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Change Detector Combination in Remotely Sensed Images Using Fuzzy Integral

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***Abstract*—**Decision fusion is one of hot research topics in classification area, which aims to achieve the best possible performance for the task at hand. In this paper, we investigate the usefulness of this concept to improve change detection accuracy in remote sensing. Thereby, outputs of two fuzzy change detectors based respectively on simultaneous and comparative analysis of multitemporal data are fused by using fuzzy integral operators. This method fuses the objective evidences produced by the change detectors with respect to fuzzy measures that express the difference of performance between them. The proposed fusion framework is evaluated in comparison with some ordinary fuzzy aggregation operators. Experiments carried out on two SPOT images showed that the fuzzy integral was the best performing. It improves the change detection accuracy while attempting to equalize the accuracy rate in both change and no change classes.

***Keywords*—** change detection, decision fusion, fuzzy logic, remote sensing.

I. INTRODUCTION

A large number of effective algorithms have been developed for detecting changes in remotely sensed imagery. Among them, methods that are based on classification procedures are of particular interest since they make an optimal use of all spectral channels and provide complete information about the nature of change. In this context, there are basically two change detection scenarios, in which multitemporal data are handled either by comparative analysis or by simultaneous analysis. The comparative analysis approach using the post classification comparison technique, was the standard change detection method, since it indicates not only that changes have occurred, and where, but will also identify the precise nature of change [1]. However, in this method, classified images must be as accurate as possible because classification disagreements have a compounding effect on change detection. Furthermore, the comparison of land cover classifications for different dates does not allow the detection of subtle changes within a land cover class [9]. Therefore, the second scenario in which a single classification process analyzes simultaneously all multispectral and multitemporal channels could be more interesting. Supervised classification methodologies, which are mostly used in remote sensing, share a common objective, to allocate each pixel to a pre-defined class on the basis of its spectral properties. Unfortunately, these methods can be very expensive in terms of the adopted statistical model of classes and training data. Moreover, they have several disadvantages. For instance, a change may be detected if in a particular date the spectral signature of a land cover class is too general to describe properly a pixel which is considered to be part of it. Furthermore, an important issue in change detection is the affectation of pixels which cover more than one land cover type. In such pixels, if only some proportions have undergone a change to another land cover type, any decision is likely to fail. Thus, fuzzy classification algorithms are used to cope with these problems [1], [8]. On the other hand, the choice of the appropriate method can be difficult, especially for applications including several kinds of change. The problem is that different change detectors produce different results since they handle the data differently. In return, they offer complementary information because the sets of patterns misclassified do not necessarily overlap [7]. Therefore, one can adopt the combination concept which is widely used in classification area to achieve the best possible result. A variety of schemes have been proposed in this context, and it has been experimentally proven that they can improve classification accuracy.

The purpose of this paper is two fold. First, the comparative and simultaneous analysis based change detectors are developed by using a fuzzy classifier. We then, combine the obtained systems to investigate the applicability of change detector combination in remote sensing. The combination is carried out by using two forms of the fuzzy integral. This method provides a useful way for aggregating information [3], and has been successfully used for combining systems in different areas such as classification, digital handwritten recognition, and image sequence analysis (See: [3-5], [7-11]). In experiments, the performance of this method will be compared to those of some ordinary fuzzy fusion operators.

The rest of this paper is organized as follows. Section 2 introduces the change detector combination as well as the fuzzy classification algorithm used in both comparative and simultaneous analysis approaches. It presents also, the different fusion rules. Experimental results are given and discussed in section 3, while the last section concludes the paper.

II. METHODOLOGY

A. Decision fusion scheme

The objective of the fusion stage is to produce a change detection system with an improved accuracy compared to individual systems. In this paper, we are interested to combine two fuzzy change detectors. The first change detector is based on comparative analysis of the independently-produced classifications of data that is mostly called the post classification comparison. In contrast, the second change detector is based on simultaneous analysis of data through a single classifier. Figure 1 summarizes the procedure of change detector fusion where (*CA*) designates

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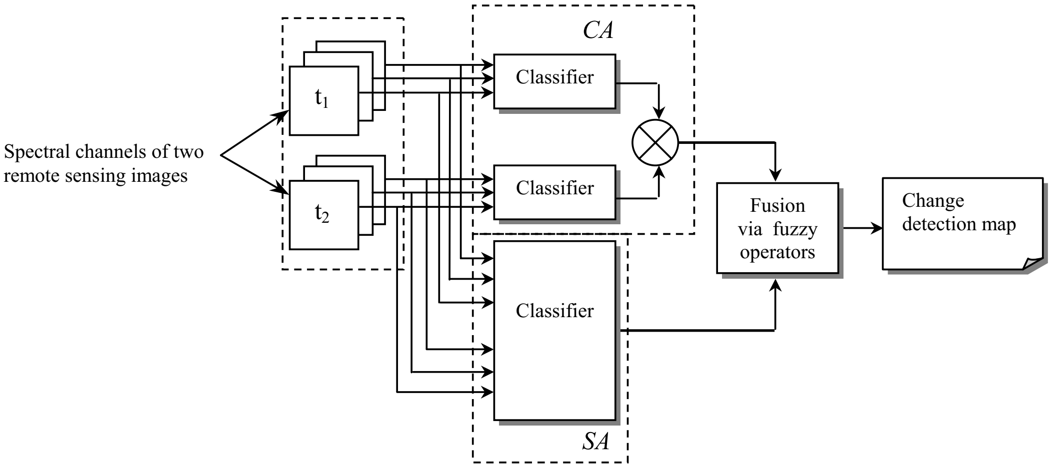


Fig. 1. Description of Change Detector Fusion

the comparative analysis, and (*SA*) designates the simultaneous analysis.

B. Comparative Analysis Based Change Detector

A large number of fuzzy classifiers are available in literature. Generally, they share the use of the basic concepts provided by fuzzy set theory. Nevertheless, there are large differences regarding how they handle the data in the training and validation stages [1]. The adopted fuzzy classification has been used in [5] to perform a classification task. In this scheme, the fuzzy class membership of a given pixel in a particular land cover class is defined as

$$h_{km} = \frac{\left(\frac{1}{d_{km}^2}\right)^r}{\sum_{j=1}^{c}\left(\frac{1}{d_{jm}^2}\right)^r} \qquad (1)$$

Where: $$d_{km}^2 = (m - p_k)^T A_k (m - p_k) \qquad (2)$$

m : pixel index.
k : class index.
d_{km} is the Mahalanobis distance between the pixel m and the class k.
p: mean vector.
A: inverse covariance matrix.
c: number of classes.
r: controls the amount of fuzziness.

The separate application of this model over two images acquired on different dates produces two fuzzy classifications. To undertake change detection we do not have single class labels to compare as we do in the traditional post classification approach [5]. Instead, we have the degree of membership of each pixel in each of the classes of interest. In this case, arithmetic operators as well as ranking techniques are useless because they do not lead to a result which can be considered as a membership value. Therefore, it is advantageous to use fuzzy aggregation operators like triangular norms and conorms [5]. Hence, the fuzzy class membership of a pixel m in the class k at t_1 is described by $h_{km}(t_1)$. Similarly, its membership in the class l at the date t_2 is described by $h_{lm}(t_2)$. To inspect at what point this situation is truth, we evaluate the fuzzy membership in the change class (k, l) that is given by:

$$h_{(k,l)m} = Min\left(h_{km}(t_1), h_{lm}(t_2)\right) \qquad (3)$$

C. Simultaneous Analysis Based Change Detector

In this section, we propose the use of the classification method described above to develop the fuzzy simultaneous analysis based change detector. The fuzzy classifier will receive the spectral bands of two images spatially aligned and concatenated at the input to automatically extract the location, the spatial extent, and the precise nature of change. The fuzzy membership values are then computed on the bitemporal space where the dimension of mean vectors and covariance matrices is equal to the number of bands in the two images.

$$h_{(k,l)m} = \frac{\left(\frac{1}{d_{(k,l)m}^2}\right)^r}{\sum_{j,p=1}^{c}\left(\frac{1}{d_{(j,p)m}^2}\right)^r} \qquad (4)$$

D. Combination Rules

Many fuzzy aggregation operators are used in decision fusion such as triangular norms and averaging operators. In this paper, our focus is on fuzzy integration operators which use a prior knowledge about the worth of individual systems. The decision fusion is then carried out by using two kinds of the fuzzy integral which is experimentally evaluated in comparison with averaging operators that are given below.

1. Averaging operators

An averaging (or mean) operator M is a function

$$M:[0,1]\times[0,1]\to[0,1]$$

satisfying the following properties

- $M(x,x)=x, \forall x\in[0,1]$,
- $M(x,y)=M(y,x), \forall x,y\in[0,1]$,
- $M(0,0)=0, M(1,1)=1$,
- $M(x,y)\leq M(x',y')\; if\; x\leq x'\; and\; y\leq y'$.

Among the different averaging operators, we use the arithmetic mean that is given by

$$M(z_1,z_2)=\frac{z_1+z_2}{2} \tag{5}$$

$Z=\{z_1,\ldots,z_n\}$ is the set of change detectors whose cardinality n is equal to 2.

A new technique of information aggregation was introduced by Yager using the ordered weighted averaging (OWA) operators. We focus on OWA-AND and OWA-OR operators [2]. The OWA-AND is defined as

$$OWA-AND(z_1,z_2)=\frac{1-\alpha}{Card\,Z}\sum_{i\in Z} z_i+\alpha \min_{i\in Z} z_i \tag{6}$$

This operator makes somewhat a transformation of the change detector outputs. Thereby, the fusion is achieved by taking the maximum of the new outputs. On the other hand, the *OWA-OR* operator is defined as

$$OWA-OR(z_1,z_2)=\frac{1-\beta}{2^n}\sum_{i} z_i+\beta \max_{i} z_i \tag{7}$$

Recall that parameters α and β must lie in the unit interval.

2. Fuzzy integral operators

The ultimate goal of the fuzzy integral is to combine objective evidences of different change detectors with respect to their performances. In this work, the objective evidence $h(z_i)$ provided by a change detector z_i, is in the form of a fuzzy membership degree, while the constructed fuzzy measure forms an evaluation of its performance. In what follows we define the main components in this fusion strategy.

a) Fuzzy measure: a set function $g:Z\to[0,1]$ is called fuzzy measure if [3-5]:

- $g(\phi)=0, g(Z)=1$
- $g(A)\leq g(B)\; if\; A\subset B$.

The fuzzy measure does not follow the addition rule, that is if $A,B\subset Z$ so that $A\cap B=\phi$:

$$g(A\cup B)\neq g(A)+g(B) \tag{8}$$

However, while combining multiple sources one must set the fuzzy measure of groups of sources. Therefore, Sugeno proposed the lambda fuzzy measure which was associated to the fuzzy integral.

b) λ-Fuzzy Measure [3], [4]*:* For each change detector z_i to be combined, we associate a fuzzy measure $g_k(z_i)$ indicating its performance in the class *k*.
For a given pixel, let $h_k(z_i)$ be the objective evidence of the change detector z_i for the class *k*. The set of change detectors is rearranged such that the following relation holds: $h_k(z_1)\geq\cdots\geq h_k(z_n)\geq 0$.

We obtain then an ascending sequence of change detectors $A_i=\{z_1,\ldots,z_i\}$, so that $A_1=z_1$ and $A_i=A_{i-1}\cup z_i$. The fuzzy measures of the obtained change detectors are constructed as

$$g_k(A_1)=g_k(z_1) \tag{9}$$

$$\begin{aligned} g_k(A_i)&=g_k(A_{i-1}\cup z_i) \\ &=g_k(A_{i-1})+g_k(z_i)+\lambda g_k(A_{i-1})g_k(z_i) \end{aligned} \tag{10}$$

For each class, λ is determined by solving an n-1 degree equation:

$$\prod_{i=1}^{n}[1+\lambda g_k(z_i)]=1+\lambda \tag{11}$$

c) Sugeno Fuzzy Integral [3-5], [12]*:* for the class *k*, the Sugeno integral is computed by:

$$I_S(k)=\int h\circ g=\mathop{Max}_{i=1}^{n}\left[Min\left(h_k(z_i)\right),g_k(A_i)\right] \tag{12}$$

d) Discrete Choquet Integral: it is another form of the fuzzy integral which is based also, on fuzzy measures. The discrete Choquet integral of a function $h: Z\to R^+$ with respect to *g* is defined as [10-11, 13]:

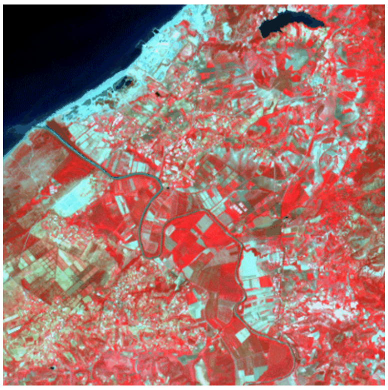
$$I_C(k)=\sum_{i=1}^{n}\{h_k(z_i)-h_k(z_{i-1})\}g_k(A_i) \tag{13}$$

Where indices i are permuted so that: $h_k(z_n)\geq\cdots\geq h_k(z_1)\geq 0$, the new sequence of change detectors is $A_i=\{z_i,\ldots,z_n\}$ and $h_k(z_0)=0$.

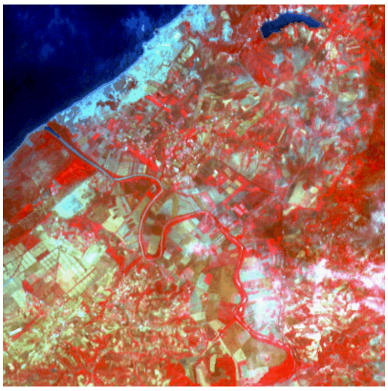
III. Experimental Results

A. Description of the Study Area

The study site is a coastal region located in the north of Algeria, in which we are interested in those land cover changes caused by human activities or extreme natural changes that are irreversible for years. Two SPOT images of this area taken respectively on May 1989, and June 1991 have been selected to evaluate the proposed approach. During this period, the studied region has undergone critical changes in vegetal surfaces and water bodies. Furthermore, the satellite images depict other changes caused by the presence of clouds in the second image (Figures 2.b). Therefore, the change class defined as X ⇨ Clouds (where X is whatever class in the first date) is added to the classes of interest that are listed in table1.



(a)



(b)

Fig. 2. False Color Composites
(a : Image taken on 1989- b : Image taken on 1991)

TABLE I
CLASSES OF INTEREST

Class label	Description (1989 ⇨1991)
1	*Water* ⇨ *water*
2	*Vegetation* ⇨ *vegetation*
3	*Construction* ⇨ *construction*
4	*Soil* ⇨ *soil*
5	*Construction* ⇨ *soil*
6	*Vegetation* ⇨ *soil*
7	*Water* ⇨ *soil*
8	*X* ⇨ *clouds*

B. Empirical Study Choice of Fuzzification Parameter

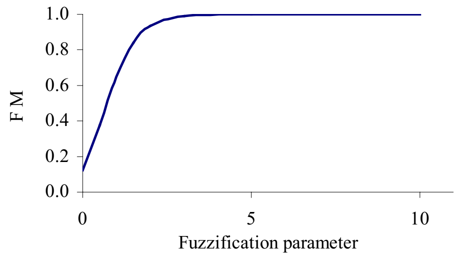
Based on the assumption that the fuzzy membership reflects the true class proportions in a given pixel, and by using expected values for each class (mean distances of the mean of each class with respect to all class prototypes) we seek the membership for various fuzzification parameters according to (14).

We present for instance, graphics that are obtained for the class *vegetation* ⇨ *vegetation* (Figure 3) and those of the class *vegetation* ⇨ *soil* (Figure 4).

$$y_{kl} = \frac{\left(\frac{1}{D_{kl}^2}\right)^r}{\sum_{j=1}^{c}\left(\frac{1}{D_{kj}^2}\right)^r} \tag{14}$$

D_{kl} : the mean distance of the class k form the class l

y_{kl} : fuzzy memebrship of the class k in the class l.



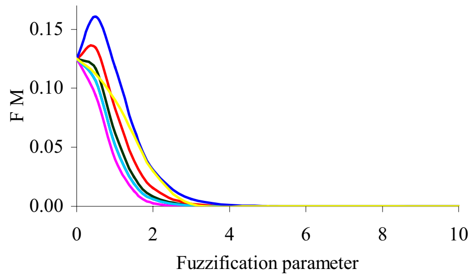
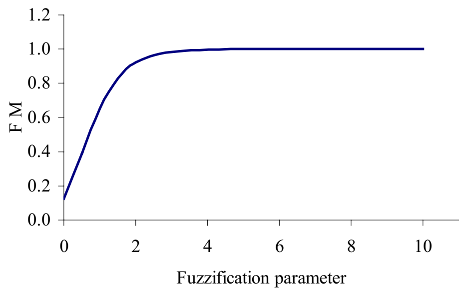


Fig. 3. Fuzzy Membership of Pixels of the Class *vegetation* ⇨ *soil*
(a : In their class, b: In other classes)



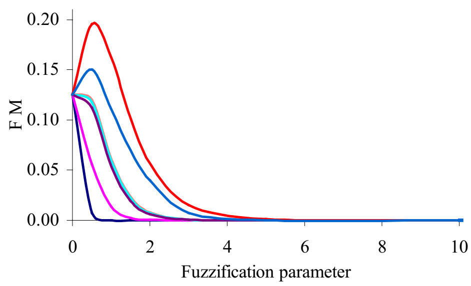


Fig. 4. Fuzzy Membership of Pixels of the Class *vegetation* ⇨ *vegetation*
(a : In their class, b : In other classes)

As can be seen, from a value of 1.5, pixels present high fuzzy membership in their classes and negligible memberships in all other classes. In this work, we take 2 as the value of the fuzzification.

C. Statistical Evaluation

Performances of the different fuzzy fusion operators are evaluated comparatively to those of individual change detectors by using the fuzzy accuracy (FA) per land cover class as well as the fuzzy overall accuracy (FOA) [1], [8]. It is worth noting that selected data for each class of interest were split into three different sets. The first was used in the training stage; the second in the evaluation stage, while the third constitutes a validation set used to compute fuzzy measures. Notice that fuzzy measures can be affected subjectively by an expert [3] but in this work, we used the FA ratio computed on the validation set to accurately express the performance of each individual change detector.

Parameters α and β of the two *OWA* operators were fixed at 0.9. These values have been experimentally determined so that they provide the best possible result. Table 2 exhibits the fuzzy accuracies as well as the FOA rates obtained for the individual systems, while table 3 reports results obtained for the different fusion operators. As can be seen, the fusion operators allow a significant improvement of the fuzzy overall accuracy rate. Specifically, the averaging operators acheived FOA values higher than those obtained by individual change detectors. However, except the *OWA-AND* operator which increases the FOA to 81.28 %, they do not improve the fuzzy accuracy for each land cover class. Moreover, the *Arithmetic Mean* was less accurate than the SA based change detector. This empirical finding can be explained by the fact that this operator takes the mean of the two grades of membership. On the contrary, the fuzzy integrals using a priori knowledge over the reliability of individual systems produce the best performances with a gain more than 10 % over individual change detectors. They globally outperform averaging operators and improve the fuzzy accuracy in both change and no change classes. It is worth noting that only in the change class *water* ⇨ *soil*, the simultaneous analysis-based change detector gives a better result. This outcome may be related to the manner with which the importance of the two change detectors was compared.

TABLE II
FUZZY ACCURACY RATES OF THE INDIVIDUAL FUZZY CHANGE DETECTORS

Classes	*CA* (%)	*SA* (%)
1	98.38	89.06
2	67.54	73.00
3	78.54	75.52
4	83.91	75.94
5	61.84	82.61
6	77.21	80.90
7	17.65	49.69
8	75.90	66.78
FOA	70.56	74.43

D. Visual Inspection

The visual inspection of the resulting change detection map indicates how the corresponding rule generalizes. Figure 3 shows the maps obtained for the two individual change detectors as well as those obtained for fused systems. In this figure, only the three change classes (Classes whose labels are 5, 6, 7) are depicted since we are particularly interested in change detection. As can be seen, the two change detectors produce considerable misclassification rates. According to figure 3.(a), the comparative analysis neglects an important change surface in the river (Rectangle in fig 3.a) and so a poor detection of the class water ⇨ soil. Moreover, it presents an important amount of omissions in the class construction ⇨ soil. Instead, the simultaneous analysis based change detector produces commission errors in the classes construction ⇨ soil (Rectangle in fig 3.b) and water ⇨ soil. In fact, errors in the first class are related to the clouds which were not selected as belonging to the class X ⇨ clouds, while errors in the second class are due to some isolated changes in vegetal areas which have not been considered in the training set. On the contrary, fusion operators produce much cleaner change maps by correcting many of these errors. Besides, the most accurate maps were produced by the two fuzzy integrals which improve the detection accuracy in the different change classes while reducing the number of false alarms. As example of this, we notice errors in the class water ⇨ soil (See circles in figures 3.a, b, c, d, e) which were only correctly classified by using the fuzzy integrals. However, it is worth noting that the OWA-AND operator was the worst performing among all fusion operators. It produces a map that is likely to that of CA.

E. Discussion

A known problem in change detection area is the choice of the appropriate method, especially when we are interested to determine the precise nature of change. For many years, the post classification comparison was the traditional change detection scheme, since it provides complete information about the land cover change. However, this method has several disadvantages which conduct generally to a poor change detection. Thereby, recently an alternative approach using simultaneous classification of multitemporal data is increasingly used to provide more accurate results. However, the problem of conventional classifiers which are commonly used is the affectation of mixed pixels located even at class boundaries. To overcome this limitation fuzzy classifiers are used. On the other hand, since the comparative and the simultaneous analysis approaches operate differently, we conjecture that their combination will be useful. Therefore, we presented at first, a fuzzy classifier to develop both comparative and simultaneous based change detectors. The adopted classifier takes advantage of the the flexibility of fuzzy systems, which allow the reasoning with the membership value of a pixel in different classes. In a second step, the obtained change detectors were combined by using various forms of the fuzzy integral which incorporate a prior knowledge about the difference of performance of combined systems. The evaluation test in comparison with individual change detectors, as well as three ordinary fusion operators, reports that the fuzzy integrals perform better both quantitatively and qualitatively. However, it is important to stress that in classes where one of the individual change detectors has a very poor accuracy, the accuracy of the combiner will be lower than that of the most precise individual change detector (This is the case of the class 7). This result is due to the fact that we have combined only two change detectors. In such a case, the fuzzy integral can be seen as doing somewhat an averaging of the objective evidences. Ultimately, in general view, the obtained results indicate that it is very effective to incorporate different change detectors into a single change detector using a collective decision strategy.

IV. Conclusion

In this paper, a fuzzy fusion framework was proposed to improve change detection in remotely sensed data. A fuzzy classifier based on the squared Mahalanobis distance measure was used to develop two change detectors based respectively on comparative and simultaneous analysis of data which were subsequently combined by using two forms of the fuzzy integral. The adopted fusion rules were evaluated in comparison with different ordinary fuzzy fusion operators. Experiments showed that the combination via the fuzzy integral tends to improve the overall precision by equalizing the accuracies in individual classes. Therefore, it derives more meaningful change detection maps with fewer isolated regions of errors. Furthermore, although the best overall accuracy was achieved by Sugeno integral, the two fuzzy integrals produce very similar results. Again, this study pointed out the usefulness of fuzzy fusion operators to achieve an improved change detection accuracy. A further work including the fusion of multiple change detectors is required to attempt to improve the accuracy in all classes of interest.

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Table III
Fuzzy Accuracy Rates Obtained for the Different Combination Rules Expressed in %

Classes	Arithmetic mean	OWA-OR	OWA-AND	Choquet Integral	Sugeno Integral
1	93.72	93.23	98.39	100.00	100.00
2	70.27	72.00	75.67	84.23	87.30
3	77.02	78.44	82.66	89.25	90.74
4	79.92	84.64	89.32	96.00	97.20
5	72.23	83.3	87.21	86.78	86.76
6	79.05	80.45	84.61	87.69	88.84
7	33.67	46.41	48.09	43.91	46.08
8	71.34	76.57	80.86	83.47	87.39
FOA	72.61	77.29	81.28	84.43	86.56

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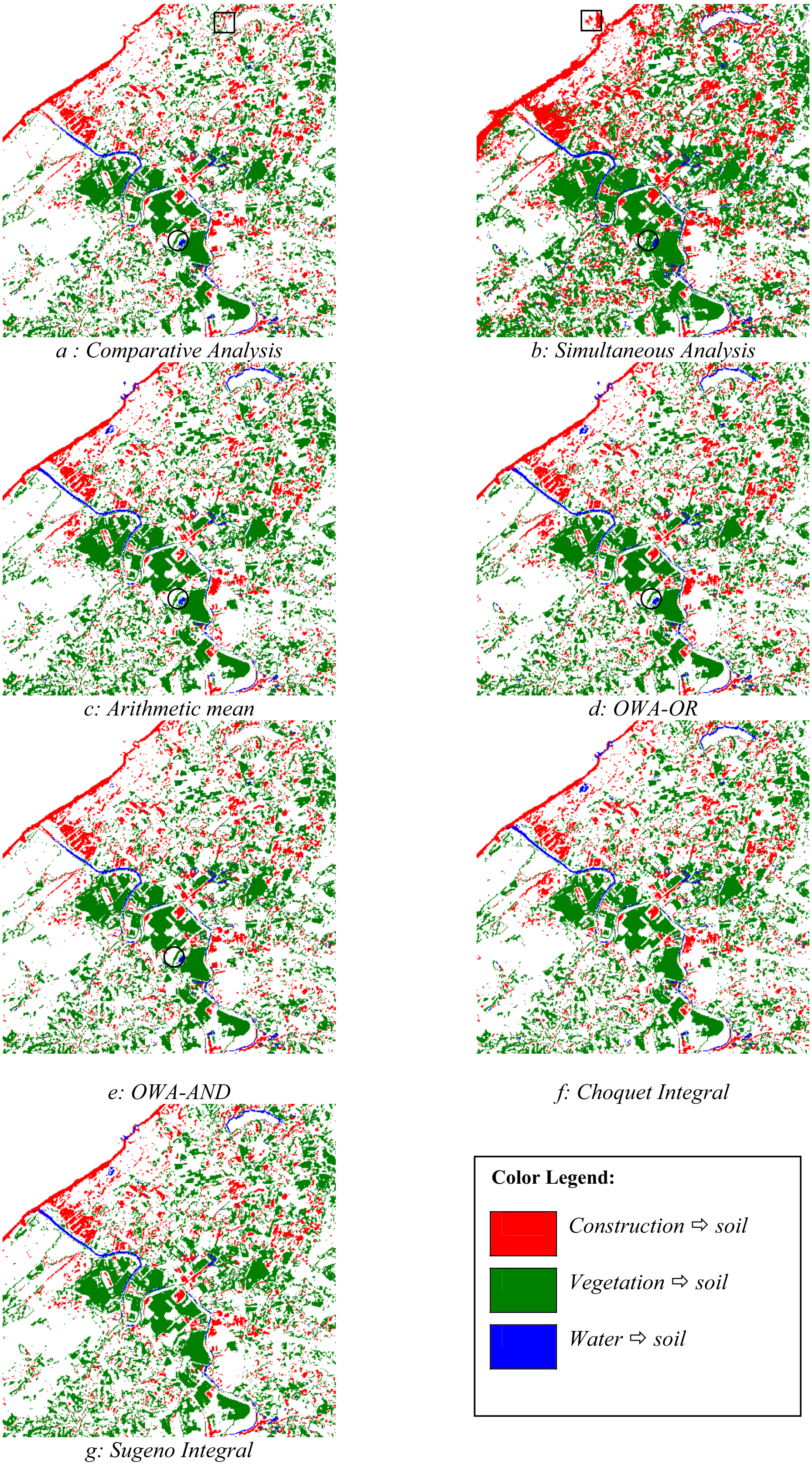

Fig. 3. Change Detection Maps Depicting the Three Change Classes