Satellite images fusion using possibility theory

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Abstract : The aim of this work is the improvement of land use map and the detection of changes in a region of globe. To this end, the database used consists of multisource multitemporal satellite images using possibility fusion process. The crucial problem in the development of this process is the estimation of possibility functions. We have, for this purpose, applied transformations from probability distributions to possibility distributions. Thus, we propose two methods to implement the fusion process:

In the first method, we implemented a model of possibility fusion: we estimated the probability distribution of each spectral class samples of the training set. This estimate is based on the histogram analysis of each class. Then we estimated the possibility distribution from probability distributions using the transformations: Dubois and Prade, improved Dubois and prade, Klir and variables transformation (VT). Next, we determined the possibility of each pixel with linear interpolation method. For the combination operator, we opted for the conjunction operator (severe) and disjunction operator (indulgent). Finally, we applied the decision rule based on the maximum of possibility.

In the second method, we implemented the fusion process monoband and multiband, whose mono-band fusion does not require a combination step. The results obtained represent maps containing classes and relatively well discerned different each other. Therefore, we used the fusion process multiband by exploiting the complementarity of their spectra and we obtained maps with predefined classes in the training set on which the spectral bands emit the same decision and a class confusion on which the spectral bands differ. The plot of the spectral signature of the confusion class is a curve which has an intermediate form between the signatures of predefined classes.

Finally, in the third method, we implemented the multisources multisensor multitemporal process of fusion where we have combined two multispectral images from the two sensors HRV of SPOT satellite and ETM + of LANDSAT 7 satellite, acquired respectively in 1997 and 2003 (different dates). For invariant zones, the result is a map containing predefined classes of sensors which on emit the same opinion and a confusion class which on the sensors are different. However, for variants zones, the result is a change map containing predefined stable classes and a change class represented by the class of confusion.

Keywords : fusion, classification, possibility theory; conjunctive operator; disjunctive operator; probability-possibility transformation

1. INTRODUCTION

Today and in the field of remote sensing, the amount of available images is increasing as a result of technological development of means acquisition about physical phenomena and Earth's surface around us.

The data acquired are issued from several information sources (sensors) and they have not the same degree of reliability. In addition, they are often marred by uncertainty and imprecision. The uncertainty is induced by the acquisition devices and atmospheric disturbances, which leads to interpret the image as the result of a random phenomenon. On the other side, imprecision is an uncertainty associated with incomplete knowledge. For optimal use of these data, it is necessary to provide a very specific processing.

A fusion process that leads to a classification can take place through several mathematical theories. The probability theory associated with Bayesian theory is the oldest and most widely used. It can well represent the uncertainty around the information but it does not represent imprecision and often leads to confuse these two concepts.

Such constraints can be minimized by using new theories more realistic and who propose as an alternative to probability theory. Among these theories, we find the evidence theory developed by Dempster and Shafer [1], the fuzzy set theory developed by Zadeh [2], possibility theory introduced by Zadeh [3] and developed by Dubois and Prade [4], the theory of plausible and paradoxical reasoning developed by Dezert and Smarandache [5], etc.

The aim of our work is the implementation of possibility model for multisource satellite images fusion and its application for the improvement of thematic land map and detection of land change. The approach involves several steps:

First, we determine the histograms associated with the probability distributions of samples of the training set. Then, we perform a transformation probability/possibility, followed by a linear estimate of possibility values of all observations belonging to classes. Subsequently, we apply a combination methods of different sources, conjunctive or disjunctive. Finally, we apply the decision rule of maximum possibility in order to obtain a classified image.

The remainder of the paper is structured as follows: In the next section, we recall a mathematical basis of the possibility theory and their application to fusion process. The third section devoted to the presentation and implementation of possibility model for multisource data fusion.

The fourth section is dedicated to the presentation, evaluation and comparison of all results. We end this paper with a general conclusion and possible future perspectives for this work.

2. Possibily theory

Possibility theory is rooted in the fuzzy sets theory developed by L. Zadeh. This theory allows the explicit representation and processing of ambiguous, imprecise and uncertain data in the form of membership functions [3], [6].

A. Possibility distribution

In the possibility model, the distribution of possibilities Π_j^s provided by the source of information S_j filled the role of characteristic function of the gradual membership $\mu_j^s(\omega_i)$. For the measure of the similarity degree of the event ω_i to different thematic classes considered ω_i. However, the classical probabilistic model that applies the concept of all or nothing concerning the membership of the event ω_i to predefined classes C_i. i.e. ω_i event belongs fully to a class considered.

A possibility distribution is a function in [0,1] with the following normalization condition:

$$\sup_{x\in\Omega}\pi_j^s(x) = 1.$$

This condition corresponds to an assumption of the closed world, in which one member at least is completely and totally possible. In the finite case, a possibility distribution allows to build a possibility measure by the formula [6]:

$$\forall A\in\Omega,\ \Pi_j^s(x)(A)=\sup\ \{\pi(x), x\in A\}$$

By duality, a necessity measure defined from a possibility distribution by:

$$\forall A\in\Omega,\ N(A)=1\ -\sup\{\pi(x), x\notin A, x\in \bar{A}\}$$

b. Transformation Probability-Possibility

The transformation from the probability function to the possibility function on a representation space $\Omega = \{\omega_i\ , i = 1,\dots,n\}$ is carried out by a direct transfer models probability/possibility available in the literature. These models are given as follows:

1) Principle of consistency of Zadeh

Zadeh defined a degree of consistency between the probability distribution and the possibility distribution corresponding [3]. This principle states the fact that through a possibility distribution it is possible to perceive the corresponding probability distribution but not the reverse. In other words, a possibility distribution corresponds to a family of probability distributions:

$$C_Z = \sum_{i=1}^{N} \pi(\omega_i) * p(\omega_j)$$

2) Principle of consistency of Dubois and Prade:

In their work [4] Dubois and Prade have proposed two nonreciprocal formulas for the passage probability to possibility and possibility to probability. They are explained by the following equations:

a) Transformation $\pi_i \rightarrow p_i$

- Asymmetric transformation (optimal)

$$\pi(\omega_i) = \sum_{j=i}^{n} p(\omega_j) \qquad i = 1,\dots,n$$

$$p(\omega_j) \le p(\omega_i) \qquad i = 1,\dots,n \qquad j = 1,\dots,n \quad j > i$$

- Symmetrical transformation and coherent

$$\pi(\omega_i) = \sum_{j=1}^{n} min\,(p(\omega_i), p(\omega_j))$$

$$\forall A \subseteq \Omega, \Pi(A) \ge P(A)$$

With $\forall\, \omega_i \in A, \pi(\omega_i) \ge p(\omega_i)$

b) Transformation $\pi_i \rightarrow p_i$

$$p(\omega_i) = \sum_{j=i}^{n} \frac{(\pi(\omega_j) - \pi(\omega_{j+1}))}{j}$$

3) Principle of consistency of Klir:

The Klir transformation allows preserving useful information originally contained in the probability distribution after the transformation probability to possibility [7]:

$$\pi(\omega_i) = \left(\frac{p(\omega_i)}{p(\omega_1)}\right)^{\alpha}$$

$$p(\omega_1) = max(p(\omega_i)\ \ , i = 1,\dots,n)$$

The parameter $\alpha \in [0\ 1]$ is the unique solution of the equation with one unknown.

C. Combination of possibilities

Possibility theory offers a multitude of mathematical operators for the combination of information. Operators are used most often, the t-norms (triangular norms) as the conjunctive operators (and logic), the T-conormes (conormes triangular) as the disjunctive operators (or logic), the mean operator, the symmetric operators and the operators taking into account measures of conflict or reliability of sources. The choice of an operator can be done according to several criteria [9].

1) Triangular norms (t-norms)

t is a triangular norm if and only if it satisfies the following properties:

$$t(x, y) = t(y, x)$$

$$t(x, t(y, z)) = t(t(x, y), z)$$

$$t(x, 1) = t(1, x) = x$$

$$t(x, y) \ge t(z, t) \ \ si\ \ x \ge z\ et\ y \ge t$$

$$\forall (x, y) \in [0,1]^2 \quad t(x, y) \le \min(x, y)$$

In our work, we choose $t\,(x, y) = min\ (x,y)$

2) *Triangular conorms (T-conorms)*

T is a triangular conorm if and only if it satisfies the following properties:

$$T(x,y) = T(y,x)$$
$$T(x, t(y,z)) = T(T(x,y),z)$$
$$T(x,0) = T(0,x) = x$$
$$T(x,y) \geq T(z,t) \;\; si \;\; x \geq z \; et \; y \geq t$$
$$\forall (x,y) \in [0,1]^2 \quad T(x,y) \geq \max(x,y)$$

In our work, we choose $T(x,y)=max(x,y)$

D. Decision

The rule we have chosen is that of the maximum of possibility which is the rule, mainly used in possibility fusion [10].

$$x \in C_i \;\Leftrightarrow\; \mu_{C_i} = max\,(\pi_{c_j}\,,\;\; j = 1,\ldots,k)$$

3. The proposed possibility model

The methodological approach of possibility fusion model is given as follows:

a) The first step is the estimation of the probability distribution of each spectral class from the samples in the training base. This estimate is based on the histogram analysis of each class:
- From all observations on an image, we define training areas (samples) which are representative of each class. After defining the number of classes, for example K thematic classes, the training base extracted is given by C={C1,…,CK}. The test base contains different data from those of learning data.
- The calculation of histograms of samples of each information source knowing each thematic class.
- Calculation of the probability distribution.

b) In the second step, having obtained the probability distributions associated with each thematic class in relation to each source of information, we perform a transformation to estimate the possibility distribution from probability distributions using the transformations mentioned in section II.B.

c) The third step is the determination of possibilities of all pixels of the image with the linear interpolation method:
Once the membership degrees of the samples in relation to thematic classes determined, we apply the linear interpolation method for the estimation of other observations (gray levels) of information sources [11].
The Observation to Estimate (OE) can be determined according to four cases:
- OE is between the lower limit of the possibility distribution which has the lowest gray levels and the zero value: in this case, the estimate is a straight line between the lower limit of this distribution and the zero value which has a null possibility.
- OE is included within the possibility distribution of a class: in this case, the estimate is made by drawing a line connecting the two closest observations samples of OE in the image.
- OE is located between the lower and upper limits of two distributions of successive classes: in this case, we determine the intermediate data located mid-distance to low and high values of the two distributions in question. From this value which has a value of null possibility, we draw two lines to the limit values of these two distributions.
- OE is located between the upper limit of the distribution which has the highest gray levels and the maximum value that can be taken by the quantified data (255): in this case, the estimate is a straight line between the maximum value of this distribution and the value 255 which has a value of null possibility.

d) In the fourth step, we combined the sources by the combination operator. We opted for the operators of conjunction (severe operator) and disjunction (indulgent operator).

e) The last step is the application of decision rule based on the maximum of possibility.

4. Application and presentation of results

The fusion process is performed on three data sets: the first is mono-band images, the second represents the multispectral images and the third represents multi-sensor images.

A. Description of study site

The methodology proposed is evaluated on a pilot area containing different themes of land use. It is located about 10 km east of Algiers and its area is approximately 3000km2. The area was previously agricultural. It is now occupied by an urban zone that becomes denser and is developed in several cities.
In our work, we have used two images covering the study site, issued from the HRV sensor (satellite SPOT, 1997) and the ETM+ sensor (satellite LANDSAT 7, 2001).
Before using the raw data available, we carried out a preprocessing of the two satellite images, which consists of a radiometric and a geometric corrections. The geometric correction carried out in the same referential where we brought the two images at the same resolution of 20m, using the method of cubic convolution.
The RGB composition of the two images is given by the Fig.2.
In our work, we have a supervised classification method. This methodology requires a training base and a test base.

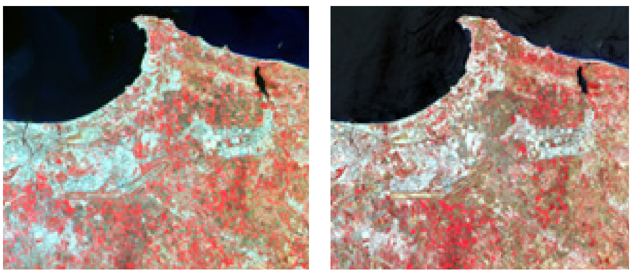


Fig. 2 RGB Composition of Algiers site a) HRV 1997 b) ETM+ 2001.

Tab 1. themes and number of samples

Classes	Themes	Number of training samples	Number of test samples
C 1	Water (W)	111	107
C 2	Urban (U)	202	186
C 3	Vegetation (V)	137	193
C 4	Bare Soil (S)	195	109

in our case, the training data base is built using a prior knowledge and the test base given the absence of a reality on the field study site, we have built with the same way which we built the training base, choosing complementary parcels in the image.

Quantitative evaluation of the results is performed using a confusion matrix that compares the result with a test base. Indeed, we identified four thematic classes: Water (W), Urban (U), Bare soil (B) and Vegetation (V). These classes are listed in Table.1 with the number of samples in each class.

B. Presentation and analysis of results

We interpret and analyze the results of three data sets: monoband images, multispectral images and multisensor images.

1) Possibility classification of monoband of HRV sensor.

The possibility fusion process developed is with estimation. It will be compared to the fusion process without estimation. Both processes are given as follows:

a) No estimate:

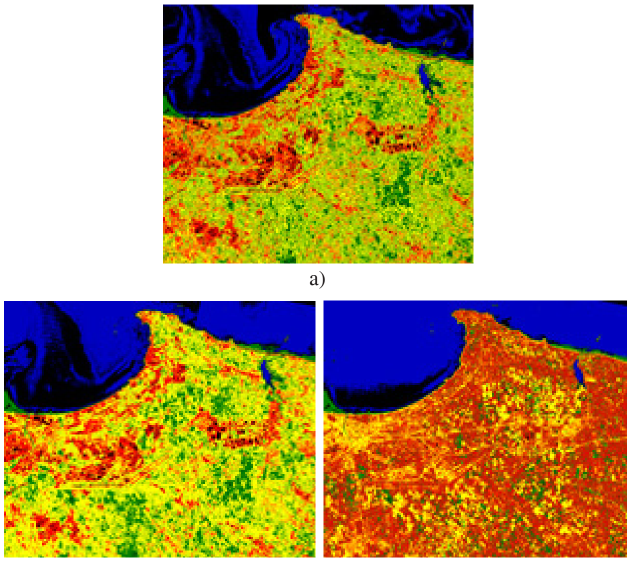
The resulting map of the application of the possibility process on three spectral bands of HRV sensor given in Fig.3, revealed a large number of dark areas formed by groups of pixels, occupying the classified image. These areas really represent the pixels that have not labeled. These pixels have put the decision step in failure. Indeed, we do not know the value of possibility membership of these pixels in relation to the thematic classes, and then it is not possible to make a decision about membership of pixels affected.

We proposed a solution which is the estimation by linear interpolation that will determine the membership values of pixels.

b) With estimate:

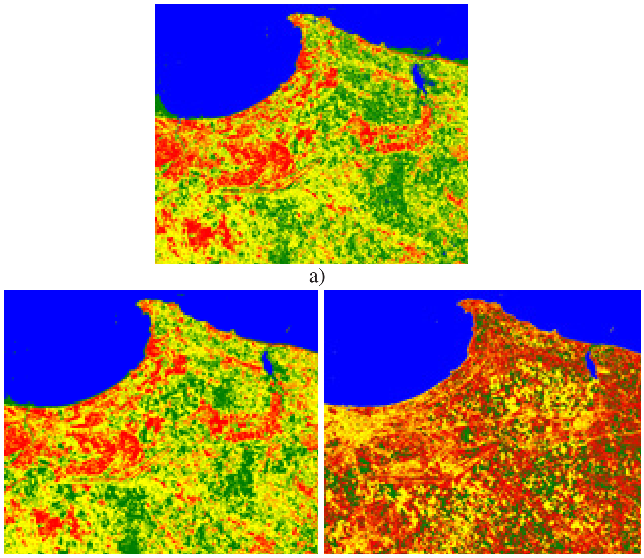
We applied the possibility fusion process to HRV multispectral image using the improved Dubois and Prade method of transformation probability-possibility:. We obtained the classified images of the HRV monobands, given in Fig.4, by applying the possibility classification process. We see on these results that thematic classes are discerned. By analyzing locally, we note in the "Lake of Reghaia" Fig.5: on the band 1, some pixels are assigned by possibility decision to the water class and on the band 2 and band 3, they are assigned to classes (bare soil or vegetation).

Moreover, we notice in Fig.6 on the band 1 and the band 2 that tracks and the structure of the "Houari Boumediene airport" of Algiers are well discriminated, which is not evident on band 3.



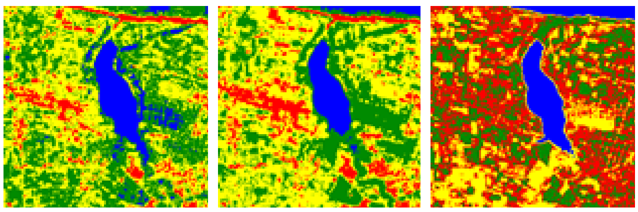
a) b) c)

Fig. 3 Images classified of HRV monobands using possibility process without estimation a)B1, b)B2, c)B3.



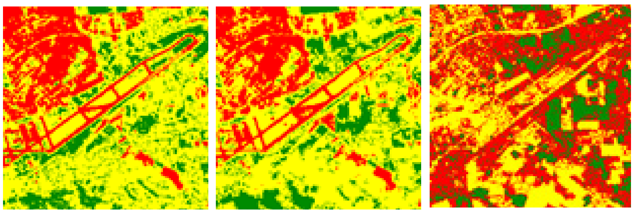
a) b) c)

Fig. 4 Images classified of HRV monobands using possibility process with estimation a)B1, b)B2, c)B3.



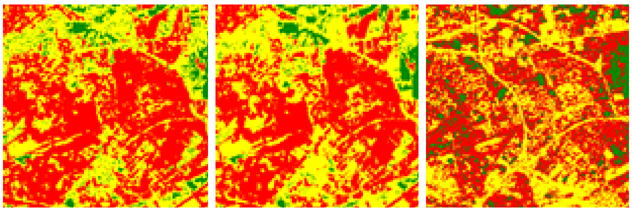
a) b) c)

Fig. 5 Zoom on the lake of "Reghaia" zone of the images classified of HRV monobands using possibility process with estimation a)B1, b)B2, c)B3.



a) b) c)

Fig. 6 Zoom on the tracks of the airport zone of the images classified of HRV monobands using possibility process with estimation a)B1, b)B2, c)B3.



a) b) c)

Fig. 7 Zoom on the roads zone of the images classified of HRV monobands using possibility process with estimation a)B1, b)B2, c)B3.

In other hands, in Fig.7, the roads are better distinguished in the band 3 relative to bands 1 and 2 . This represents confusion between these spectral bands. Therefore, we proceed to step possibility fusion of the three spectral bands to exploit their complementarities.

2) Possibilty classification of multibands sensor

We interpret and analyze the results of multiband possibility fusion of the two sensors. This step was applied after a step of estimating the values of possibility membership of pixels to thematic classes considered (Water, Urban, vegetation, soil) for each spectral band.

a) HRV multispectral sensor:

The image classified of HRV multibands using conjunctive operator is given by Fig.8.a, which constitutes from predefined classes on which the spectral bands emit the same opinion and a class of confusion on which the spectral bands do not emit the same opinion. The image classified of HRV multibands using disjunctive operator is given by Fig.8.b, which constitutes from only predefined classes and the confusion is represented by one of these classes because the disjunctive operator is tolerant.

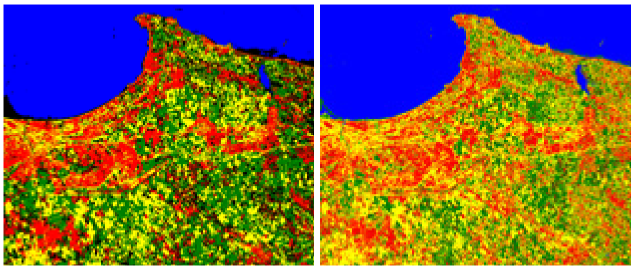
By comparing the possibility result using conjunctive operator and that of the Maximum of Likelihood (MLL) (Fig.9), we notice that in the MLL result, there is no class of confusion and does not reflect the reality performed by the possibility result of conjunctive operator because it is a correlation between the different thematic classes.

For a visual interpretation of this result, we choose a representative example of a confusion area of the mouth of "Oued ElHarrach" given in Fig.10.b. We find that the result of MLL affects parcels of water (river) to bare soil, while the possibility result of the conjunctive operator (Fig.10.c) affects these parcels to a class of confusion. This result is approved by tracing the spectral signatures of this region from the plot of HRV multispectral image (Fig.10.a).

In quantitative analysis, we see on the mean signature of the class that the signature of the confusion class (black) is intermediate between two mean spectral signatures which are: vegetation and bare soil (see Fig.11). Therefore, the confusion class is considered a correlation between all classes. Moreover, the overall accuracy and the Khat parameters of the image classified result by conjunctive operator are better than the result given by MLL. These validation parameters are calculated from confusion matrices given in Tables II and III.

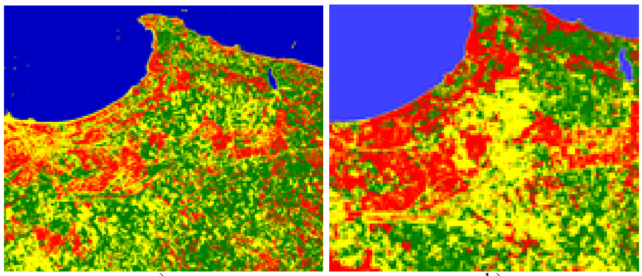
b) ETM+ multispectral sensor:

As the result of the HRV sensor, multisource multispectral image ETM + obtained by conjunctive fusion (Fig.12.a) constitutes from predefined classes and a class of confusion. The multisource multispectral image obtained by disjunctive fusion (Fig.12.b) constitutes from only predefined classes and the confusion class is represented by one of these classes because the disjunctive operator is indulgent. By comparing the result of conjunctive possibility fusion and that of MLL (Fig.9.b), we note that the result of MLL, there



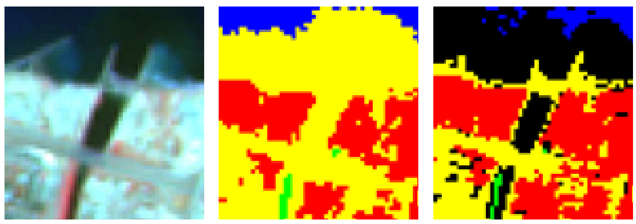
a) b)

Fig. 8 Image classified of HRV multibands using possibility model a)conjunctive operator, b)disjunctive operator.



a) b)

Fig. 9 Image classified using Maximum Likelihood (MLL) a) HRV multibands, b)ETM+ multibands.



a) b) c)

Fig. 10 Zoom on the mouth of "Oued ElHarrach" a) composed RGB of raw HRV multibands, b) Bayesian operator (MLL), c) Conjunctive operator.

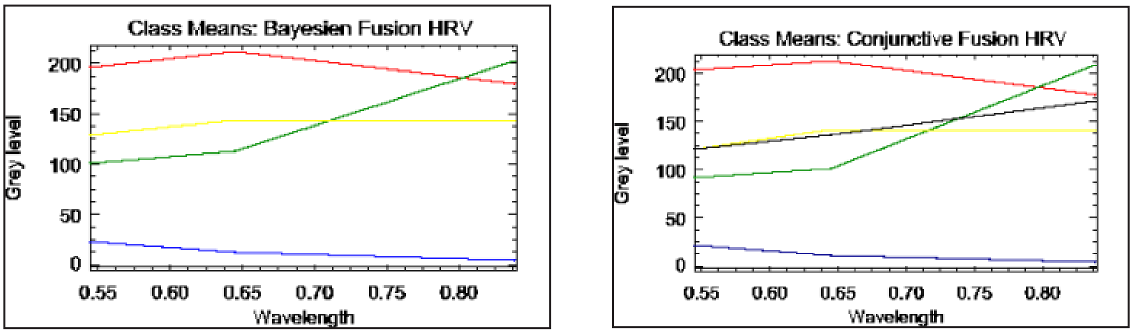


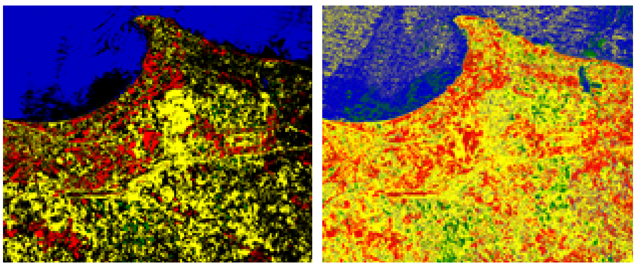
Fig. 11 Mean of spectral signatures of the confusion class (black) and predefined classes of HRV classified image. a) Bayesian fusion, b)Conjunctive fusion

Tab 2. confusion matrix of the bayesian result: overall accuaracy=95,79%, khat=94,23%.

HRV Sensor		Test Base			
		W	U	V	B
Classified Image by Maximum Likelihood	W	107	0	0	0
	U	0	186	0	16
	V	0	0	187	3
	B	0	0	6	90

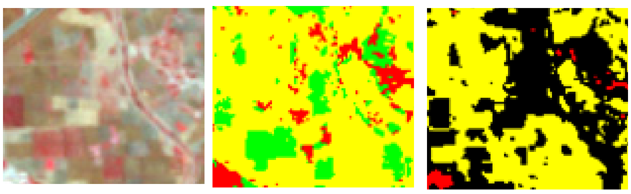
Tab 3. confusion matrix of the bayesian result: overall accuaracy=95,79%, khat=94,23%.

HRV Sensor		Test Base			
		W	U	V	B
Classified Image by Conjunc-tive Fusion	W	107	0	0	0
	U	0	174	1	2
	V	0	0	185	2
	B	0	1	4	105



b) c)

Fig. 12 Image classified of ETM+ multibands using possibility model a)conjunctive operator, b)disjunctive operator.



a) b) c)

Fig. 13 Zoom on the "Oued ElHamiz "a) composed RGB of raw ETM+ multibands, b) Bayesian operator (MLL), c) Conjunctive operator.

is no class of confusion and does not reflect reality interpreted by the result of conjunctive possibility fusion because it is a correlation between the different thematic classes.

For a qualitative analysis of the result, we choose a representative example of the river of El-Hamiz "Oued El-Hamiz "shown in Fig.13. We notice in the result of MLL (Fig.13.b) that parcels of "Oued El-Hamiz" are assigned to the vegetation class or bare soil class. However, these parcels are classified in a confusion class by the result of possibility using the conjunctive operator (see Fig.13.c).

Concerning the quantitative analysis, it is performed in the same manner as that of evaluating the results of the multispectral classification of HRV sensor. In fact, the mean spectral signature of the confusion class (black) is intermediate between two mean spectral signatures which are: vegetation and bare soil (see Fig.14).

3) Possibility fusion of multitemporal satellite images

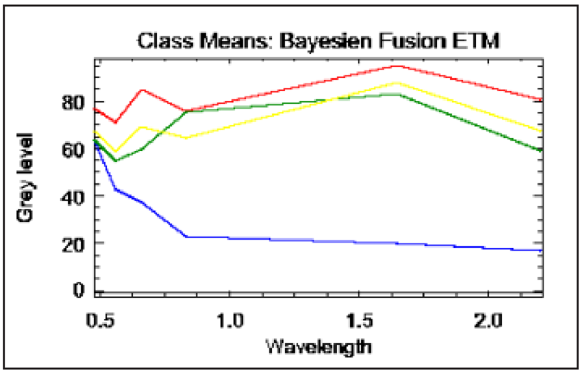
After applying the possibility classification process to the two sensors HRV and ETM+ separately and obtained possibility maps of land use by conjunctive and disjunctive operators, we will combine these two sensors for the detection of changes areas between the two dates. We obtained two results by both conjunctive and disjunctive combinations, given respectively by the Fig.15.a and Fig.15.b.

We note that on the conjunctive map that pixels (invariant sites) confused between the two sensors are assigned to a class of confusion on which these sensors do not emit the same opinion and other pixels assigned to predefined classes, on which the sensors emit a joint opinion.

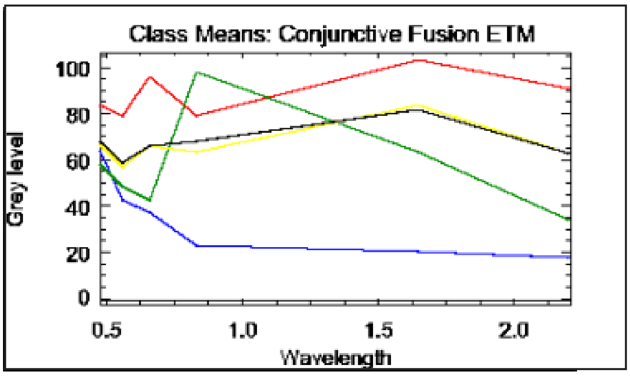
We also note that the pixels representing the variant sites are assigned to a change class and the stable pixels are assigned to predefined classes.

Note that the disjunctive map is obtained by combination of conjunctive possibilities combined of each sensor.

For a qualitative analysis of the result, we choose a representative example of the area between "El-Hamiz" and "Dar El-Beida" shown in Fig.16. We notice in the result of classified image using conjunctive fusion (Fig.13.a) that parcels of this zone are assigned to the confusion class. This result is approved by composed RGB of HRV and ETM+ (raw images) which they dont emit the same opinion. Moreover, the overall accuracy and Khat parameters of the multisensor classified image result using conjunctive operator are good. This result is listed in Table IV.

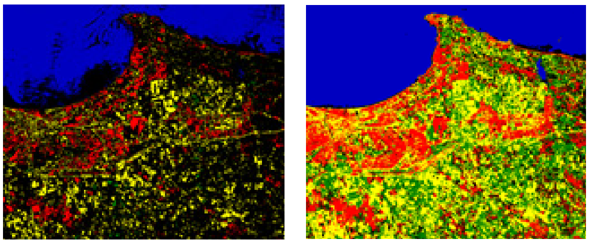


a)



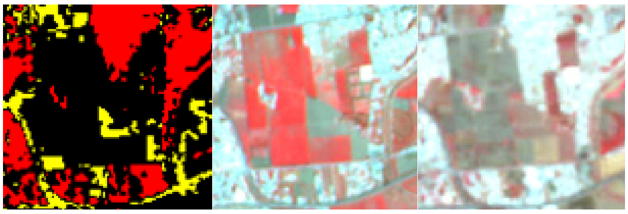
b)

Fig. 14 Mean of spectral signatures of the confusion class (black) and the predefined classes of ETM+ classified image a) Bayesian fusion, b)Conjunctive fusion.



a) b)

Fig. 15 Image classified of multisources multisensors possibility fusion (HRV and ETM+) a)conjunctive operator, b)disjunctive operator.



a) b) c)

Fig. 16 Zoom on the Area between El-Hamiz and Dar El-Beida a) classified Multisensor Multitemporal image using Conjunctive Fusion b) composed RGB of raw HRV multibands, b) composed RGB of raw ETM+ multibands,

Tab 04. confusion matrix of the possibility multisource result: overall accuaracy=100%, khat=100%.

HRV Sensor		**Test Base**			
		W	U	V	BS
Classified Image by Maximum Likelihood	W	**98**	0	0	0
	U	0	**164**	0	0
	V	0	0	**127**	0
	BS	0	0	0	**106**

4. Conclusion

In this paper, we applied the possibility fusion process, for the detection of changes between the two dates 1997, 2001.

Through this process applied to the two optical multitemporal satellite images, considered in our approach. We generated maps of land use which take into account the confusion between the different sources.

First, we applied it to spectral bands taken individually, which provided maps containing classes well discerned, but these bands provide different results. Therefore, we used a combination of these bands to exploit their spectra complementary and we obtained maps with predefined classes on which spectral bands emit the same decision and a class of confusion on which the bands has not the same opinion. We demonstrated that this class has a spectral signature intermediate between the signatures of other predefined classes.

Subsequently, we combined the two multispectral images from two separate sensors, acquired on different dates, by developing a multisensor multitemporal classification-fusion process.

The result for invariant sites is a map containing predefined classes of sensors which emit the same opinion and a class of confusion on which the sensors are not in agreement. However, for variants sites, the result is a change map that contains predefined classes and a class of stable change.

We applied this theory, efficiently and in minimum time (in terms of computing resources, computing time, etc.) for the improvement of the land use map for the monosource and multi-source classification and the establishment of the change map for multitemporal classification.

These results are conclusive and closer to the ground truth. We can say that the changes detected by the theory are consistent with changes in the study area between 1997 and 2001. The results are satisfactory because they reflect the reality of the imaged scene, but the result will be better if we include other information. For this reason we propose as perspectives for our work to integrate, within the fusion-classification process different types of satellite data such as, the heterogeneous contextual information or a SAR image.

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