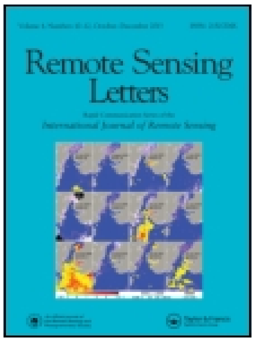

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A novel dynamic threshold method for unsupervised change detection from remotely sensed images

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In this letter, a dynamic threshold method is proposed for unsupervised change detection from remotely sensed images. First, change vector analysis technique is applied to generate the difference image. Then the statistical parameters of the difference image are estimated by Expectation Maximum algorithm assuming that the change and no-change pixel sets are modelled by Gaussian Mixture Model. As a result, a global initial threshold can be identified based on Bayesian decision theory. Next, a dynamic threshold operator is proposed by incorporating the membership value of each pixel generated by the Fuzzy c-means (FCM) algorithm and the global initial threshold. Lastly, the change map is obtained by segmenting the difference image utilizing the dynamic threshold proposed. Experimental results indicate that the proposed dynamic threshold method has significantly reduced the speckle noise comparing to the global threshold method. At the same time, weak change signals are detected and detail change information are preserved much better than the FCM does.

1. Introduction

Change detection (CD) in remotely sensed images is the process aiming to identify differences by analysing a pair of images acquired on the same geographical area at different times (Singh 1989; Ghosh, Mishra, and Ghosh 2011). Over the past few years, a variety of CD methods have been researched and proposed owing to its wide range of significant applications such as global change observing, disaster monitoring and detecting local changes by artificial factors, etc. The CD approaches can be generally categorized into two kinds (Bruzzone and Prieto 2000): the supervised and the unsupervised approach. Actually, the unsupervised methods are more appealing at an operational level because the ground truth information for supervised methods are generally not available in many practical CD applications.

One of the most popular unsupervised CD techniques is to assign the label ‘change’ or ‘no-change’ to a difference image obtained by finding the difference in the spectral vector for corresponding pixels at different times (Bazi, Melgani, and Al-Sharari 2010). To differentiate the change and no-change pixels, the most common solution is based on the use of a thresholding algorithm to select the global threshold (Bruzzone and Prieto 2000; Bazi, Bruzzone, and Melgani 2005; Bovolo, Marchesi, and Bruzzone 2012). Despite its simplicity and generally well-working, the selection of the optimum threshold should be usually associated with a prior knowledge about the scene or visual

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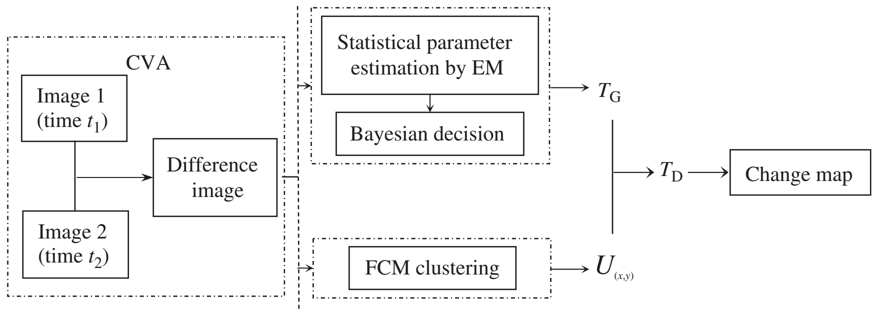


Figure 1. Flow chart of the proposed method for dynamic threshold decision. T_G: global threshold, T_D: dynamic threshold, $U_{(x,y)}$: membership matrix, CVA: change vector analysis.

interpretation to be meaningful (Schowengerdt 1983). However, most threshold decision methods have not considered the prior information. Besides, the global threshold is usually not fit for all the pixels because of the general overlap problem of the two clusters in the difference map (Bazi, Melgani, and Al-Sharari 2010). Thus, sometime a global threshold would generate poor results.

Another solution is clustering method (Ghosh, Mishra, and Ghosh 2011; Mishra, Ghosh, and Ghosh 2012). Therein, the Fuzzy *c*-means (FCM) algorithm (Bezdek 1981) is the most popular method because it has robust characteristics for ambiguity and can retain much more information than hard clustering methods (Pham and Prince 1999). However, the general cluster-overlap problem effects the performance of FCM in CD. It makes the FCM algorithm has difficulties detecting the weak change signals and preserving the change details, especially when the pixel has similar membership values belonging to change and no-change pixel sets, respectively.

In this letter, a novel dynamic threshold method is proposed for CD, in which the membership values of each pixel by FCM are considered as the prior information to guide the threshold decision for each pixel. Figure 1 shows the flowchart of the proposed method and it is explained in detail in the following paras:

First, change vector analysis (CVA) technique is applied to generate the difference image. Then the statistical parameters of difference image are estimated by Expectation Maximum (EM) algorithm assuming the change and no-change pixel sets are modelled by Gaussian Mixture Model (GMM). Thus, a global initial threshold T_G can be identified based on Bayesian decision theory. Lastly, a dynamic threshold T_D can be obtained by modifying the initial global threshold using the membership value of each pixel $U_{(x,y)}$ generated by FCM algorithm.

2. Methodology

Considering two multispectral images $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ of size $M \times N$ with B bands acquired over the same geographical area at two different times, let us assume that such images have been well-preprocessed. Let $\boldsymbol{X}_{b,i} (i = 1, 2)$ be the values of $M \times N$ pixels in the bth $(1 \le b \le B)$ band of X_i. Let $\boldsymbol{X}_\mathrm{D} = \{\boldsymbol{X}_{b,\mathrm{D}} | \boldsymbol{X}_{b,\mathrm{D}} = \boldsymbol{X}_{b,2} - \boldsymbol{X}_{b,1}, 1 \le b \le B\}$ be the spectral change vector (SCV) found by subtracting the value for each pixel in one image from the value in the other image. The final values of pixels in the two-dimensional difference image can be defined as (Bovolo, Marchesi, and Bruzzone 2012):

$$X'_{\mathrm{D}} = \sqrt{\sum_{b=1}^{B} X_{b,\mathrm{D}}^2} = \sqrt{\sum_{b=1}^{B} \left(X_{b,2} - X_{b,1}\right)^2} \tag{1}$$

2.1. Initial global threshold identification

In this letter, the change and no-change pixels, notated as $\mathrm{C_c}$, $\mathrm{C_n}$, respectively, of the two-dimensional difference image are initially distinguished from each other by a global threshold identified by the EM algorithm and Bayesian decision theory (EM–Bayes). Under simple assumptions, the statistical distribution of the pixels in difference image can be modelled by mixed Gaussian model of $\mathrm{C_c}$ and $\mathrm{C_n}$, which can be formulated as

$$p(x) = \sum_{i=1}^{M} \alpha_i N_i\left(x; \mu_i, \sigma_i^2\right) \tag{2}$$

where $N_i(x; \mu_i, \sigma_i^2)$ is normal distribution with expectation μ_i and variance σ_i^2; α_i is the mixture weights of each distribution; M is the number of Gaussian distributions; i takes value from 1 to M and here M equals to 2.

On this basis, EM algorithm is used to estimate the parameters of the GMM by an iterative process (Redner and Walker 1984). Then, according to the Bayes rule for minimum error, each pixel in the difference image should be assigned to the class that maximizes the posterior conditional probability (Bruzzone and Prieto 2000). Lastly, the initial global threshold can be obtained by solving the following quadratic equation.

$$\left(\sigma_{\mathrm{n}}^2 - \sigma_{\mathrm{c}}^2\right) T_{\mathrm{G}}^2 + 2\left(\mu_{\mathrm{n}}\sigma_{\mathrm{c}}^2 - \mu_{\mathrm{c}}\sigma_{\mathrm{n}}^2\right) T_{\mathrm{G}} + \mu_{\mathrm{c}}^2\sigma_{\mathrm{n}}^2 - \mu_{\mathrm{n}}^2\sigma_{\mathrm{c}}^2 - 2\sigma_{\mathrm{n}}^2\sigma_{\mathrm{c}}^2 \ln\left[\frac{\sigma_{\mathrm{n}}\alpha_{\mathrm{c}}}{\sigma_{\mathrm{c}}\alpha_{\mathrm{n}}}\right] = 0 \tag{3}$$

where (μ_{n}, σ_{n}^2, α_{n}) and (μ_{c}, σ_{c}^2, α_{c}) are the expectation, variance and mixture weight of the change and no-change pixel sets, respectively.

2.2. FCM clustering algorithm

The FCM algorithm is an iterative clustering method that makes the pixels in the same cluster have high similarity, while lower similarity between each cluster and the cluster of each pixel is identified by a fuzzy way with membership matrix. FCM attempts to find fuzzy partitioning of the given data set by minimizing the objective function J_m iteratively

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ji}^m d^2\left(x_i, v_j\right) \tag{4}$$

where $X = \{x_1, x_2, \ldots, x_N\}$ is the data set in the m-dimensional vector space, c is the number of clusters with $2 \le c \le N$, u_{ji} is the degree of membership of x_i in the jth cluster, m is the weighting exponent on each fuzzy membership, v_j is the centre of cluster j, d^2 (x_i, v_j) is a distance measure between object x_i and cluster centre v_j.

2.3. *Proposed dynamic threshold formation*

In view of the drawbacks of thresholding method and FCM method, a compromise scheme incorporating the both methods is proposed by modifying the dynamic threshold for each pixel to:

$$T_{D(x,y)} = \ln\left[1 + \frac{\boldsymbol{u}_n(x,y)}{\boldsymbol{u}_c(x,y)}\right] T_G \tag{5}$$

where T_G is the optimal threshold obtained by EM algorithm and Bayes decision theory, $\boldsymbol{u}_n(x, y)$ and $\boldsymbol{u}_c(x, y)$ are the membership values of pixel at position (x, y) belonging to no-change pixels and change pixels, respectively.

The theoretical explanation for the proposed method can be described as follows:

If $0 < \boldsymbol{u}_n(x, y)/\boldsymbol{u}_c(x, y) < 1$, it means the pixel has a greater probability to be identified as the change pixels, so the threshold for pixel (x, y) will be decreased by Equation (5) on the basis of T_G.

As a solution to the high misdetection rate of FCM algorithm, if $1 < \boldsymbol{u}_n(x, y)/\boldsymbol{u}_c(x ,y) < \mathrm{e}-1$, the threshold for pixel (x, y) will also be decreased by Equation (5) on the basis of T_G to give the pixel a probability to be identified as the change pixels instead of the misidentification as no-change pixels in FCM.

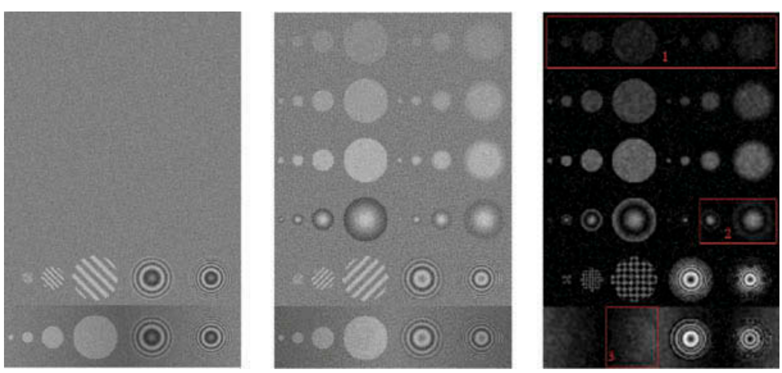
If $\boldsymbol{u}_n(x, y)/\boldsymbol{u}_c(x, y) > \mathrm{e} - 1$, it means the pixel has a greater probability to be identified as the no-change pixels, so the threshold for pixel (x, y) will be increased by Equation (5) on the basis of T_G.

3. Experiments and results

In order to verify the effectiveness of the proposed method, three different data sets were tested: a simulation data set and two multispectral remote sensing data sets. The experiments were conducted by programming the proposed method with Matlab 8.0. In the following, both the data sets and the carried out experiments are detailed.

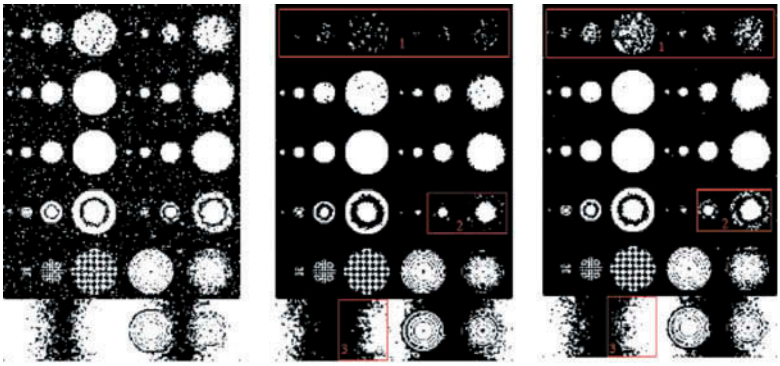
3.1. *Experiment 1*

A couple of simulation data with greyscale images (256 pixels × 384 pixels) were firstly tested as Figure 2 (*a*) and (*b*) show. Figure 2(*c*) is the difference image obtained by



(*a*) (*b*) (*c*)

Figure 2. Simulation data with different degree of changes utilized for change detection. (*a*) Image of time t_1. (*b*) Image of time t_2. (*c*) Difference image yielded based on (*a*) and (*b*).



(*a*) (*b*) (*c*)

Figure 3. Change detection based on different methods: (*a*) EM–Bayes threshold, (*b*) FCM, (*c*) proposed method.

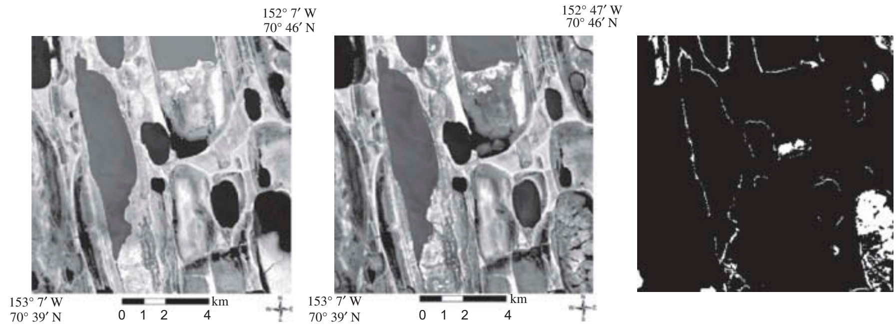
subtracting one image from another and three regions are marked out with rectangles as examples of weak change information. The data set contains a good simulation of different degrees of change with Gauss noise distributed all over the whole image.

EM–Bayes threshold, FCM and the proposed method had been employed, respectively, for CD as comparisons to verify the effectiveness and benefits of the proposed method. The experimental results are shown in Figure 3. It is obvious that the effects of noises have significantly been reduced by using the proposed method (see Figure 3(*c*)) compared to the EM–Bayes threshold based method (see Figure 3(*a*)). At the same time weak change signals have been preserved and detected better than FCM does (see Figure 3(*b*)). The improved results could be owed to the proposed dynamic thresholding method which does not identify each pixel as change or no-change pixel simply according to its membership values, but uses the membership values as prior information to optimize the threshold decision for identification. Seen from the region 1, 2, 3 (regions with weak changes) in Figure 3, compared to the EM–Bayes threshold and FCM, the proposed method has the best performance and can deal well with pixels with similar membership values to change and no-change pixels. The change map obtained by the proposed method is more accurate compared to the high false detection of (*a*) and the high omission detection of (*b*).

3.2. *Experiment 2*

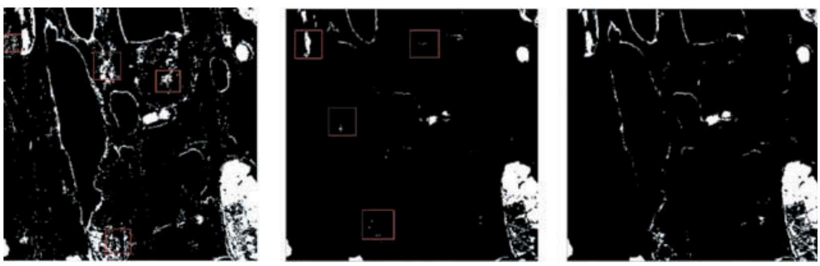
The second experiment was conducted with the data set made up of two multispectral images (1305 pixels × 1520 pixels) in Alaska in 22 July 1985 and 13 July 2005 by Landsat 5 Thematic Mapper (TM) sensor. A section (400 pixels × 400 pixels) of the two scenes was selected for the experiment as presented band 4 in Figure 4 (*a*) and (*b*). It's obvious that the ice cover has changed and the resulting changes of the boundary are also easily found by flickering the two overlaid images. The ground truth of the CD map which is shown in Figure 4(*c*) was created by the manual analysis (flipping between the two overlaid images and analysis the difference image) of the input images based on Figure 4(*a*) and (*b*).

Figure 5 presents the results of three different methods as comparison. It is clear from the qualitative results shown in Figure 5 that EM–Bayes threshold based method (see Figure 5(*a*)) results in lots of false detections and speckle noises because the global threshold is not actually suited for all the pixels. For example, many pixels in the marked region shown in Figure 5(*a*) are falsely detected as change pixels because the EM-Bayes



(*a*) (*b*) (*c*)

Figure 4. Data set used in Experiment 1. Landsat-5 TM Band 4 optical image acquired on (*a*) 22 July 1985 and (*b*) 13 July 2005, (*c*) manually created ground truth of the change detection map yielded based on (*a*) and (*b*).



(*a*) (*b*) (*c*)

Figure 5. Change detection based on different methods. (*a*) EM–Bayes threshold, the marked regions are examples of false detected regions. (*b*) FCM, the marked regions are examples of misdetected regions. (*c*) Proposed method.

threshold is a little small. In contrast, in the regions with weak change signals such as the boundary changes of ice cover, FCM algorithm (see Figure 5(*b*)) does not work well and results in a high rate of omission detection because FCM identifies the label of each pixel simply, regardless of the general overlap problem of change and no-change classes. As for the proposed method shown in Figure 5(*c*), it provides better qualitative results compared to the other approaches obviously on account of considering the membership values of each pixel as the prior information to give a threshold adaptively.

As a further illustration, Table 1 shows the quantitative assessment of each method, which verifies the aforementioned qualitative analysis well.

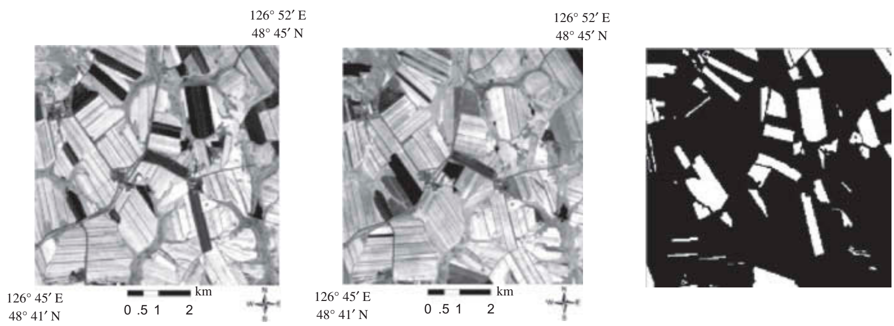
Table 1. Accuracy assessment for Experiment 1.

	False alarms		Misdetections		Total errors	
Change detection method	No. of pixels	%	No. of pixels	%	No. of pixels	%
EM–Bayes threshold	7949	5.29	69	0.71	8018	5.01
FCM	123	0.08	3544	36.4	3667	2.29
Proposed method	794	0.53	1310	13.45	2104	1.31

3.3. Experiment 3

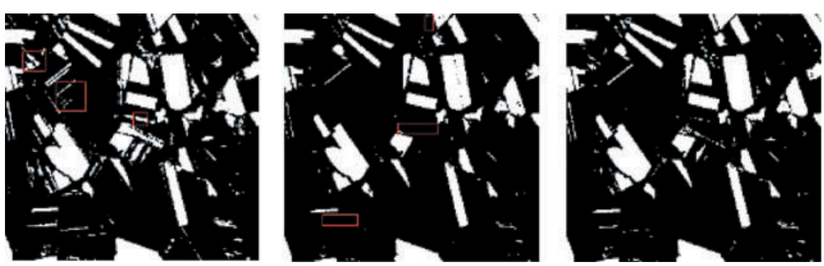
Another experiment was carried out to eliminate the contingency of the proposed method performance. The data set was acquired by Landsat-7 Enhanced Thematic Mapper Plus (ETM+) in August 2001 and August 2002 in Heilongjiang Province of China. A section (262 pixels × 257 pixels) of the two scenes was selected as presented band 4 in Figure 6 (*a*) and (*b*). The ground truth of the CD map which is shown in Figure 6(*c*) was created by the manual analysis of the input images based on Figure 6 (*a*) and (*b*).

The experimental results are shown in Figure 7. Identically, the EM–Bayes threshold method results in much noises and the global threshold is not suited for some regions as shown in Figure 7(*a*). FCM method has made some misdetections (see Figure 7(*b*)) because the weak change pixel are wrongly identified as no-change pixel according to the membership values simply. Through both qualitative analysis (Figure 7) and quantitative analysis (Table 2), a same conclusion could be made that the proposed method is indeed an effective compromise scheme of the EM–Bayes threshold method and FCM method. The CD result has been more accurate by utilizing the proposed dynamic threshold method.



(*a*) (*b*) (*c*)

Figure 6. Data set used in Experiment 2. Landsat ETM+ Band 4 optical image acquired in (*a*) August 2001 and (*b*) August 2002, (*c*) manually created ground truth of the change detection map yielded based on (*a*) and (*b*).



(*a*) (*b*) (*c*)

Figure 7. Change detection based on different method. (*a*) EM–Bayes threshold, the marked regions are examples of false detected regions. (*b*) FCM, the marked regions are examples of misdetected regions. (*c*) Proposed method.

Table 2. Accuracy assessment for Experiment 2.

Change detection method	False alarms No. of pixels	False alarms %	Misdetections No. of pixels	Misdetections %	Total errors No. of pixels	Total errors %
EM–Bayes threshold	2192	3.94	212	1.80	2404	3.57
FCM	93	0.17	1629	13.86	1722	2.56
Proposed method	521	0.94	873	7.43	1394	2.07

4. Conclusion

In consideration of the respective advantages and disadvantages of threshold based and clustering method in remotely sensed image CD, the primary goal of the research was to develop and evaluate a dynamic threshold method for unsupervised CD using remotely sensed images. The proposed method considers the membership value of each pixel by FCM as the prior information to guide the threshold decision procedure. This method is simple yet effective in identifying meaningful changes with a relative high detection accuracy as the experiment results have shown.

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References

Bazi, Y., L. Bruzzone, and F. Melgani. 2005. "An Unsupervised Approach Based on the Generalized Gaussian Model to Automatic Change Detection in Multitemporal SAR Images." *IEEE Transactions on Geoscience and Remote Sensing* 43: 874–887. doi:10.1109/TGRS.2004.842441.

Bazi, Y., F. Melgani, and H. D. Al-Sharari. 2010. "Unsupervised Change Detection in Multispectral Remotely Sensed Imagery with Level Set Methods." *IEEE Transactions on Geoscience and Remote Sensing* 48: 3178–3187. doi:10.1109/TGRS.2010.2045506.

Bezdek, J. 1981. *Pattern Recognition with Fuzzy Objective Function Algorithms*. New York: Plenum.

Bovolo, F., S. Marchesi, and L. Bruzzone. 2012. "A Framework for Automatic and Unsupervised Detection of Multiple Changes in Multitemporal Images." *IEEE Transactions on Geoscience and Remote Sensing* 50: 2196–2212. doi:10.1109/TGRS.2011.2171493.

Bruzzone, L., and D. F. Prieto. 2000. "Automatic Analysis of the Difference Image for Unsupervised Change Detection." *IEEE Transactions on Geoscience and Remote Sensing* 38: 1171–1182. doi:10.1109/36.843009.

Ghosh, A., N. S. Mishra, and S. Ghosh. 2011. "Fuzzy Clustering Algorithms for Unsupervised Change Detection in Remote Sensing Images." *Information Sciences* 181: 699–715. doi:10.1016/j.ins.2010.10.016.

Mishra, N. S., S. Ghosh, and A. Ghosh. 2012. "Fuzzy Clustering Algorithms Incorporating Local Information for Change Detection in Remotely Sensed Images." *Applied Soft Computing* 12: 2683–2692. doi:10.1016/j.asoc.2012.03.060.

Pham, D. L., and J. L. Prince. 1999. "An Adaptive Fuzzy C-Means Algorithm for Image Segmentation in the Presence of Intensity Inhomogeneities." *Pattern Recognition Letters* 20: 57–68. doi:10.1016/S0167–8655(98)00121–4.

Redner, R. A., and H. F. Walker. 1984. "Mixture Densities, Maximum Likelihood and the EM Algorithm." *SIAM Review* 26: 195–239. doi:10.1137/1026034.

Schowengerdt, R. A. 1983. *Techniques of Image Processing and Classification in Remote Sensing*. New York: Academic Press.

Singh, A. 1989. "Review Article Digital Change Detection Techniques Using Remotely-Sensed Data." *International Journal of Remote Sensing* 10: 989–1003. doi:10.1080/01431168908903939.