A SEMI-AUTOMATED APPROACH FOR THE PRODUCTION OF LAND-COVER CHANGE MAPS USING FUZZY SETS AND REMOTELY SENSED DATA

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ABSTRACT

This paper presents the framework for the implementation of a non-heuristic technique for thresholding of change images derived from multi-temporal analysis of remotely sensed data using pre-classification techniques. The approach is based on fuzzy sets and fuzzy logic, and it assumes that accurate separation of change/no-change areas can be achieved if the membership function of the fuzzy model is adapted to the shape of the histogram of the change image. The output from the model is a 'possibility of changes' image, as opposed to the traditional binary change/no-change image. The accuracy in the separation of change/no-change areas is assessed using the error matrix and its associated user's, producer's and overall accuracy measures. The overall and per class kappa coefficient are used as additional measures of accuracy. The study also compares the performance of the 'fuzzy thresholding' against the 'symmetric thresholding', and determines a fuzzy linguistic value (and its associated fuzzy interval) that better reflect the separation between areas of change/no-change.

1. INTRODUCTION

Change detection can be defined as the process of identifying differences in the state of an area by undertaking multi-temporal observations. Remote detection of changes uses the reflectance values from different co-registered images to indicate where changes in land cover have occurred. Therefore, changes can be detected provided the phenomenon of interest results in detectable changes in radiance, emittance or backscatter values (Smits and Annoni, 2000).

Traditional methods of change detection using either air- or satellite-borne remotely sensed data can be broadly divided in two categories: spectral change identification methods or classification-based change detection (Lunetta and Eldvidge, 1999). In the spectral-based change identification, the operator can identify areas of change, but is unable to label the kind of change. On the other hand, classification-based change detection requires a complete classification of the individual dates of remotely sensed data, whereupon the operator produces a matrix of change that identifies '*from-to'* land cover change classes (Jensen, 1997). Although this approach exhibits some advantages over the spectral one (e.g., capability to explicitly recognise the kinds of land cover transitions, ability to process multi-sensor images), misclassification errors associated with the images being compared will be present in the final change detection analysis. Another approach for remote detection of land cover changes using generalised linear models has been proposed by Morisette *et al* (1999). They use variogram analysis on the image data for initial sampling considerations, facilitating an assessment of change metrics. Because 'probability of change' images are derived, the method can evaluate the uncertainty associated to change detection.

Every change detection method requires determining if a given change in digital values is relevant enough to be labelled as 'change'. Although relatively simple, the spectral based (or pre-classification) approaches lack automatic, non-heuristic techniques for the analysis of the change image. For changes based on image differencing, Jensen (1996) states that most analysts prefer to experiment empirically, being the amount of changes isolated subjective and mainly based on familiarity with the study area. These manual trail and error procedures either based on asymmetric (ie. different values are arbitrarily determined by the analyst) or symmetric (*n* standard deviations from the mean value of the difference image) thresholding techniques significantly affect the reliability and accuracy of the final change detection map (Bruzzone and Prieto, 2000).

This paper presents a methodology for computing land cover changes by using remotely sensed data and fuzzy modelling. The discussion concentrates on the formulation of a standard procedure that, applying the concept of fuzzy sets and fuzzy logic on the change image, can separate change areas from unchanged ones in a reliable way. The output from the model is a 'possibility of changes' image, as opposed to the traditional binary change/no-change image. Such an image can be further de-fuzzyfied and converted to a binary change/no-change image.

2. BACKGROUND TO THE FUZZY THRESHOLDING OF THE CHANGE IMAGE

The framework for separating change/no-change areas uses a decision threshold based on fuzzy set theory. It is based on the hypothesis that by adapting the membership function of the fuzzy model to the shape of the histogram characterising the change image derived from any of the pre-classification techniques aforementioned, accurate separation of areas of change from unchanged ones can be achieved. The approach is based on early suggestions brought about by Jensen and Toll (1982) and Jensen (1997). They mention that change between dates may not always be classified into discrete classes, but rather, there may exist a continuum of change within a parcel (pixel), or one pixel could have changed only partially. Thus, it is their recommendation that change detection algorithms should incorporate some fuzzy logic that takes into account the imprecise nature of digital remote sensing change detection. The fuzzy change model presented hereafter intends to fulfil these earlier observations.

2.1 Accurate separation of change/no change areas

The general form of change detection can be written as

$$Change = f(x) \qquad (1)$$

Where x is a vector of radiance values from the two images. The change variable may be a binary 0-1 response, where 0 represents 'no change' and 1 represents 'change' (Morisette et al., 2000). Two types of errors, namely omission and commission can occur when thresholding the change image. Assuming the histogram tails represent areas of change, and that two separate thresholds for negative and positive differences are used, errors of commission in the estimation of areas that have changed occur when a threshold lower than the actual one for the positive differences is determined, thus including unchanged pixels into the areas of change. Similarly, errors of omission are produced when the operator sets a threshold lower than the actual one for the negative differences, including pixels of change in the unchanged areas (Metternicht, 1999).

One common technique to analyse the change detection image consist on fixing the decision threshold at $n\sigma_D$ from the mean value of the change image, σ_D being the standard deviation of the density function of the pixel values in the change image and n being a number derived by a trial-and-error procedure (Bruzzone and Prieto, 2000). The selection of the parameter n (i.e. 0.5, 1 or more standard deviations from the mean) depends on the end-user's subjective criteria, which may lead to unreliable change detection results, as reported by Macleod and Congalton (1998).

2.2 Fuzzy logic and fuzzy sets

Fuzzy logic is valuable where the boundaries between sets of values are not sharply defined or there is partial occurrence of an event. The fuzzy sets theory was developed by Zadeh in 1965, to account for vagueness, imprecision and 'shades of gray' that are common in real world events (Klein, 2000). When using fuzzy reasoning it is valid to express that a specific area is *'extremely likely to have changed within the period of time being considered*', as opposed to the crisp reasoning of change or no-change. Fuzzy logic furnishes a systematic basis for the computation of certainty factors in the form of fuzzy numbers. The numbers may be expressed as linguistic probabilities or fuzzy quantifiers, as for instance, 'likely', 'very unlikely', 'almost certain' or 'extremely likely' (Zadeh, 1984).

2.3 Basic elements of a fuzzy system

A fuzzy system is composed of three primary elements, namely fuzzy sets, membership functions, and fuzzy production rules. A fuzzy set (class) *A* in *X* is characterised by a membership function $f_A(x)$ which associates with each point in *X* a real number in the interval [0, 1]. The value of $f_A(x)$ represents the grade of membership of *x* in *A* (Zadeh, 1965). This grade corresponds to the degree to which that point is compatible with the concept represented by the fuzzy set. Thus, points may belong to the fuzzy set to a greater or lesser degree as indicated by a larger or smaller membership grade.

There are two possible ways of deriving these membership functions. The first approach, named by Robinson (1988) as the Similarity Relation Model, resembles cluster analysis and numerical taxonomy in that the value of the membership function is a function of the classifier used. A common version of this model is the fuzzy *k*-means or *c*-means method (McBratney and Gruijter, 1992; Wang, 1990; McBratney and Moore,1985). The second approach, known as the Semantic Import Model (SI), uses an *a priori* membership function to which individuals can be assigned a membership grade. This second approach was adopted, as the research hypothesis requires the membership function to fit the shape of the change image histogram. Thus, the user decides on the kind of membership function, its boundary values and transition widths.

Several functions (e.g. linear, triangular, bell-shaped, sigmoidal) can be easily adapted to specific users' requirements, can be used for defining flexible membership grades. We implemented the model proposed by Dombi (1990):

$$\mu A(x)=[(1-\nu)^{\lambda-1}(x-a)^{\lambda}]/[(1-\nu)^{\lambda-1}(x-a)^{\lambda}+\nu^{\lambda-1}(b-x)^{\lambda}] \quad ; \quad x\in[a,b] \qquad (2)$$

$$\mu A(x)=[(1-\nu)^{\lambda-1}(c-x)^{\lambda}]/[(1-\nu)^{\lambda-1}(c-x)^{\lambda}+\nu^{\lambda-1}(x-b)^{\lambda}] \quad ; \quad x\in[b,c] \qquad (3)$$

where:

λ (sharpness) is an indicator of increasing membership to a fuzzy set (e.g. 'no changes');

ν (inflection) is the turning point of the function, interpreted as an expectation level;

a and *c* are the typical points of the function, with a membership degree of zero to the fuzzy set considered; and

b represents the standard point of the variable *'x'* (e.g., the reflectance value characterising areas of no change) at the central concept, that is a grade of membership equal to 1.

Equations (2) and (3) represent the monotonically increasing and decreasing parts of the membership function, respectively. Sharpness and inflection are the two parameters governing the shape of the function. By varying these values, the form of the membership function and the position of the crossover point can be easily controlled. Thus, the sharpness and inflection values can be manipulated in such a way that the resulting membership function is in accordance with the shape of the histogram characterising the 'change image'. In such a way, it is thought to minimise inaccuracies in the separation of areas of change/no change produced by histograms of asymmetric shape.

3. MEASURES OF CLASSIFICATION ACCURACY

A statement of the accuracy of a change map is a fundamental requisite in using the map for further spatial modelling or decision making. Ideally, classification accuracy should be expressed in the form of a single index which is readily interpretable and which allows the relative performance of different change detection techniques and/or image thresholding approaches to be evaluated. Most common measures of classification accuracy are derived from the error or confusion matrix (Foody, 1996, Jager and Benz, 2000, Biging et al., 1999). The overall accuracy (OA) provides the percentage of the pixels correctly classified in all reference areas; producer's accuracy (PA) measures the percentage of the image pixels in the reference area that are classified correctly; and user's accuracy (UA) represents the probability that a sample from the classified image represents that category on the ground (Jager and Benz, 2000).

Additional measures of accuracy such as the kappa coefficient of agreement adjust for the chance of agreement, for the whole image and for individual classes. Conditional kappa value, showing the breakdown of agreement by class can be computed as well (Bonham-Carter, 1993). A detailed discussion of these measures and their interpretations are provided in Story and Congalton (1986) and Foody (1996).

4. TEST SITE SELECTION AND DATA SET

To demonstrate the utility of fuzzy thresholding of change images, a set of multi-temporal aerial photographs acquired on 13 January 1992 and 8 January 1996, at scale 1:40,000 and 1:20,000 respectively, were used (Figure 1). These images were available from a previous study sponsored by the Department of Land Administration of Western Australia which focussed on the feasibility of using digital satellite imagery for map revision tasks at medium scales (Metternicht et al., 1997). Changes in the area are related to deforestation and urban development with the construction of new buildings, roads, roundabouts, landscaping and differences in vegetation density in the urban fringe of the Perth City, in Western Australia.

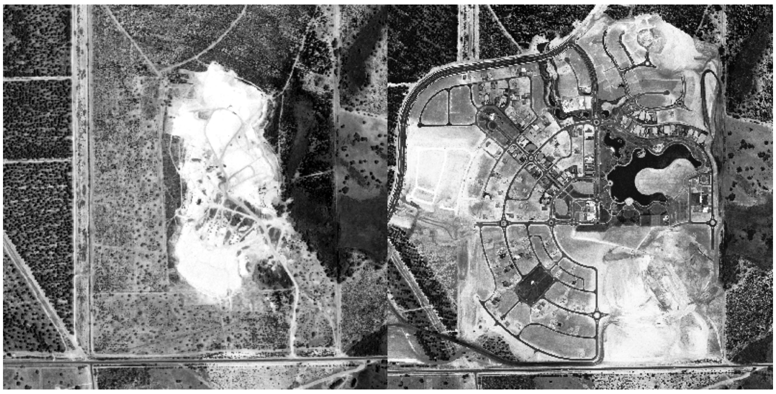

Figure 1: Aerial photographs of the test site: January 1992 (letf) and January 1996 (right)

5. METHOD

The methodological approach comprised:

1. Selecting and implementing a spectral change identification technique (e.g., image ratioing, differencing, etc.). Near-anniversary images were selected to minimise atmospheric and soil condition effects. Furthermore, accurate geometric registration was required to minimise local mis-registration effects;
2. Fuzzy analysis and thresholding of the change image. This step involved defining a membership function and selecting the function's typical and standard points; constructing a fuzzy linguistic scale; and fuzzification of the change image;
3. Accuracy assessment of the change image using the accuracy measures described in section 3;
4. Quantitative comparison between the fuzzy thresholding and symmetric thresholding (e.g. based on *n* number of standard deviation from the mean value of the change image) on their ability to accurately separate change/no-change areas; and
5. Determining the fuzzy linguistic value (and its associated fuzzy interval) that better reflect the separation between areas of change/no-change.

5.1 Deriving the change image

The images were geo-referenced to an existing digital vector database in AMG (Australian Map Grid) coordinates. Twenty-three well-distributed control points were selected from the images and their coordinates extracted from the database existing at the Department of Land

Administration. First-order polynomial transformation and nearest neighbour resampling techniques were adopted, resulting in root-mean square error (RMSE) values lower than the circular map accuracy specified for the mapping scale considered (Metternicht et al., 1997). All data were resampled to 1 m resolution. Image differencing as described in Jensen (1997) was applied to the data set. The change image yielded a histogram where pixels of no change are distributed around the mean and pixels representing changes between Time 1 and 2 are found in the tails of the distribution.

5.2 Selecting the membership function

Once the change image has been derived, the next step consists of selecting a membership function that 'fits' to the shape of the change image histogram. To this end, it is assumed that the histogram mean represent pixels of no change, with a membership degree of 1 assigned to the fuzzy set 'no change'. Conversely, the tails of the histograms represents pixels of change, thus having a membership of zero in the fuzzy set 'no change'. Applying the concepts presented in Equations (2) and (3), the mean corresponds to the standard point of the membership function implemented here, while the tails are the typical points of the function. Table 1 summarises the values of the histogram's mean and tail values corresponding to the change image.

Table 1: Values for the sharpness (λ) and inflection (ν) parameters, standard and typical points of the membership function matching the shape of the change image histogram (see Figure 2)

CHANGE IMAGE	SHARPNESS		INFLECTION		STANDARD	TYPICAL POINTS
	MI[(1)]	MD[(2)]	MI[(1)]	MD[(2)]		
Image difference	1.7	1.3	0.95	0.9	37	-234 and 253

[(1)]MI: monotonically increasing part of the function; [(2)]MD: monotonically decreasing part of the function

Equations (2) and (3) were subsequently applied, modifying the sharpness (λ) and inflection (ν) in order to obtain a membership function whose shape coincide with the histogram of the change image. Figure 2 shows the 'best' membership function representing a continuous change of the membership degree (MD) for the fuzzy set 'no change' from 1, for the mean value of the histograms depicting areas of no change, decreasing to 0 for the tails of the histograms (indicating changes). Subsequently, fuzzification was performed on the change image by relating each pixel value to its corresponding fuzzy membership degree to the fuzzy set 'no change', as determined by the fuzzy membership function. This fuzzy image representing possibilities of changes will be discussed in section 6.

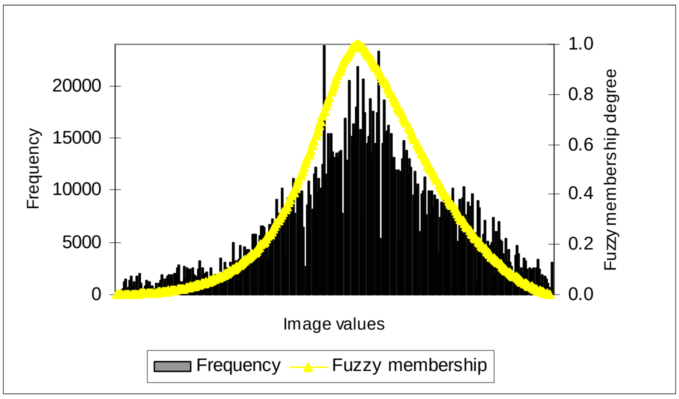

Figure 2: Best matching between the change image histogram (background) and the membership function representing the fuzzy set 'no change'. Values close to the histogram mean have a MD close to 1 in the fuzzy set 'no change'. Conversely the histogram tails (representing areas of change), are assigned a MD close to 0 to the fuzzy set 'no change'.

5.3 Constructing a fuzzy linguistic scale

The methodology considers that experts often use linguistic constructs to describe changes. The experts' knowledge is presented as terms expressing the possibility of a change to have occurred. These terms can be expressed as certainty factors within the range of 0 to 1. Instead of a continuously measured function, a fuzzy linguistic scale can be used to recode the change image into 'degrees of possibility for a change to occur'. Fuzzy production rules were generated using ten fuzzy linguistic values selected from an empirical scaling of common verbal phrases associated with numerical probabilities (Lichtenstein et al., 1967). Fuzzy intervals, and their associated digital numbers on the change image, were attached to this scale (Table 2). For instance, all the pixel values with a membership degree of 0.11 to 0.2 represent areas of *very likely changes*. The boundaries of the ten '*degrees of possibility*' scale presented in Table 2 were derived from the membership function presented in Figure 2. These boundary values were used to recode the change image into 10 classes, according to the fuzzy linguistic scale of Table 2.

Table 2: Fuzzy linguistic scale, associated fuzzy intervals and fuzzy boundaries

CODE	IMAGE DIFFERENCE MF			
	INCREASING PART	DECREASING PART	FUZZY LINGUISTIC SCALE	FUZZY INTERVAL
1	-234; -85	188; 253	Changes	0.1
2	-83; -62	163; 186	Very likely changes	0.2
3	-60; -45	161; 144	Likely changes	0.3
4	-43; -32	142; 127	Fairly likely changes	0.4
5	-30; -20	125; 112	Neither nor	0.5
6	-18; -11	110; 96	Uncertain changes	0.6
7	-9; -1	95; 83	Somewhat unlikely changes	0.7
8	1; 11	81; 68	Unlikely changes	0.8
9	12; 22	66; 51	Very unlikely changes	0.9
10	24-49		No changes	1.0

5.4 Accuracy assessment of the change image: creating the ground reference data set

Sample areas were determined by using a stratified random approach, so that the 10 classes representing different degrees of possibility of change could be represented. A total of 130 point samples were selected on the 1992 and 1996 aerial photographs, with a minimum of 10 points per class. An area of 3x3 pixels was interpreted for each sample point. In determining the land cover at each point, a classification scheme distinguishing amongst roads, buildings, quarries and bare soil, water features, and vegetation (subdivided in sparse, medium and dense), was used. If the land cover classification was different for the two time periods, the sample point was assigned a 1 (e.g, change). Areas without changes were assigned a 0. This binary reference image was used to: a) quantitatively compare the performance of the fuzzy image thresholding approach and the symmetric approach using *n* standard deviations from the mean; and b) determine the fuzzy linguistic value that better reflects the separation between areas of change/no-change.

5.5 Symmetric thresholding of the change image

A series of threshold values (ie. 0.5, 1, 1.5 and 2) based on *n* standard deviations from the mean of the change image were used to separate changed from unchanged pixels. An accuracy assessment on the output change/no-change images was performed using the accuracy measures presented in section 3, and the reference data described in section 5.4. Threshold values with the highest accuracy, and a comparison between the fuzzy and symmetric thresholding approaches were determined in this way. The following section discusses the results of these analyses.

6. RESULTS

6.1 The Fuzzy Possibility of Changes Image (FPOC)

Fuzzy thresholding of the change image allows using the results to estimate the 'possibility of change' (POC) for each pixel as a continuous variable ranging from 0 to 1. Additionally, by setting a threshold in a specific fuzzy membership degree (or certainty factor), a binary change/no-change image can be derived. The FPOC image (Figure 3) was obtained by fuzzification of the change image, as discussed in section 5.1. A part-spectral colour plan (Dent, 1996), where blue-cyan colours represent very unlikely changes (codes 8 to 10 in Table 2); whereas red-yellowish colours represent areas of very likely changes (codes 1 – 2 in Table 2) was applied for visual display.

The FPOC image reveals subtle changes that may be of value for some applications where users may be interested in areas that experienced slight changes (e.g. vegetation density), rather than significant ones (e.g. forest to residential areas). For instance, signs of vegetation stress can be evidenced by subtle changes in the canopy cover (e.g. loss of foliage, reduction of the canopy size). Likewise, healthy vegetation growth over time would be characterised by denser canopies. These changes would be associated to subtle, rather than remarkable, changes in reflectance values of the images being compared. The upper left corner of Figure 3 represents changes in vegetation density over the period 1992-1996, which are shown in yellowish-greenish colours associated to fuzzy membership degrees of 0.3 to 0.7 to the fuzzy set 'no change'. The red colours are associated to 'extreme' changes such as forest areas to bare land and roads, and bare areas to residential, all with membership degrees ranging from 0 to 0.2 to the fuzzy set 'no changes'. A traditional binary thresholding may place the threshold such that it misses the more subtle changes (e.g. errors of omission would be high), or it may include the slight changes, without differentiating them from more extreme changes.

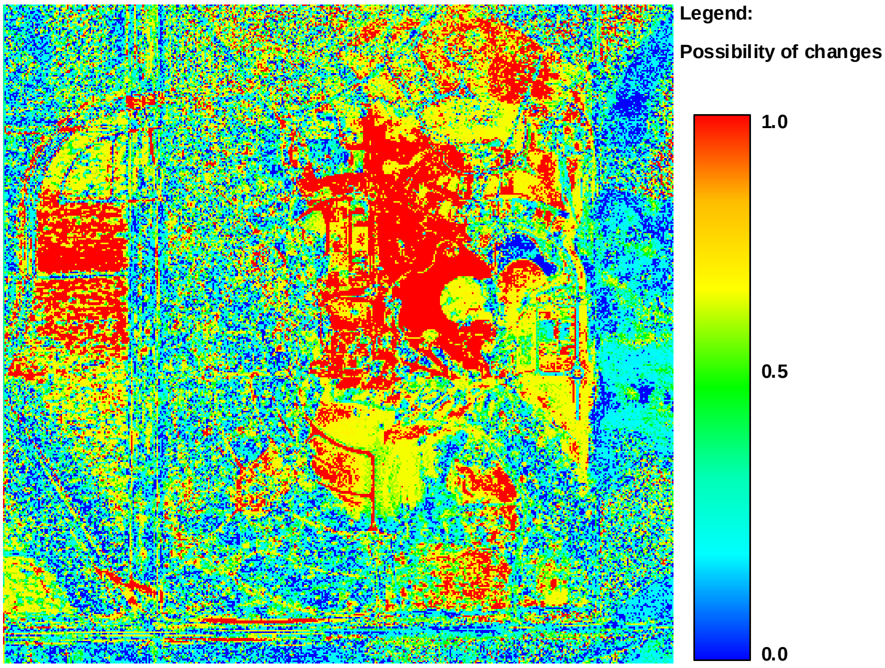

Figure 3: Fuzzy possibility of change (FPOC) image. A part-spectral colour plan (red-yellow-green-cyan-blue) is associated to the possibility of changes for an area. The fuzzy intervals and fuzzy linguistic scale associated to the legend are presented in Table 2.

Additionally, a change image that represents continuous changes in a scale of 0 to 1, allows communicating the uncertainty of the changes detected. Information derived from remotely sensed data is not crisp and definite in isolating changed from unchanged areas. Binary images might create a false impression that there is a clear differentiation between change/no change. In this regard, the FPOC image provides the end users the freedom to either use the continuos image where changes are graded from 0 to 1, or to select a fuzzy interval reflecting the changes of interest. In either case, the FPOC reflects not only changes in land cover associated to spectral variations between the dates being compared, but it provides an idea on the uncertainty associated with deriving the change information from remotely sensed data. The next section analyses the fuzzy linguistic values (and its associated fuzzy intervals) that better reflected the separation between areas of change/no-change.

6.2 Defuzzification

To determine the fuzzy interval that better separated areas of change from no-changed ones, the FPOC image was converted to a binary change image by placing the threshold at different fuzzy membership degrees (FMD). The following thresholds were trialed:

Change image = 1 if FMD $\leq$ 0.4; 0 if FMD $>$ 0.4;
1 if FMD $\leq$ 0.5; 0 if FMD $>$ 0.5;
1 if FMD $\leq$ 0.6; 0 if FMD $>$ 0.6;

where 0 is assigned to pixels of 'no change' and 1 represents areas of change.

The output images were compared against the reference data discussed in section 5.4. The computed error matrix and its associated overall (OA), users (UA), producers (PA) accuracy and kappa coefficients are presented in Table 3. The highest overall accuracy and kappa coefficient correspond to the change image whose threshold is placed at 0.5. As reported in previous studies (MacLeod and Congalton, 1998), the sole use of the UA or PA misleads the interpretation of the image accuracy. The PA (associated to the errors of omission) decreases as the threshold to generate the binary image is placed at a lower FMD to the fuzzy set 'no change'. Placing the threshold at a FMD equal to 0.4 instead of 0.6, means that larger proportions of pixels will be labelled as 'no change areas' and therefore the chances of labelling pixels of change as unchanged ones are larger. The PA increases, with a consequent decrease in the errors of omission, when the threshold is shifted to a FMD of 0.6 (see Table 3), but the chances of over-estimating areas of changes increases accordingly.

Table 3: Accuracy measures derived from a fuzzy thresholding of the change image at fuzzy intervals of 0.4, 0.5 and 0.6

METHOD	PA_CHANGE	UA_CHANGE	OVERALL	KAPPA	KCHANGE	KNOCHANGE
FMD0.4	59.7	88.9	75.3	0.51	0.77	0.38
FMD0.5	79	88	84	0.68	0.76	0.61
FMD0.6	86.6	80.5	82.3	0.64	0.6	0.7

Table 3 also shows that per class kappa values behave in a similar way. Placing the threshold at a lower FMD increases the accuracy of the change class (KCHANGE), while decreasing the accuracy of unchanged areas (KNOCHANGE). It seems that a joint use of the OA and kappa coefficient can reflect the accuracy of the binary change/no-change image in a better way. Jager and Benz (2000) propose using either the minimum or the product of the PA and UA, as a measure of accuracy for change detection analysis. The integrated analysis of the OA, kappa coefficient and the product of the users' and producers' accuracy assigned the highest accuracy values to the binary change/no-change image obtained when placing the threshold value at a FMD of 0.5 (i.e., pixels with a FMD to the fuzzy set 'no change' $\leq$ than 0.5 where considered as 'change areas'). Table 3 shows that placing the thresholds at FMDs of 0.4 or 0.6 did not improve the results.

These results show a good relationship between the fuzzy linguistic values presented in table 2 and their expression of changes. The highest accuracy in separating change areas from unchanged ones occur when the FMD associated to 'neither nor' changes are included as changes. The inclusion of the fuzzy linguistic value 'uncertain changes' (i.e. FMD of 0.6) decreases the accuracy in the change/no-change image.

6.3 Separating change/no-change areas using the symmetric approach

Table 4 shows that selecting higher standard deviation values to threshold the change image leads to a higher UA, with an absence of errors of commission (i.e. very low probabilities of including areas of no change into the changed ones). The PA associated to the error of omission increases accordingly. As with the fuzzy thresholding, a joint evaluation of the overall (OA), kappa coefficient and the product of the users' and producers' accuracy provided a better assessment of the change images. Table 4 shows the most accurate change image obtained when the symmetric thresholding was placed at 0.5 SD from the mean of the change image.

Table 4: Accuracy measures derived when using a symmetric thresholding approach

METHOD	PA_CHANGE	UA_CHANGE	OVERALL	KAPPA	KCHANGE	KNOCHANGE
0.5SD	89.5	75	79	0.58	0.48	0.73
1SD	47.7	94	71.5	0.44	0.88	0.29
1.5SD	19	100	58.4	0.19	1	0.1
2SD	7.5	100	52	0.07	1	0.04

6.4 Comparison of the image thresholding techniques

The accuracy measures implemented in this research, whose results are presented in tables 3 and 4 suggest that a more accurate thresholding of the change image is achieved when a fuzzy thresholding is adopted. The highest OA (84 percent), kappa coefficient (0.68) and UA*PA product (0.7) were obtained when a fuzzy thresholding of 0.5 was applied to the change image. A symmetric thresholding of 0.5 SD produced a change/no change image with a OA equal to 79 percent, kappa coefficient of 0.58 and UA*PA equal to 0.67. The change image derived using the symmetric approach report 103 ha of changes, whereas the fuzzy thresholding labelled a total of 80 ha as changed over time. The main disagreements seem to correspond to areas where changes are related to variations in vegetation density.

7. CONCLUSIONS

This study presented the framework for the implementation of a semi-automated, non-heuristic technique for thresholding of change images derived from multi-temporal analysis of remotely sensed data using pre-classification techniques. The approach is based on fuzzy sets and fuzzy logic, and it assumes that accurate separation of change/no-change areas can be achieved if the membership function of the fuzzy model is adapted to the shape of the histogram of the change image. The following conclusions can be drawn:

- ✓ The fuzzy Semantic Import Model implemented using the fuzzy membership function proposed by Dombi (1990), allows enough flexibility to adapt the shape of the function to the histogram of the change image;
- ✓ Good correspondence between the fuzzy linguistic values (or fuzzy quantifiers) and their expression of change. The inclusion of the fuzzy quantifier 'uncertain changes' (FMD of 0.6) decreased the accuracy of the changes detected. Best results (84 percent overall accuracy, 0.68 kappa value) were achieved when pixels with a FMD equal or lower than 0.5 to the fuzzy set 'no change' were labelled as 'areas of change';
- ✓ The accuracy measures implemented in this research suggest that a more accurate thresholding of the change image is achieved when a fuzzy thresholding, as compared to a symmetric one based on *n* standard deviations from the mean of the change image, is adopted;
- ✓ The joint use of the overall accuracy, kappa coefficient, and the product of users' by producers' accuracy better reflected the accuracy of the binary change/no-change image. This confirms similar findings by Jager and Benz (2000).

Further research is needed to test the fuzzy image thresholding on change images obtained by using other spectral change detection techniques such as image ratioing, principal component analysis, change vector analysis, etc. In such a way the question posed by McLeod and Congalton (1998), on whether the different techniques actually detect different types of changes, or if differences between the techniques are more a factor of threshold placement could be addressed. Our results indicate differences in accuracy of up to 32 percent are obtained by using different thresholding techniques (e.g. symmetric vs fuzzy approaches).

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