Application of DSmT-ICM with Adaptive decision rule to supervised classification in multisource remote sensing

A. Elhassouny, S. Idbraim, A. Bekkari, D. Mammass , D. Ducrot

Abstract—In this paper, we introduce a new procedure called DSmT-ICM with adaptive decision rule, which is an alternative and extension of Multisource Classification Using ICM (Iterated conditional mode) and DempsterShafer theory (DST). This work confirmed the ability of the Dezert-Smarandache Theory (DSmT) used for the modeling of the classes sets of themes to significantly improve the quality of ICM classification algorithm with constraints by the fusion of the multidates images. The proposed approach uses a fusion process based on hybrid DSmT model finalized by a new adaptive decision rule (ADR) that allows to take in account the parcellary aspect of the thematic classes, thus, the introduction of the contextual information in the fusion process has enabled us to better identify the topics of surface. While the ICM with constraints provided an overall accuracy of 76.40%, the hybrid DSmT models with maximum credibility decision rule and with our adaptive decision rule increase the overall accuracies coefficient to 82.02% and 84.63% respectively.
In addition, the fusion of three different dates achieves a value of 96.29% for overall accuracy and 94.70% of the kappa.

Keywords—Fusion, Classification, DSmT, ICM, Adaptive decision rule, Remote sensing

1 INTRODUCTION

MANY multisource classification approaches have been proposed to solve problems of classification in uncertain environment. Amongst, these methods, DST-ICM (Multisource Classification Using ICM and Dempster Shafer Theory) method was proposed by Samuel Foucher [1], which incorporates Dempster Shafer theory with ICM, shows potential on dealing with multisource classification problems with incomplete information.

The DST-ICM method is useful in order to relax Bayesian decisions given by a Markovian classification algorithm (ICM). The Dempster Shafer rule of combination enables us to fuse decisions in a local spatial neighborhood which further extend to be multisource, and also enables to more directly fuse information.

Our work environment is the Dezert-Smarandache theory (DSmT) [2], [3], [4] which is an alternative and extension of Dempster Shafer Theory [5], [6]. DSmT is recent and was applied in multidates fusion for the prediction of the winter land cover [7], [8], [9], [10], [11] and recently, for the multidates fusion/classification [12], [13], [14], [15], although the theory of evidence, it is more exploited for fusion/classification [12], [13], [1], [16], [17], [18], [19], also for classifier fusion [20], [21], [22]. The paper is organized as follows. The DSmT and ICM with constraints method are brievly introduced in $Section\ 2$ and $section\ 3$ respectively. The proposed method of incorporating DSmT_ICM with adaptative decision rule is described in $Section\ 4$. In $Section\ 5$ an evaluation using FORMOSAT-2 images to illustrate the method with interpretation and discussion of the classification result. Followed by conclusions remark in $section\ 6$.

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Manuscript received mmmm dd, aaaa; accepted mmmmm dd, aaaa.

2 DEZERT SMARANDACHE THEORY $(DSmT)$

2.1 Principles of the DSmT

The DSm Theory was conceived jointly by Jean Dezert and Florentin Smarandache [2],

[3], [4], it is a new way of representing and fusioning uncertain information. DSmT, considered as a generalization of the evidence theory of Demspter-Shafer [1], was developed to overcome the inherent limitations of DST (Dempster-Shafer Theory) [2], [3], [4], [7], [8], [9], [10], [1], [23]. The basic idea of DSmT rests on the definition of the *hyper power set*, from which the mass functions, the combination rules and the generalized belief functions are built.

The *hyper power set* D^Θ is defined as the set of all composite propositions/subsets built from elements of Θ with $\cup$ and $\cap$ operators such as:

We define *hyper power set*, D^Θ as follow :

1) $\phi, \theta_1, \theta_2, ...\theta_n \in D^\Theta$
2) If $X, Y \in D^\Theta$, then $X \cup Y \in D^\Theta$ and $X \cap Y \in D^\Theta$.
3) No other elements belong to D^Θ, except those obtained by using rules 1) and 2) [2], [3], [4].

with $\Theta = \{\theta_1, \theta_2, ...\theta n\}$,$\phi$ is empty set.

We define a map as follows:

$$m_s(.) : D^\Theta \to [0, 1] \tag{1}$$

associated to a given body of evidence s as

$$m_s(\phi) = 0 \tag{2}$$

and

$$\sum_{X \in D^\Theta} m_s(X) = 1 \tag{3}$$

with $m_s(X)$ is called the generalized basic belief assignment/mass (gbba) of X made by the source s.

The DSmT contains two models : the free model and the hybrid model [2], [3], [4], [7], [7], [8], [10], [12], [23], the first presents limits concerning the size of the *hyper power set* D^Θ, whereas the second has the advantage of minimizing this size, for this reason, it will be used in the continuation of our study.

2.2 Combination rules

The masses from the sources must be combined using a combination rule to have a new masses distribution for the elements of the *hyper power set* in order to promote an item compared to others.

Within the framework of DSmT, there are several rules combination, for examples: Smets combinations rules, Dempster-Shafer (standardized) rule, Yager rule, disjunctive rule, Florea criterium, PCR5 (Proportional Conflict Redistribution), Dubois and Prade rule, Martin and Osswald criterium (DPCR, MDPCR), Zhang and DSmH rule [2], [3], [4], [14]. In our application, we have applied and implemented the majority of these rules in order to choose those which allow us to have good performances such as the PCR5.

Mainly, the PCR5 rule is based on the principle of the (total or partial) conflicting masses redistribution [4], [24] to the non-empty sets involved in the conflicts proportionally with respect to their masses assigned by the sources (it can be also generalized for sources).

Considering the frame of discernment $\Theta = \{A, B\}$, two independent experts, and the two following bbas $m_1(.)$ and $m_2(.)$. The conflict induced by $m_1(A)$ and $m_2(B)$ is $m_1(A) \times m_2(B)$, this conflict grows the mass of the empty set and it is not taken in account when deciding, which is often done in DST. In DSmT, PCR5 rule redistributes the conflict [4], [24], by adding
$m_1^2(X_1)m_2(X_2)/(m_1(X_1) + m_2(X_2))$ to $m_1(X_1)$
and
$m_2^2(X_1)m_1(X_2)/(m_1(X_1) + m_2(X_2))$ to $m_2(X_2)$.

The formula of PCR5 for $s > 2$ sources is given in [4], [24].

2.3 Generalized belief functions

From the masses functions, the generalized belief functions (Credibility (Cr), Plausibility (Pl) [2], [3], [4], [24], [14], pignistic probability $BetP$, etc [4], [12], [25], [26]) are defined, which model the imprecision and the uncertainty according to the hypothesis considered by a given source.

The generalized belief functions used in this study namely the Credibility, Plausibility and pignistic probability are defined for D^Θ in $[0, 1]$ and are given respectively by: Belief, plausibility and probability pignistique of an element:

The generalized belief functions used in this study namely the Credibility (Cr), Plausibility (Pl) and pignistic probability are defined for D^Θ in $[0, 1]$ and are given respectively by: Belief, plausibility and DSmP of an element $X \in D^{\Theta}$:

$$Bel(X) = \sum_{\substack{v \subseteq X \\ v \in D^{\Theta}}} m(v) \tag{4}$$

$$Pl(X) = \sum_{\substack{v \cap X \neq \phi \\ v \in D^{\Theta}}} m(v) \tag{5}$$

$$BetP(A) = \sum_{X \in D^{\Theta}} \frac{C_M(X \bigcap A)}{C_M(X)} m(X) \tag{6}$$

where D^{Θ} possibly reduced by the introduction of the integrity constraints of the hybrid DSmT model. $C(X \cap Y)$ and $C(Y)$ respectively indicate the cardinalities of the $Y \cap X$ and Y.

2.4 Decision rule

The last step in a process of information fusion system is the decision step [4]. The decision is also a difficult task because no measures are able to provide the best decision in all the cases. Generally, there are several decision criteria namely Maximum of the gbba, maximum of the pignistic probability, maximum of the credibility(with or without reject), maximum of the plausibility, Appriou criterium, DSmP criterium, Incertitude criterium [27], [19], [28], rules based on confidence intervals [29].

As mentioned before, we can decide using one of the functions mentioned above: three functions among them given by the equations (4), (5) and (6). These functions are increasing functions. Hence, the decision can be taken on the elements in Θ by the maximum of these functions, where the goal is to reduce the complexity, for this we only have to calculate these functions for the singletons. However, we can provide a decision on any element of D^{Θ} depending to applications [23], so the singletons are not interesting elements on D^{Θ}.

Hence, the calculation of these decision functions on all the reduced *hyper power set* could be necessary, but the complexity could not be inferior to the complexity of D^{Θ} which can be a real problem [4]. Therefore, the first considered problem has not been solved which means: it will never be possible to decide with the maximum of credibility, plausibility and pignistic probability. In this case the limits of the decision rules are reached [27].

To overcome this problem, Martin, Appriou and others has proposed a new decision rule [27]. Concerning martin's decision rule, it can be tacked after selecting a subset of $E(\Theta)$ where all elements are pairwise incomparable, by example by fixing the cardinal of a possible decision, generally limiting it to the singletons. It is also possible to use a discounting method to deceive the larger elements of $E(\Theta)$. The cardinal of X is the number of singletons of Θ included in X when $E(\Theta)$ is 2^{Θ} , and it is defined by the number of regions of the Venn diagram [2] of Θ included in X when $E(\Theta)$ is D^{Θ} [4]. However Appriou [30] shows how to decide on matters of D^{Θ} other than singletons. In this study we have not tested this because of its complexity [31]. The more reasonable approach to reduce the complexity is to consider either only the focal elements or a subset of D^{Θ} on where we calculate the decision functions [4].

In our study we have tested the following decision rules

- Maximum of plausibility (of element A) [4], [3], [12], [13] which is often too optimistic, considers the mass products B intersecting the hypothesis A.
- Maximum of credibility on the simple hypothesis (A) (which is the most used and too pessimistic), which is based upon the sum of the mass products B strictly supporting the hypothesis A.
- Maximum of credibility without overlapping of belief intervals which is very strict and called absolute decision rule [4], [3], [12], [13], [27].
- Maximum of pignistic probability [14], [16],(which introduced by Smets [32]), remains the compromise is the most widely used [4], [10].

We conclude that in the context of belief functions, a pessimistic decision is preferable [33]. Applying this decision rule, even that can improve performance compared to the results obtained by ICM with constraints, it caused the loss of the contextual aspect of classification produced by the latter, which requires the implementation of a new decision rule that takes into account aspect. This decision rule will be explained by below.

2.5 Proposed Adaptive Decision Rule (ADR)

Every pixel of the image is characterized by its original graylevel (the spectral information) and by its inter-pixel dependency (the spatial information). The easiest way to use both informations is to build a rule decision. In this paper, we propose to exploit the decision rule of DSmT to build an adaptive decision rule that allows tuning the relative influence of the two extracted features (spectral and spatial).

Our Adaptive Decision Rule (ADR) is an extension of the decision rule based on the one of the generalized belief functions and incorporates the contextual information to take in account the parcellary aspect of the thematic classes. The integration of spatial information is performed using the decision rule of the dominant pixel and the decision rule based on the maximum Credibility proposed in Dezert-Smarandache Theory (DSmT) of plausible and paradoxical reasoning [2], [3], [4].

Any positive linear combination of decision rule actually defines a new acceptable decision rule. This enables the definition of a decision rule that works with both the spatial and the spectral information at the same time:

$$ADR(x/C_i) = \mu * Cr(x/C_i) + (1-\mu) * Dspat(x/C_i) \quad (7)$$

Where:

$Cr(x/C_i)$ is a credibility function of pixel x for each class C_i .

$Dspat(x/C_i)$ Value of inter-pixel dependency of pixel x for each class C_i.

μ a weighting parameter that controls the relative influence of each information. It has to be tuned during the training process.

For the value of μ, there are several simulations of $[0, 1]$ at intervals of 0.1. The results showed that: When you give more importance to the spectral information to spatial information, the value of μ is very close to 1, this is normal when it comes to a hyperspectral image, which most of the information is the spectral information, while its spatial resolution provide us as much information on the objects in the scene. However, the value of μ equal to 1, does not give the best results. This justifying the value added of the spatial information. The value of μ for which are given more importance to the spatial information (value of μ close to 0) and for the spectral information due to the fact that the image contains a single spectral component and its spatial resolution is higher.

For the image used, we have optimized the parameter : after several tests, the optimal value for which one gets highest accuracy is 0.5. For this value we give importance to both: spectral and spatial information.

The ADR consists in the following steps(Algorithm 1):

Algorithm 1 Adaptive decision rule

1: **for** each pixel x **do**
2: **for** each Class C_i **do**
3: Calculate $Cr(x/C_i)$ and $Dspat(x/C_i)$
4: $ADR(x/C_i) = \mu Cr(x/C_i) + (1 - \mu) Dspat(x/C_i)$
5: **if** $ADR(x/C_k) = max\{ADR(x/C_i), i = 1 \cdots card(\Theta)\}$ **then**
6: x affected to C_k
7: **end if**
8: **end for**
9: **end for**

3 ICM CLASSIFICATION WITH CONSTRAINTS

The information contained in a satellite image is usually in the form of homogeneous objects. Indeed, an image of rural areas often consists of large homogeneous parcels, and therefore, an acceptable classified image must respect this property. Thus, the use of Markov Random Fields (MRF) takes in account this property of the neighborhood influence of a pixel on it. and therefore insists on coherence between the class of a pixel and that of its neighbors. It is a powerful mathematical tool for regularizing the classification of the satellite images.

Moreover, the Markovien formalism constitutes a gateway to introduce a several constraints (spatial context, map of contours, temporal context, etc), for this reason, we have used the suggested method by [34], [35] as a method of classification in order to generate the probabilities for DSmT. This technique of classification provides, in addition to the constraint of regularization, a new constraint of segmentation so to refine the classification. these contextual constraints are controlled by a parameter of temperature in an iterative algorithm of optimization ICM (Iterated Conditional Mode).

The used method of classification opts for a MAP (maximization of the a *posteriori*) solution approached by the ICM initialized with maximum likelihood (ML), because, given the big size of the treated images, this deterministic method proves being more interesting thanks to the convergence speed towards the solution.

4 PRPOSED FUSION PROCEDURE

The procedure of calculation for this proposed fusion process can be described as follows:

Step 1: A supervised ICM classification with constraints is applied to the two images, in order to recover the probabilities matrixes.

A result of ICM classification can be concisely expressed in matrixes of probabilities:

$$\text{I21\_03p}=\begin{pmatrix} x_{11} & . & . & . & x_{1m} \\ . & . & & & . \\ . & & x_{ij} & & . \\ . & & & . & . \\ x_{n1} & . & . & . & x_{nm} \end{pmatrix}$$

$$\text{I03\_05p}=\begin{pmatrix} x_{11} & . & . & . & x_{1m} \\ . & . & & & . \\ . & & x_{ij} & & . \\ . & & & . & . \\ x_{n1} & . & . & . & x_{nm} \end{pmatrix}$$

$$\text{I26\_07p}=\begin{pmatrix} x_{11} & . & . & . & x_{1m} \\ . & . & & & . \\ . & & x_{ij} & & . \\ . & & & . & . \\ x_{n1} & . & . & . & x_{nm} \end{pmatrix}$$

Each pixel $I(i,j)$is assessed on a vector of probabilities $x_{ij} = [P(I(i,j)/C_1), \ldots, P(I(i,j)/C_k)]$, and the set of all Classes is denoted $C = \{C_1, C_2 \ldots, C_k\}$.

Step 2: The estimation of the mass functions of each focal element A of the framework.

Θ is established on training sample as follow : Taking in consideration the prior knowledge of the study area, we have identified 6 classes constituting the framework Θ which are: Water(W), Deciduous(D), Summer_culture(SC), Winter_culture(WC), Built(B) and Prairie(P). So, Θ is defined as follows: $\Theta = \{W, D, SC, WC, B, P\}$

Exploiting information of the study area and also those obtained by ICM classifications with constraints, some elements of the hyper power set D^{Θ} seem not being adjacents and exclusives.

To realize a better adapted study to the real situations, some exclusivity constraints will be taken (hybrid DSmT model), for example $W \cap D = \varphi$, $W \cap WC = \varphi$, etc , which reduces the number of focal elements of the D^{Θ} .

The choice of the mass function is the crucial step of the fusion process, because all: imprecision, uncertainty and paradox inter sources of the classification must be introduced in this step. However, there is no general method to define the mass function. In the image processing application, the most widely used mass functions are usually derived from the probability of the pixel level, or from the information between neighboring pixels [12]. As the outcome data are considered (which are partially redundant and complementary) from different classification approaches of the same image, the method of computing the mass function from the conditional probability of the class is used here and described as follow:

For each pixel I_{ij} , the no null mass functions are defined as follows:

$$m(A) = \begin{matrix} m(A) = \frac{1}{z} P(Iij/A) \\ m(\Theta) = 1 - m(A) \end{matrix} \tag{8}$$

Where z is a normalization term, which makes sure $\sum m = 1$

Step 3: The PCR5 fusion rules for combining the masses can be directly used (defined in section 2.2).

Step 4: The calculation of the generalized belief functions $Cr(x/C_i)$ (defined in section 2.3) of each Classes.

Step 5: The calculation of the $Dspat(x/C_i)$ of each Classes

Step 6: The DSmT fusion process is completed by applying a decision rule, which can be a maximum of generalized belief functions maximum of Cr, maximum of Pl or maximum of BetP or our Adaptive Decision Rule(ADR) (defined in 2.4 section).

In our application, we have applied the two decision rules: the maximum of credibility (Cr) and our ADR.

5 RESULTS AND INTERPRETATION

5.1 Study area and used data

Midi Pyrenees area taken by FORMOSAT satellite is located in the Midi Pyrenees region, centered on the city of Rieumes south-west of Toulouse area (50 km x 50 km), French. The area covered by FORMOSAT represents about a quarter of that covered by Spot (Figure 1). The region is subject to various climatic influences:

- Atlantic temperate oceanic climate
- Continental: occasionally very cold climate
- Mediterranean: southerly

The date of acqusition corresponds to a good state of the green vegetation and permits then an optimal response of covering vegetation. The study area is specified by a red rectangle.

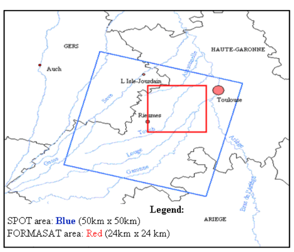


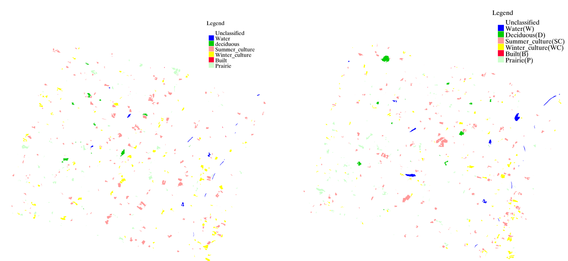
Fig. 1: Area covered by the FORMOSAT 2006 and SPOT of previous years

Satellite images and theirs results of the supervised ICM classification are given by CESBIO laboratory (Centre dEtudes Spatiales de la BIOsphre, Toulouse, France), indeed the purpose of CESBIO is to develop knowledge about the functioning and dynamics of the continental biosphere at different spatial and temporal scales. This unit conducts research in the field of observation and modeling of continental surfaces, participates in the definition of space missions and processing of remote sensing data and develops methods of analysis and modeling.

5.2 Preprocessing of images and Trainings samples

The preprocessing gathers the following processes: the sampling, the selection of the region of interest and the registration of the images.

The samples are established by laboratory CESBIO, six topics of land occupation are identified: Water(W), Deciduous(D), Summer_culture(SC), Winter_culture(WC), Built(B) and Prairie(P). The figure 2 (a) (b) represent the training and test samples used in ICM classification with contraintes established respectively.



(a) (b)

Fig. 2: (a) Training and (b) Test samples

The number of pixels of training and test samples per class is shown in the following Table 1.

TABLE 1: Training and Test sample

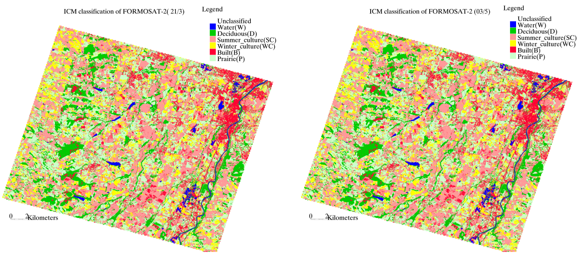
Class	Training sample	Test sample
W	21494	8226
D	20589	13147
SC	211310	135526
WC	99548	78274
B	340	489
P	111178	48334

With: W: Water, D: Deciduous, SC: Summer_culture, WC: Winter_culture, B: Built and P: Prairie.

5.3 Supervised ICM classification with constraints

Supervised ICM classification with constraints of the two images and theirs Matrix confusion are presented as follow (figure 3 (a)-(b) and Tables 2-3):

Obtained results were of the ICM with constraints for two images are presented in Table2 and Table3. These results are compared to those



(a) FORMOSAT-2(21/3) (b) FORMOSAT-2(03/5)

Fig. 3: Supervised ICM classification with constraints of the two images (France)

TABLE 2: Matrix confusion of ICM with constraints of image 21/3

Class	W	D	SC	WC	B	P
W	99.79	0.01	0	0	0.19	0
D	0	99.19	0.16	0	0.40	0.25
SC	0	0.23	84.04	2.67	5.94	7.11
WC	0	0	15.38	55.52	1.40	27.70
B	0	0	24.95	1.02	70.96	3.07
P	0	2.12	7.09	11.07	0.81	78.92

With 0A=76.40% and Kappa Coefficient=65.45%.

TABLE 3: Matrix confusion of ICM with constraints of image 03/5

Class	W	D	SC	WC	B	P
W	98.87	0	0.05	0	0.89	0.19
D	0	83.34	0.01	0.39	2.22	14.04
SC	0	0.01	90.02	0.47	5.50	4.00
C	0	7.05	0.72	79.15	0.54	12.54
B	0	0	3.68	0	94.89	1.43
P	0	13.60	4.62	17.16	4.68	59.94

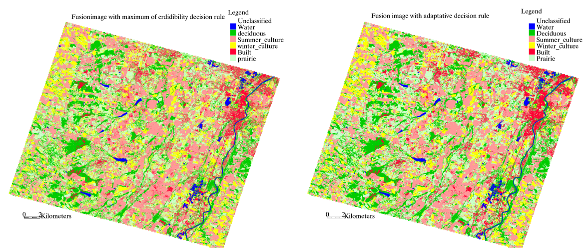
With 0A=82.26% and Kappa Coefficient=74.06%.

obtained with the fusion algorithms. According to the confusion matrixes, the ICM with constraints provided better results for both classes Water and Deciduous with accuracy rate of 99.79% and 99.19% compared to author classes that theirs percentages varies between 55.52 and 84.04. Thing which can be explained by the small difference between the spectral responses of these classes.

5.4 Fusion with the DSmT of two dates

In this section, we compare the performance of different decision rules for the used classifiers, which are among two, DSmT-ICM-Cr with maximum credibility(Cr) as a decision rule and DSmT-ICM-ADR with ADR as a decision rule. For this comparison, we have used ICM with constraints as a reference method of classification.

The results of classification based on DSmT-ICM with both decision rules are given in Figure 4 (a) and Figure 4 (b) followed by their confusion matrix respectively in Table 4 and Table 5.



(a) (b)

Fig. 4: Fusion map obtained with (a) DSmT-ICM-Cr and with (b) DSmT-ICM-ADR on the singleton elements

TABLE 4: Confusion matrix of fusion with maximum Credibility (DSmT-ICM-Cr)

Class	W	D	SC	WC	B	P
W	97.61	0.00	0.00	0.00	0.00	0.00
D	0.22	97.69	0.14	7.17	1.02	10.47
SC	0.00	0.02	88.91	2.48	14.93	5.43
WC	0.00	0.33	1.23	74.34	2.25	16.46
B	2.16	0.41	4.08	0.40	72.80	0.94
P	0.01	1.55	5.64	15.61	9.00	66.70

With OA=82.0221% and Kappa Coefficient=73.68%.

TABLE 5: Confusion matrix of fusion with Adaptive Decision Rule (DSmT-ICM-ADR)

Class	W	D	SC	WC	B	P
W	98.88	0.00	0.00	0.00	0.00	0.00
D	0.36	99.13	0.11	6.36	0.20	10.43
SC	0.00	0.05	90.43	2.33	7.57	5.55
WC	0.00	0.10	0.90	78.51	1.02	13.03
B	0.75	0.04	2.98	0.21	88.75	0.66
P	0.00	0.69	5.58	12.60	2.45	70.34

With OA=84.6282% and Kappa Coefficient = 77.36%.

In this study, in order to compare the results, we have calculated the overall accuracy(OA) and Kappa coefficients. The results of the satellite image classification obtained by fusion based on DSmT-ICM with our adaptive decision rule (DSmT-ICM-ADR) are better than those obtained by ICM with constraints (Table 5). We note that the DSmT-ICM-ADR method provides an improvement of 5.3% of overall accuracy (OA) and 7.6% of Kappa coefficient, on the other hand, the results obtained by DSmT-ICM with maximum credibility decision rule (DSmT-ICM-Cr) even if it is lower than that obtained by DSmT-ICM-ADR, it provides at least an improvement compared to that obtained by the reference method ICM with 2.29% and 3.92% for the two coefficients Kappa and OA respectively.

TABLE 6: Overall Accuracy and Kappa coefficients of classification results from different fusion strategy

	ICM_21/3	ICM_03/5	ICM_mean	Cr*	ADR*
OA	76.4	82.26	79.33	82.02	84.63
Kappa	65.45	74.06	69.75	73.68	77.36

With Cr*: DSmT-ICM-Cr and ADR*: DSmT-ICM-ADR

TABLE 7: Accuracy of classes of classification results from different fusion strategy

	W	D	SC	WC	B	P
ICM_21/3	99.79	99.19	84.04	55.52	70.96	78.92
ICM_03/5	98.87	83.34	90.02	79.15	94.89	59.94
ICM_mean	99.33	91.27	87.03	67.34	82.92	69.43
DSmT-ICM-Cr	97.61	97.69	88.91	74.34	72.80	66.70
DSmT-ICM-ADR	98.88	99.13	90.43	78.51	88.75	70.34

This is explained by the fact that even if the DSmT-ICM-Cr improves the classification accuracy for the classes D and WC compared to those obtained by the ICM method with constraints, it reduces the classification accuracy for the other classes, which leads to a redistribution of the value of each coefficient to the other classes.

We can conclude from the results obtained by the fusion based on DSmT with different decision rules that DSmT improves significantly the results compared to the reference method ICM with constraints and the fusion with DSmT using precisely adaptive decision rule (DSmT-ICM-ADR) provided the best results.

5.5 Fusion of three dates

In order to show the contribution of the proposed fusion method with our decision rule (ADR) and also to refine the results of classification, a third image (information source) is complementary used. Below are the results of the fusion by : ICM with constraints, DSmT-ICM-Cr and DSmT-ICM-ADR presented respectively in Figure 5 and Figure 6 (a) - (b), and their confusion matrices in Tables 8, 9 and 10.

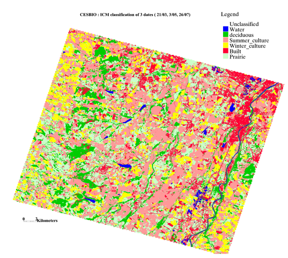
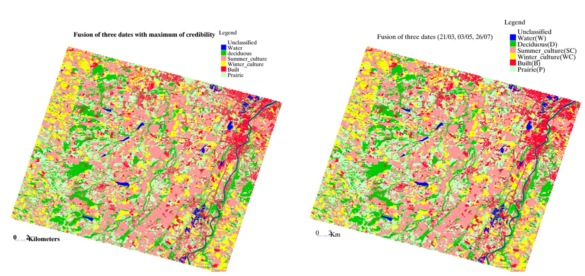


Fig. 5: Supervised ICM classification with constraints of three dates of FORMOSAT-2 (21/03, 03/5, 26/07)

TABLE 8: Confusion matrix of ICM with constraints of three dates (Percent)

Class	W	D	SC	WC	B	P
W	98.70	0	0	0	1.30	0
D	0	99.16	0.33	0	0.17	0.33
SC	0	0	97.33	0.56	0.73	1.39
WC	0	0	0.33	94.41	1.00	4.25
B	0	0	0.20	0	98.77	1.02
P	0	0.94	4.54	3.04	3.36	88.12

With 0A=95.21% and Kappa coefficient = 92.77%



(a) (b)

Fig. 6: Fusion map of three dates obtained with (a) DSmT-ICM-Cr and with (b) DSmT-ICM-ADR

TABLE 9: Confusion matrix of fusion of three dates with DSmT-ICM-Cr (Percent)

Class	W	D	SC	WC	B	P
W	98.77	0.00	0.00	0.00	0.00	0.00
D	0.03	99.33	0.11	0.01	0.33	1.23
SC	0.00	0.09	96.23	1.38	4.35	2.36
WC	0.00	0.00	0.63	92.53	2.34	2.50
B	1.20	0.09	1.87	1.63	87.29	1.91
P	0.00	0.49	1.16	4.46	5.69	92.01

With OA=95.18% and Kappa Coefficient=93.14%

TABLE 10: Confusion matrix of fusion of three dates with DSmT-ICM-ADR (Percent)

Class	W	D	SC	WC	B	P
W	99.13	0.00	0.00	0.00	0.00	0.00
D	0.04	99.75	0.09	0.01	0.33	0.99
SC	0.00	0.02	96.96	1.18	0.00	2.06
W	0.00	0.00	0.59	94.34	0.33	1.47
B	0.83	0.05	1.54	1.19	93.98	1.57
P	0.00	0.18	0.81	3.29	5.35	93.91

With OA=96.2855% and Kappa Coefficient=94.70%

Visually, we can note from the two maps obtained by the ICM with constraints (Figure 5) and the DSmT-ICM-ADR (Figure 6-(b)) that the structure and the parcellary form are more homogeneous and regular comparing to those of the map obtained by the DSmT-ICM-Cr.

TABLE 11: Accuracy and errors of classification results from different fusion strategy

Dataset and Fusion	Fusion strategy	*OA*(%)	*Kappa*
Tow dates	*ICM*	79.33	69.75
	DSmT-ICM-Cr	82.02	73.68
	DSmT-ICM-ADR	84.63	77.36
Three dates	*ICM*	95.21	92.77
	DSmT-ICM-Cr	95.18	**93.14**
	DSmT-ICM-ADR	**96.29**	**94.70**

In order to quantitatively evaluate the effectiveness of the DSmT fusion theory in the classification for both cases (two dates and three dates), the precision indices are calculated from the confusion matrices and are presented in table 11.

From the results, we can note that: Compared to the use of the ICM classification method with constraints (reference method), methods based on DSmT-ICM-Cr and DSmT-ICM-ADR have made an increase from 0.37 to 1.93 respectively for the kappa coefficient ranging from 92.77% to 94.7%, while the associated overall accuracies (OA) are from 95.21% to 96.29%.

The improvement of the results by fusion based on DSmT-ICM-CR reduces omission errors to a reasonable level, and produces an increasing precision of Kappa coefficient from 92.77 to 93.14, but this improvement is however, accompanied by a crossing of the commission errors (reduction of the OA from 95.21% to 95.18%).

In general, the two methods of data fusion based on DSmT give better results compared with the reference method, with a slight advantage of the DSmT-ICM-ADR method. This shows the effectiveness of the DSmT theory and the adaptive decision rule (ADR) in improving the overall quality of the classification. Consequently, the fusion based on DSmT-ICM-ADR can be used as solution to optimize the results of others classification methods and to reduce their errors. We also note the significant effect of the use of three information sources instead of two in the process of fusion, for example for DSmT-ICM-ADR, the overall accuracy has increased from 84.63% to 96.29% and the kappa coefficient from 77.36% to 94.70%.

6 Conclusion

In this article, we have opted for an analytical approach by applying a new contextual and multitemporal classification method based on fusion by DSmT, this framework provides a useful tool to include the spatial information in the fusion process through the use of a new adaptive decision rule (ADR). First, we have showed that the joint use of DSmT and ICM with a chosen decision rule improves the performance of the classification in terms of precision and accuracy compared to the reference method ICM. Secondly, we have proposed a new adaptive decision rule (ADR), which showed its performance and has enabled us to overcome the limitations of decision rules based on the generalized belief function (Cr). In addition, we have noted the significant effect of the use of three information sources (images) instead of two in the fusion process that yielded to an overall accuracy of 96.29% and a Kappa coefficient of 94.70% for the new proposed method "DSmT-ICM-ADR."

Acknowledgements: This work was funded by CNRST Morocco and CNRS France Grant under Convention CNRST CRNS program SPI09/12.

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