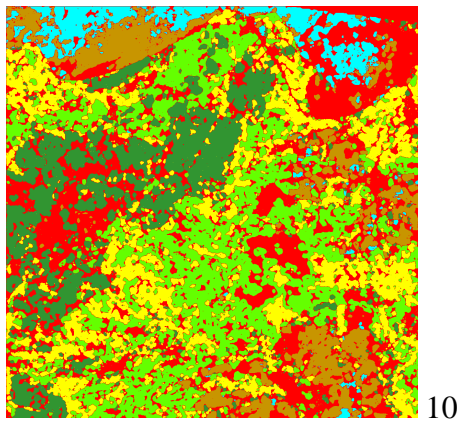
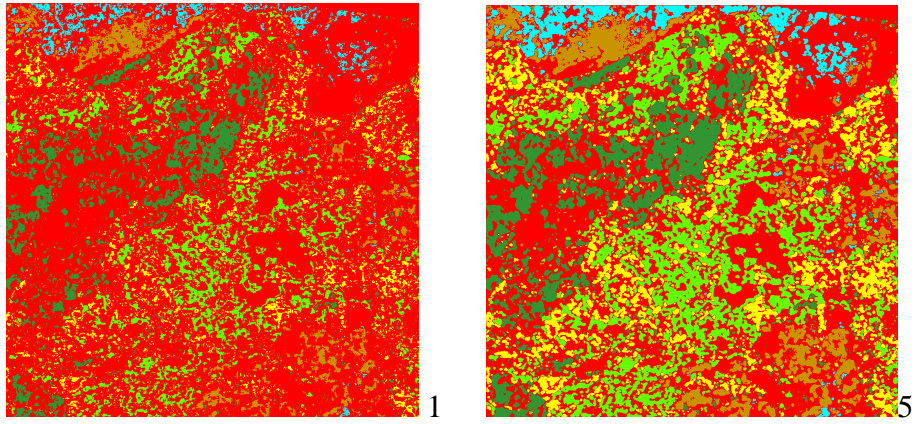
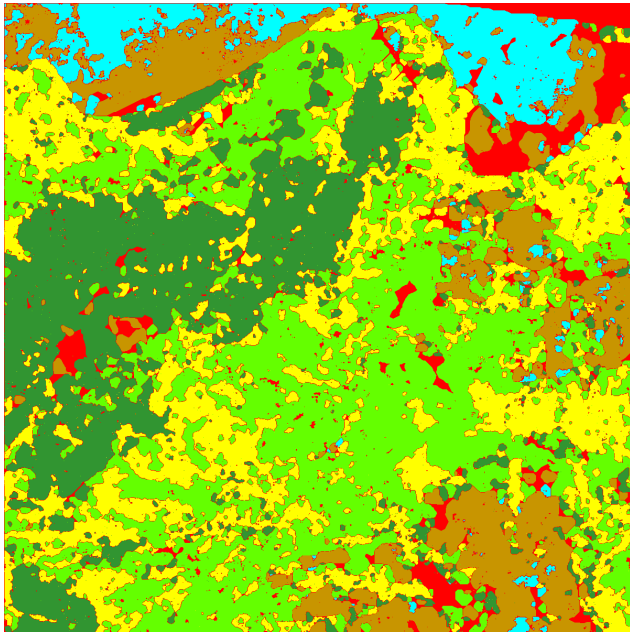
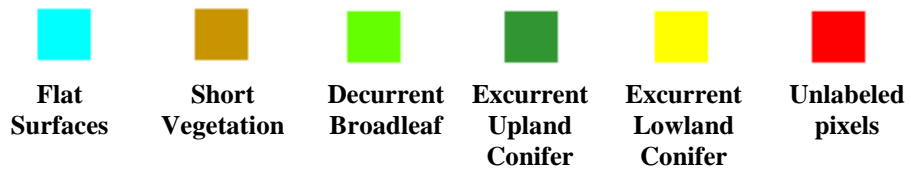
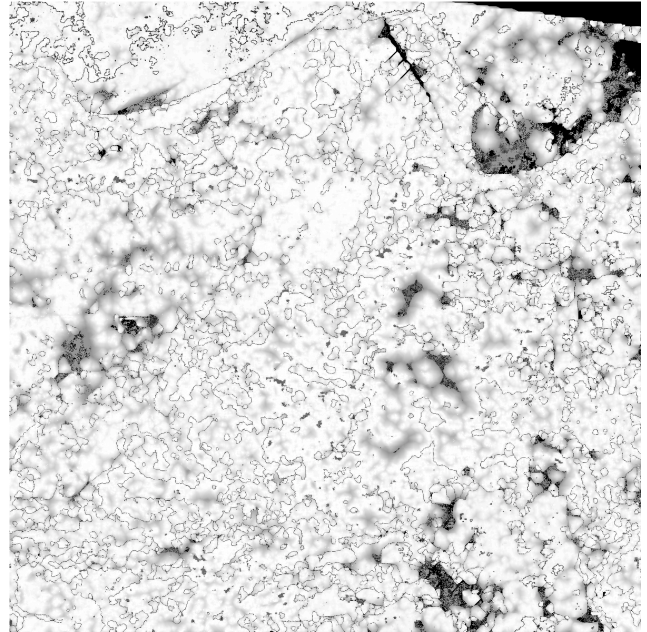


Figure 9, Intermediate thematic maps obtained after one (res. 5, 10, 15, 20 and 25) contextual fuzzy membership functions updating iterations



(a)



(b)

Figure 10, Final thematic (a) and confidence (b) maps

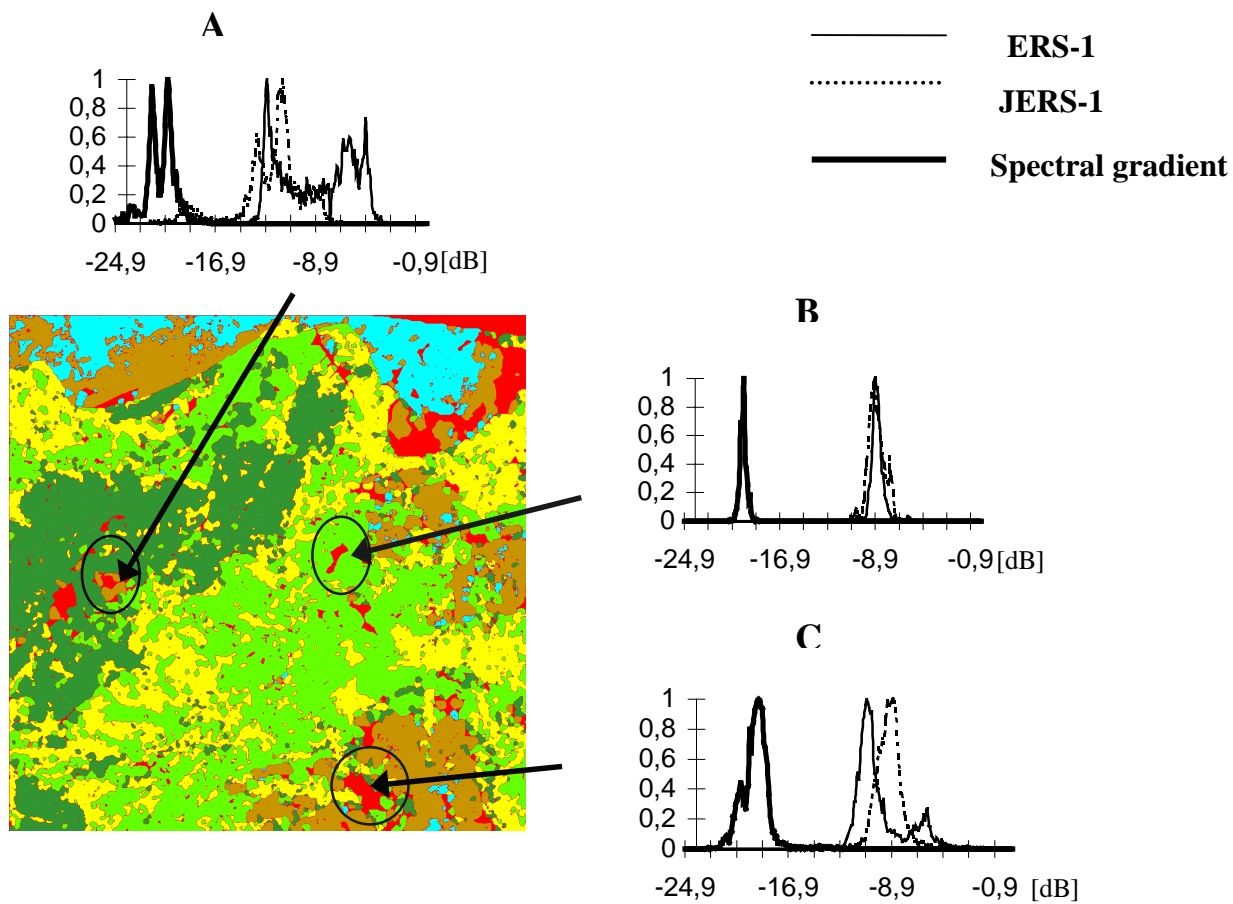


Figure 11, Some « residual » unlabeled regions as well as their corresponding normalized histograms as functions of backscattering values expressed in dB

Table I : Classification accuracy of the fuzzy-based classifier

		Flat Surface	Short Veget.	Decurrent Broadleaf	Excurrent Upland Conifer	Excurrent Lowland Conifer	Unlabeled
Flat Surfaces	Training set	71.4%	23.3%	—	0.1%	—	5.2%
	Test set	64 %	26%	0.1%	—	0.1%	9.8%
Short Vegetation	Training set	7.4%	87.2%	0.2%	—	0.1%	5.1%
	Test set	12.6%	77.5%	—	0.2%	0.3%	9.4%
Decurrent Broadleaf	Training set	—	—	91%	1.3%	3.7%	4 %
	Test set	—	0.2%	90%	1.5%	5.4%	4.9%
Excurrent Upland Conifer	Training set	0.1%	—	1.1%	94.3%	2.3%	2.2 %
	Test set	0.1%	0.4%	0.8%	91.1%	4.5%	3.1%
Excurrent Lowland Conifer	Training set	0.2%	0.6%	0.4%	3.2%	93.2%	2.4%
	Test set	0.2%	0.3%	1.6%	3.4%	90.4%	4.1%