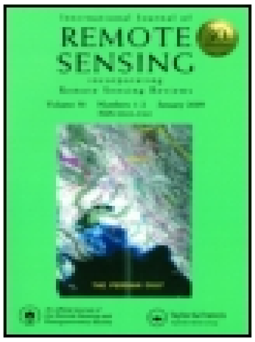

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Review Article

Digital change detection techniques using remotely-sensed data

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Abstract. A variety of procedures for change detection based on comparison of multitemporal digital remote sensing data have been developed. An evaluation of results indicates that various procedures of change detection produce different maps of change even in the same environment.

1. Introduction

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multitemporal data sets. One of the major applications of remotely-sensed data obtained from Earth-orbiting satellites is change detection because of repetitive coverage at short intervals and consistent image quality (Anderson 1977, Ingram *et al.* 1981, Nelson 1983, Singh 1984). Change detection is useful in such diverse applications as land use change analysis, monitoring of shifting cultivation, assessment of deforestation, study of changes in vegetation phenology, seasonal changes in pasture production, damage assessment, crop stress detection, disaster monitoring snow-melt measurements, day/night analysis of thermal characteristics and other environmental changes. Manual handling of data for change detection using sequential imagery is a formidable task (Adeniyi 1980). The digital nature of most satellite data make it easily amenable for computer-aided analysis. There is a definite need for a change detector which will automatically correlate and compare two sets of imagery taken of the same area at different times and display the changes and their locations to the interpretor (Shephard 1964). It has been suggested that a significant increase in speed can be achieved for image processing by representing only the changes rather than expose the human viewer to all of the information in both images (Lillestrand 1972).

2. Change detection

The basic premise in using remote sensing data for change detection is that changes in land cover must result in changes in radiance values and changes in radiance due to land cover change must be large with respect to radiance changes caused by other factors (Ingram *et al.* 1981). These 'other' factors include (1) differences in atmospheric conditions, (2) differences in Sun angle and (3) differences in soil moisture (Jenson 1983). The impact of these factors may be partially reduced by selecting the appropriate data. For example, Landsat data belonging to the same time of the year may reduce problems from Sun angle differences and vegetation phenology changes.

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Several researchers have attempted to use digital satellite data to address the change detection problem. Several procedures of land cover change detection using digital data have been proposed which could aid in updating resource inventories. These methods include comparison of land cover classifications, multidate classification, image differencing/ratioing, vegetation index differencing, principal components analysis and change vector analysis.

Digital change detection approaches may be broadly characterized by (1) the data transformation procedure (if any) and (2) analysis techniques used to delineate areas of significant alterations. A tabular summary of variety of change detection approaches modified from Nelson (1983) is given in table 1 along with references to those who have used that particular approach. The list is not exhaustive. There are two basic approaches for change detection; (1) comparative analysis of independently produced classifications for different dates and (2) simultaneous analysis of multitemporal data.

It may be mentioned here that accurate spatial registration of the two images is essential for most change detection methods. This necessitates the use of geometric rectification algorithms that register the images to each other or to a standard map projection.

Also most of the methods, as we shall see later, require a decision as to where to place threshold boundaries in order to separate areas of change from those of no change. This technique is briefly described below.

3. Thresholding

If an image $I(x,y)$ contains light objects (change) on a dark background (no change), then these objects may be extracted by a simple thresholding

$$I(x,y)=\begin{cases}1 & I(x,y)>T\\ 0 & I(x,y)\leqslant T\end{cases}$$

where T is the threshold value supplied empirically or statistically by the analyst. All the pixels which belong to the object (change) are coded 1, and the background (no change) is coded 0. If one wants to define more than one threshold one may use the technique of density slicing. In this, several objects of different pixel values are grouped into pre-defined slices. Grey level thresholding can be done interactively with a monitor and operator-controlled cursor, but selection of the best threshold level should be usually associated with *a priori* knowledge about the scene or visual interpretation to be meaningful (Schowengerdt 1983). The threshold values may also be derived from the histogram of the image.

4. Digital change detection techniques

4.1. *Univariate image differencing*

In this technique, spatially registered images of time t_1 and t_2 are subtracted, pixel by pixel, to produce a further image which represents the change between the two times. Mathematically,

$$Dx_{ij}^k=x_{ij}^k(t_2)-x_{ij}^k(t_1)+C$$

where x_{ij}^k = pixel value for band k and i and j are line and pixel numbers in the image, t_1 = first date, t_2 = second date and C = a constant to produce positive digital numbers.

The input data can be comprised of raw images or spatially filtered ones. This

Table 1. Digital change detection research categorized by (1). The data transformation used (if any) and (2) The analysis technique used to detect change (modified from Nelson (1983)).

Analysis technique used to detect change	Raw data	Difference	Ratio	Vegetation index difference	Regression	Principal components	Change vector	Post-classification comparison
Standard deviation threshold		Ingram *et al.* (1981) Jenson and Toll (1982) Miller *et al.* (1978) Nelson (1983) Stauffer and McKinney (1978) Toll *et al.* (1980) Singh (1984, 1986)	Howarth and Wickware (1981) Nelson (1983) Todd (1977) Wilson *et al.* (1976) Singh (1984, 1986)	Angelici *et al.* (1977) Banner and Lynham (1981) Howarth and Boasson (1983) Nelson (1983) Singh (1984, 1986)	Ingram *et al.* (1981) Singh (1984, 1986)	Byrne *et al.* (1980) Lodwick (1979) Richardson and Milne (1983) Toll *et al.* (1980) Singh (1984, 1986)		
Supervised	Banner and Lynham (1981) Williams and Hover (1976)	Anuta and Bauer (1973)						Gordon (1980) Howarth and Wickware (1981) Singh (1984, 1986)
Spectral (unsupervised)	Weismiller *et al.* (1977)	Anuta and Bauer (1973) Weismiller *et al.* (1977)						Joyce *et al.* (1980) Riordan (1980) Swain (1978) Weismiller *et al.* (1977)
Spectral–spatial (unsupervised)							Malila (1980) Colwell and Weber (1981)	
Layered spectral/temporal	Weismiller *et al.* (1977)							

procedure yields a difference distribution for each band. In such a distribution, pixels showing radiance change are found in the tails of the distribution while pixels showing no radiance change tend to be grouped around the mean (Stauffer and McKinney 1978, Singh 1986).

A critical element of the image differencing method is deciding where to place the threshold boundaries between change and no-change pixels displayed in the histogram. Stauffer and McKinney (1978), Nelson (1983) and Singh (1984) selected several different thresholds on the basis of the number of standard deviations from the mean and assessed their relative performance in detecting changes. The method of change detection by computing the threshold use by Ingram *et al.* (1981) is based on a *t* test in comparing differencing of averaged images. An empirically-derived formula by Weismiller *et al.* (1977) uses a difference in the visible/infrared ratio between two dates as well as a difference in the summed response in all four bands for each date as a test for change. Woodwell *et al.* (1983) have advocated a technique in which the analyst sets the cursor thresholds interactively while viewing the results of his decisions on the image display of the processing system.

Image differencing is the most widely used technique for change detection and has been used in a variety of geographical environments. Weismiller *et al.* (1977) found that change detection based on the method of image differencing worked well in the Texas coastal zone environment despite many small areas of change not being identified accurately. Miller *et al.* (1978) applied Landsat image differencing successfully to the mapping of changes in tropical forest cover in northern Thailand. Williams and Stauffer (1978) utilized the technique to monitor gypsy moth defoliation in the forests of Pennsylvania. They observed that the colour composite created by superimposing three of the four possible difference images depicts the areas of change in unique colour tones which are easier to interpret than the individual black and white images. Singh (1984, 1986) used the technique for monitoring changes due to shifting cultivation in a tropical forest environment.

Image differencing has also been performed on pre-processed (spatial filter) data. Ingram *et al.* (1981) used an edge-preserving smoothing procedure to minimize variation in adjacent pixels without blurring the edges of image features. When the images were differenced they found slight improvements in overall classification accuracy. However, Riordan (1980) found the method ineffective. Ingram *et al.* (1981) also used a normalization procedure, in which a selected value for the mean and for the standard deviation was input along with the image to be normalized. The value for each pixel was transformed according to the following formula:

$$G' = U' + \left(\frac{S'}{S}\right) \times (G - U)$$

where G, U and S are the old pixel values, old mean and old standard deviations respectively, and G', U' and S' are the new values. Normalization generally improved the results slightly although not at every threshold level.

Jenson and Toll (1982) reported the detection of residential land use development at the urban fringe was improved from 77 to 81 per cent when band 5 spectral image differencing was used in conjunction with texture differencing based on a use of grey tone spatial dependency matrices (Haralick 1979).

Riordan (1980) has pointed out some of the general difficulties in image differencing. Examples are its sensitivity to misregistration and the existence of mixed pixels. She also found that simple image differencing failed to consider the starting and ending location of a pixel in the feature space. For example, an agricultural pixel with a radiance value of 190 in band 4 on one date and 160 on the second date showed a change of 30 digital counts. However, despite this substantial change relative to other types of change, the pixel may still represent an agricultural pixel. Weismiller *et al.* (1977) concluded that the method may be too simple to deal adequately with all the factors involved in detecting changes in a natural scene. Too much information may be discarded from the data in the subtraction process whereby only the four band difference data remains from the two sets of original four bands. However, they failed to specify the mechanism of type of information loss. Furthermore, since two sets of different absolute values may have an identical diferenced value (e.g. $180-150=30$ and $40-10=30$) there is a potential loss of information with the use of simple differencing transformations.

4.2. *Image regression*

In the regression method of change detection, pixels from time t_1 are assumed to be a linear function of the time t_2 pixels. So one can regress $x_{ij}^k(t_1)$ against $x_{ij}^k(t_2)$ using a least-squares regression (x is pixel value of line i, column j of band k). If $\hat{x}_{ij}^k(t_2)$ is the predicted value obtained from the regression line, the difference image can be defined as follows

$$Dx_{ij}^k=\hat{x}_{ij}^k(t_2)-x_{ij}^k(t_1)$$

A thresholding technique, as described earlier, is applied to detect areas of change. The regression technique accounts for differences in the mean and variance between pixel values for different dates so that adverse effects from differences in atmospheric conditions or Sun angles are reduced (Jenson 1983). Ingram *et al.* (1981) and Singh (1984, 1986) have reported that the regression procedure performed marginally better than the univariate image differencing technique in detecting urban land cover changes and tropical forest cover changes, respectively.

4.3. *Image ratioing*

Ratioing is considered to be a relatively rapid means of identifying areas of change (Howarth and Wickware 1981, Howarth and Boasson 1983, Nelson 1983, Todd 1977, Wilson *et al.* 1976). In ratioing two registered images from different dates with one or more bands in an image are ratioed, band by band. The data are compared on a pixel by pixel basis. One computes

$$Rx_{ij}^k=\frac{x_{ij}^k(t_1)}{x_{ij}^k(t_2)}$$

where, $x_{ij}^k(t_2)$ is the pixel value of band k for pixel x at row i and column j at time t_2.

If the intensity of reflected energy is nearly the same in each image then $Rx_{ij}^k=1$, this indicates no change.

In areas of change the ratio value would be significantly greater than 1 or less than 1 depending upon the nature of the changes between the two dates. The critical element of the methodology is selecting appropriate threshold values in the lower and upper tails of the distribution representing change pixel values. The usual practice has been in selecting arbitrary threshold values and testing them empirically to determine if the change detection was performed accurately (Nelson 1982).

Ratioing has not been as intensively investigated as image differencing (Nelson 1982). Todd (1977) used the ratio of band 5 data from two dates to determine urban change in Atlanta, Georgia. Only ratios to the low side of the mean were considered changed. His overall evaluation indicated that 91·4 per cent of all land cover change was correctly identified. Nelson (1983) used this technique along with image differencing and vegetation index differencing techniques to delineate gypsy moth defoliation in Pennsylvania.

Ratioing as a means of change detection has been criticized due to the non-normal distribution on which it is based (Robinson 1979). If the distributions are non-normal and functions of the standard deviations are used to delimit change from non change, the areas delimited on either side of the mode are not equal. Therefore, the error rates on either side of the mode are not equal. Nevertheless Robinson (1979) recommends that the further studies of the ratioing method under a variety of conditions would be useful.

4.4. *Vegetation index differencing*

Spectral radiance values as recorded on Landsat computer compatible tapes (CCTs) can be analysed independently on a band by band basis or in combinations of two or more bands. One of the most commonly used band combination techniques in vegetation studies is band ratioing (Curran 1981, Tucker 1979).

Ratioing two spectral bands negates the effect of any extraneous multiplicative factors in sensor data that act equally in all wave bands of analysis (Lillesand and Kieffer 1979). The general form for band ratioing is

$$R_{ij}=\frac{x_i}{x_j}$$

where R_{ij} is the ratio of corresponding pixel values x_i and x_j in band i and j, respectively. The ratio images have two important properties. First, strong differences in the intensities of the spectral response curves of different features may be emphasized in ratioed images (Short 1982) and, secondly, ratios can suppress the topographic effects and normalized differences in irradiance when using multidate images. But the ratio technique may enhance random noise or coherent noise that is not correlated in different bands.

In vegetation studies the ratios, commonly known as vegetation indices, have been developed for the enhancement of spectral differences on the basis of strong vegetation absorbance in the red and strong reflectance in the near-infrared part of the spectrum. It has been shown that a ratio of near-infrared Multispectral Scanner (MSS) band 4 and red MSS band 2 is significantly correlated with the amount of green leaf biomass (Tucker 1979). There are a number of vegetation indices such as

(1) Ratio vegetation index $=\dfrac{\text{band 4}}{\text{band 2}}$

(2) Normalized vegetation index $=\dfrac{\text{band 4}-\text{band 2}}{\text{band 4}+\text{band 2}}$

(3) Transformed vegetation index $=\sqrt{\left(\dfrac{\text{band 4}-\text{band 2}}{\text{band 4}+\text{band 2}}+0{\cdot}5\right)}$

which are commonly used in vegetation studies with Landsat MSS data.

In addition, there are numerous other indices involving linear transformations of various MSS bands and coefficients which have been developed for specific application purposes. For example, Kauth and Thomas (1976) used the technique of sequential orthogonalization underlying the Gram–Schmidt process to produce an orthogonal transformation of the original Landsat data, called 'tasselled cap', to a new four-dimensional space. The name attached to four new axes, i.e. brightness, greenness, yellow stuff and nonsuch, indicate the characteristics the indices were intended to measure. Richardson and Wiegand (1977) have developed a perpendicular vegetation index that is orthogonal to the soil line in two dimensions and a generalization of vegetation indices in N dimensions has been given by Jackson (1983). Most formulae fall into one of two basic categories; those that use ratios or those that use differences to exploit the spectral characteristics of soil and vegetation (Perry and Lautenschlager 1984). Lautenschlager and Perry (1981) studied the empirical relationship among the vegetation indices and found that they were highly correlated with each other.

As far as change detection is concerned, the difference of vegetation indices (say, (band 4/band 2)(t_1) − (band 4/band 2)(t_2)) should provide an avenue for deciding whether or not a vegetation canopy has been significantly altered (Nelson 1982). Angelici *et al.* (1977) used the difference of ratio data and the thresholding technique to delineate changed areas. However, they did not produce any quantitative assessment of the results obtained. Nelson (1982, 1983) tested the method quantitatively in the study of gypsy moth defoliation in Pennsylvania. His results indicated that of the three methods tested, i.e. differencing, ratioing and a vegetative index difference, the latter most accurately delineated forest canopy change. Banner and Lynham (1981) used a vegetation index difference transformation and thresholding to delineate forest clearcuts. They compared the result with a supervised classification approach, using multitemporal MSS band 5 data, found that the vegetation index difference method was less accurate for delineating forest clearcuts. Hence it is difficult to draw any firm conclusion about the capability of this technique.

4.5. *Principal components analysis (PCA)*

This multivariate analysis technique is used to reduce the number of spectral components to fewer principal components accounting for the most variance in the original multispectral images. In multitemporal studies the principal components for two or more dates are often compared as in image differencing or image regression (Lodwick 1979). Alternatively, two four-band Landsat scenes of the same area, which are recorded on different dates, can be superimposed and treated as a single eight-band data set. Principal component analysis of this data set should result in the gross differences associated with overall radiation and atmospheric changes appearing in the major component images and statistically minor changes associated with local changes in land cover appearing in the minor component images (Byrne *et al.* 1980, Richardson and Milne 1983).

Byrne *et al.* (1980) and Richardson and Milne (1983) studied the effectiveness of principal components analysis for the identification of land cover changes and mapping of bush fires and subsequent vegetation regeneration, respectively. However, they did not provide any quantitative analysis of their results. Toll *et al.* (1980) reported that principal components transformation when used for urban change detection produced poor change detection results compared with simple image differencing of band 2 or 4 data.

Townshend *et al.* (1985) used this technique to examine the underlying structure of relations between normalized difference vegetation index images derived from NOAA Advanced Very High Resolution Radiometer (AVHRR) of the continents of Africa and North America for several time periods within a single calendar year.

Furthermore, in remote sensing, principal components analysis is usually performed using unstandardized variables (variance—covariance matrix). However, it has been clearly demonstrated by Singh and Harrison (1985) that the use of standardized variables (correlation matrix) in the analysis yields significantly different results. Singh (1984, 1986) has used both standardized and unstandardized PCA for tropical forest change detection.

4.6. *Post-classification comparison*

This is the most obvious method of change detection which requires the comparison of independently produced classified images. By properly coding the classification results for times t_1 and t_2, the analyst can produce change maps which show a complete matrix of changes. In addition, selective grouping of classification results allows the analyst to observe any subset of changes which may be of interest. Post-classification comparison holds promise because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates. The method also bypasses the problem of getting accurate registration of multidate images.

However, if one considers the land cover classification generated from a single date of Landsat data, it is not difficult to see that the change map product of two Landsat classifications is likely to exhibit accuracies similar to the product of multiplying the accuracies of each individual classification (Stow *et al.* 1980). Hence it can produce a large number of erroneous change indications since an error on either date gives a false indication of change. For example, two images classified with 80 per cent accuracy might have only a $0{\cdot}80 \times 0{\cdot}80 \times 100 = 64$ per cent correct joint classification rate. Computationally, it requires classification of the whole scenes twice (Robinson 1979). Weismiller *et al.* (1977) found that the post-classification comparison technique reliably identified areas of change but they did not use any coincident ground information for comparison purposes. Riordan (1980) produced unsupervised classifications of 1973 and 1978 Landsat MSS data and compared the classifications to detect non-urban to urban change and reported an accuracy of 67 per cent. Gordon (1980) used the method to monitor land use change in Ohio and, after a rigorous quantitative assessment, observed '... we must conclude that substantial errors are associated with the use of Landsat data for land cover and change analysis.' Toll *et al.* (1980) noted that the poor performance of this approach may, in part, be attributed to 'the difficulty of producing comparable classifications from one date to another'.

4.7. *Direct multidate classification*

Such methods are based on a single analysis of a combined data set of two or more dates to identify areas of change. For example, in a two-date Landsat data set with its four bands, a data set of eight bands is produced and then is analysed at one time in supervised or unsupervised mode. In the supervised approach training sets pertaining to change and no-change areas are used to derive statistics to define sub-spaces of the feature space. In the unsupervised approach, inspection of a small portion of the scene where known changes have occurred is used to derive classes by cluster analysis. In either case, change classes should have significantly different statistics from no-change classes.

Weismiller *et al.* (1977) used a clustering technique as well as layered spectral/temporal classification approach for detecting changes in a Texas coastal zone environment. The layered spectral/temporal method employs a classifier that uses multistage decision logic (Swain and Hauska 1977). In this technique, a decision tree is followed using selected bands in the multidate image as input to decision functions. A decision function exists at each node in the decision tree. The decision trees for each of the two dates, t_1 and t_2, were obtained automatically and then manually linked, introducing within the tree a logic for detecting the desired change. This method produced the results which showed the best agreement with the post-classification comparison results. Weismiller *et al.* (1977) state that a major problem with the decision tree approach is the complexity and large amount of computer core required to implement the algorithms. The method also requires *a priori* knowledge of the logical inter-relationship of the classes.

While this method requires only a single classification it is a very complex one, often requiring many classes and too many features, i.e. bands, some of which may be redundant in information content (Estes *et al.* 1982). The problem of redundancy can be overcome by using a principal component transformation on the original data set. The first few components containing significant amounts of variance from the two dates can be used in the classification analysis. Another problem is that the temporal and spectral features have equal status in the combined data set (Schowengerdt 1983). Thus spectral changes within one multispectral image cannot be easily separated from temporal changes between images in the classification.

Swain (1978) developed a Bayesian (minimum risk) 'cascade' classifier to remove this coupling between the spectral and temporal dimensions. In this classifier, preliminary classification is done at time t_1 and, when data become available, from time t_2 transition probabilities and t_2 likelihood values are determined and an updated classification is made. However, this method has not attracted further attention, apparently because of the complexity of the algorithms and computational requirements.

4.8. *Change vector analysis*

When a forest stand undergoes a change its spectral appearance changes accordingly. The vector describing the direction and magnitude of change from the first to the second date is a spectral change vector. The decision that a change has occurred is made if the magnitude of the computed spectral change vector exceeds a specified threshold criterion. The direction of the vector contains information about the type of change, i.e. clearcut or regrowth (Malila 1980). This method was applied to forest change detection in northern Idaho (Malila 1980) and in South Carolina (Colwell and Weber 1981). In this method, a multitemporal Landsat data set is transformed into greenness and brightness data sets (Kauth and Thomas 1976). The transformed data set is clustered using a spectral/spatial clustering algorithm called BLOB (Kauth *et al.* 1977). Each BLOB has four components, consisting of the means of the greenness and brightness values for the two dates. BLOBs formed over change areas should vary significantly in the transformed channel values. The method is computationally very demanding as the data have to be geometrically corrected and digitally merged, then transformation coefficients have to be developed and finally spectral/spatial clustering is done. Also, it has been reported (Malila 1980) that the performance of the procedure is sensitive to its parameter setting. However, there are no guidelines for their selection.

In one of the studies (Colwell and Weber 1981) it was found that the post-classification comparison approach resulted in identifying six times more change than was indicated by a dot grid estimate of change derived from a Landsat multitemporal colour composite, whereas results obtained from the change vector analysis procedure and dot grid estimates were comparable. However, unavailability of a reference data set makes any assessment of true performance somewhat uncertain.

4.9. *Background subtraction*

In change detection analysis no-change areas can be treated as having slowly varying background grey levels in the context of looking for changed areas. Background subtraction attempts to remove these variations by first approximating them with a background image f_b then subtracting this approximation from the original image. That is, the new image f_n is

$$f_n(x) = f(x) - f_b(x)$$

(Ballard and Brown 1982). A convenient background subtraction technique is to use a low pass filtered variant of the image. Singh (1984) used the technique for tropical forest change detection.

4.10 *Other methods*

Eghbali (1970) used the Kalmogorov–Smirnov test (K–S test) to determine whether two samples (two dates of imagery of the same location) have been drawn from the same population. If the maximum difference between the cumulative distributions of the two data sets is lower than a derived threshold, a decision is made that no change has occurred. This technique does yield information on whether or not a change had taken place but no information on the kind of change or specific location of the change can be obtained. Coiner (1980) used the correlation coefficient between two dates' scenes as an indicator of change. The correlation coefficient measures $r = 1$ for no change and $r < 1$ for changes. There is nothing inherent in this measurement that will distinguish actual changes from changes of interest.

5. Evaluation of digital change detection technique

An analysis of the literature reviewed indicates that different methods of change detection produce different maps of cover change. Unfortunately, the majority of the studies concerned with comparative evaluation of some of the techniques in a particular application area have not supported their conclusion by quantitative analysis of the results. Colwell and Weber (1981) used post-classification comparison, change vector analysis and visual estimate of change from two dates' images for forest change detection, but no ground reference accuracy assessment was done. Howarth and Wickware (1981) only qualitatively compared ratioing and post-classification comparison method for environmental change detection. The same is true for Toll *et al.* (1980) who used univariate image differencing, post-classification comparison and principal component differencing for urban change detection. Weismiller *et al.* (1977) used image differencing, post-classification comparison and a spectral/temporal layered classifier for change detection in a coastal zone environment, but results were not compared with coincident ground truth. Thus the capability of such techniques remains poorly evaluated.

Ingram *et al.* (1981) have provided a quantitative comparison of results obtained by using image differencing and image regression techniques for urban change detection. They concluded that the regression procedure performed slightly better than univariate image differencing. Based on rigorous quantitative assessment, Nelson (1983) found that a vegetative index difference transform was superior in comparison to a differencing and ratioing transformation for detecting gypsy moth defoliation. Banner and Lynham (1981) suggested that the sensitivity of the near-infrared band to the vegetation within the clear cut boundaries resulted in higher classification error rates for the vegetative index difference approach. However, this sensitivity was responsible for defining areas defoliated by the gypsy moth (Nelson 1983).

Singh (1984, 1986) objectively evaluated automated methods for the change detection in order to identify an optimal algorithm for forest change detection. Multitemporal Landsat MSS data were analysed to detect changes in tropical forest cover due to shifting cultivation. Several digital change detection techniques such as univariate image differencing, image ratioing, normalized vegetation index differencing, image regression, principal component analysis, post-classification comparison and direct multidate classification were used in the analysis. In addition, many different local spatial processing techniques such as image smoothing, background subtraction, edge enhancement and texture defined by standard deviation were investigated to determine whether they improved the performance of the change detection technique. A thresholding technique was applied and a number of standard deviation threshold levels were tested in the upper and lower tail of the distribution in order to find a threshold value which produced the highest change classification accuracy. A summary of the results obtained by applying various techniques is given in table 2.

The conclusions of the study were as follows: (1) The regression method using Landsat MSS band 2 produced the highest change detection accuracy followed by image ratioing and image differencing. (2) The various local preprocessing techniques such as image smoothing, edge enhancement and standard deviation texture, when combined with the raw image, did not improve the change detection accuracy. (3) The multispectral classification approach produced the lowest change classific-

Table 2. Summary of the best classification performance for the change detection techniques studied.

	Techniques	Accuracy (per cent)
1(*a*)	Univariate image differencing, band 2	73·16
1(*b*)	Univariate image differencing, band 4	63·33
2(*a*)	Image ratioing, band 2	73·71
2(*b*)	Image ratioing, band 4	64·99
3	Normalized vegetation index differencing	71·05
4	Image regression, band 2	74·43
5	Low pass filtered image differencing, band 2	72·09
6	Background subtraction, band 2	72·32
7	High pass filtered image differencing, band 2	70·07
8	Standard deviation texture (3 × 3) differencing, band 2	69·95
9(*a*)	Principal component-2, image differencing (unstandardized)	71·49
9(*b*)	Principal component-2, image differencing (standardized)	64·32
10	Post-classification comparison	51·35
11	Direct multidate classification	57·29

Bands refer to Landsat MSS.

ation accuracy. (4) The simple technique such as image differencing performed better than much more sophisticated transforms such as principal components analysis. The fundamental conclusion is that even in the same environment various techniques may yield different results.

6. Discussion

It may be appreciated that when a difference in radiance values between two dates is taken as an indicator of change, the difference may be due to several factors (Riordan 1980) such as actual change in land cover (signal), differences in illumination, differences in atmospheric conditions, differences in sensor calibration, differences in ground moisture conditions and differences in the registration of the two images. Thus, radiance changes due to changes in the object scene should be large relative to radiance changes due to other factors for good signal-to-noise ratios. Models accounting for temporal variation in digital images need to be developed. These should attempt to distinguish useful temporal variation, i.e. changes in land cover from variation arising due to external factors such as atmospheric conditions, moisture conditions, Sun angle differences and differences in sensor calibration.

Furthermore, the majority of digital change detection techniques depend, critically, upon the accuracy of geometric registration of two images. In the case of misregistration, a number of false alarms, especially in the region of rapid intensity change such as edges, occur. Precise geometric registration of images is often difficult to achieve due to lack of accurate ground control points. So there is a need to explore the possibility of developing digital change detection techniques which require less precise registration of images or which bypass the registration process.

The comparative performance of various techniques in different environments must be evaluated quantitatively, otherwise those interested in monitoring changes in a specific environment may not achieve optimal results because of lack of knowledge about tried and tested procedures of change detection. Remote sensing specialists and resource managers need to know which techniques to apply in an operational monitoring programme.

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References

ADENIYI, P. O., 1980, Land-use change analysis using sequential aerial photography and computer technique. *Photogrammetric Engineering and Remote Sensing*, **46**, 1447–1464.

ANDERSON, J. R., 1977, Land use and land cover changes. A framework for monitoring. *Journal of Research by the Geological Survey*, **5**, 143–153.

ANGELICI, G. L., BRYNT, N. A., and FRIEDMAN, S. Z., 1977, Techniques for land use change detection using Landsat imagery. *Proceedings of the American Society of Photogrammetry*, 217–228.

ANUTA, P., and BAUER, M., 1973, An analysis of temporal data for crop species identification and urban change detection. LARS Information Note 110873, Laboratory for Applications of Remote Sensing, Purdue University, Indiana, U.S.A.

BALLARD, D. H., and BROWN, C. M., 1982, *Computer Vision* (New Jersey: Prentice Hall).

BANNER, A. V., and LYNHAM, T., 1981, Multitemporal analysis of Landsat data for forest cut over mapping—a trial of two procedures. *Proceedings of the 7th Canadian Symposium on Remote Sensing held in Winnipeg in 1981* (Winnipeg: Canadian Remote Sensing Society), pp. 233–240.

BYRNE, G. F., CRAPPER, P. F., and MAYO, K. K., 1980, Monitoring land cover change by principal component analysis of multitemporal Landsat data. *Remote Sensing of Environment*, **10**, 175–184.

COINER, J. C., 1980, Using Landsat to monitor changes in vegetation cover induced by desertification processes. *Proceedings of the 14th International Symposium of Remote Sensing of Environment held in Costa Rica in 1980* (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 1341–1351.

COLWELL, J. E., and WEBER, F. P., 1981, Forest change detection. *Proceedings of the 15th International Symposium on Remote Sensing of Environment held in Ann Arbor in 1981* (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 839–852.

CURRAN, P. J., 1981, Multispectral remote sensing for estimating biomass and productivity. In *Plants and the Day-light Spectrum*, edited by H. Smith (New York: Academic Press), pp. 65–99.

EGHBALI, H. J., 1979, K–S test for detecting changes from Landsat imagery data. *I.E.E.E. Transactions on Systems, Man and Cybernetics*, **9**, 17–23.

ESTES, J. E., STOW, D., and JENSON, J. R., 1982, Monitoring land use and land cover changes. In *Remote Sensing for Resource Management*, edited by C. J. Johannsen and J. L. Sanders (Iowa: Soil Conservation Society of America), pp. 100–110.

GORDON, S., 1980, Utilizing Landsat imagery to monitor land use change: A case study of Ohio. *Remote Sensing of Environment*, **9**, 189–196.

HARALICK, R. M., 1979, Statistical and structural approaches to texture. *Proceedings of the I.E.E.E.*, **67**, 786–804.

HOWARTH, J. P., and BOASSON, E., 1983, Landsat digital enhancements for change detection in urban environment. *Remote Sensing of Environment*, **13**, 149–160.

HOWARTH, J. P., and WICKWARE, G. M., 1981, Procedure for change detection using Landsat digital data. *International Journal of Remote Sensing*, **2**, 277–291.

INGRAM, K., KNAPP, E., and ROBINSON, J. W., 1981, Change detection technique development for improved urbanized area delineation, technical memorandum CSC/TM-81/6087, Computer Sciences Corporation, Silver Springs, Maryland, U.S.A.

JACKSON, R. D., 1983, Spectral indices in N-space. *Remote Sensing of Environment*, **13**, 409–421.

JENSON, J. R. (editor), 1983, Urban/suburban land use analysis. *Manual of Remote Sensing*, Vol. 2, second edition (Falls Church, Virginia: American Society of Photogrammetry), pp. 1571–1666.

JENSON, J. R., and TOLL, D. L., 1982, Detecting residential land use development at the urban fringe. *Photogrammetric Engineering and Remote Sensing*, **48**, 629–643.

JOYCE, A. T., IVEY, J. H., and BURNS, G. S., 1980, The use of Landsat MSS data for detecting land use changes in forest land. *Proceedings of the 14th International Symposium on Remote Sensing of Environment held in Costa Rica in 1982* (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 979–988.

KAUTH, R. J., and THOMAS, G. S., 1976, The tasselled cap—a graphic description of the spectral temporal development of agricultural crops as seen by Landsat. *Proceedings of the 2nd Annual Symposium on Machine Processing of Remotely sensed data held at Purdue University in 1976* (Indiana: Purdue University), pp. 4B41–4B49.

KAUTH, R. J., PENTLAND, A. P., and THOMAS, G. S., 1979, BLOB an unsupervised clustering approach to spatial preprocessing of MSS imagery. *Proceedings of the 11th International Symposium on Remote Sensing of Environment held in Ann Arbor in 1979* (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 1309–1317.

LILLESTRAND, R. L., 1972, Techniques for change detection, *I.E.E.E. Transactions on Computers*, **21**, 654–659.

LAUTENSCHLAGER, L. F., and PERRY, C. R., 1981, An empirical graphical and analytical study of the relationship between vegetation indices. Internal Report No. AGRISTARS EW-JI-04150 JSG 17424, NASA, Houston, Texas, U.S.A.

LILLESAND, T. M., and KIEFER, R. W., 1979, *Remote Sensing and Image Interpretation* (New York: John Wiley & Sons).

LODWIK, G. D., 1979, Measuring ecological changes in multitemporal Landsat data using principal components. *Proceedings of the 13th International Symposium on Remote Sensing of Environment held in Ann Arbor in 1979* (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 1–11.

MALILA, W. A., 1980, Change vector analysis: an approach for detecting forest changes with Landsat. *Proceedings of the 6th Annual Symposium on Machine Processing of Remotely Sensed Data held at Purdue University in 1980* (Indiana: Purdue University), pp. 326–335.

MILLER, L. D., NUALCHAWEE, K., and TOM, C., 1978, Analysis of the dynamics of shifting cultivation in the tropical forests of northern Thailand using landscape modelling and classification of Landsat imagery, NASA technical memorandum 79545, Goddard Space Flight Centre, Greenbelt, Maryland, U.S.A.

NELSON, R. F., 1982, Detecting forest canopy change using Landsat, NASA technical memorandum 83918, Goddard Space Flight Centre, Greenbelt, Maryland, U.S.A.

NELSON, R. F., 1983, Detecting forest canopy change due to insect activity using Landsat MSS. *Photogrammetric Engineering and Remote Sensing*, **49**, 1303–1314.

PERRY, C. R., and LAUTENSCHLAGER, L. F., 1984, Functional equivalence of spectral vegetation indices. *Remote Sensing of Environment*, **14**, 169–182.

RICHARDSON, A. J., and MILNE, A. K., 1983, Mapping fire burns and vegetation regeneration using principal components analysis. *Proceedings of IGARSS' 83 held in San Francisco in 1983* (New York: I.E.E.E.), pp. 51–56.

RICHARDSON, A. J., and WIEGAND, C. L., 1977, Distinguishing vegetation from soil background information. *Photogrammetric Engineering and Remote Sensing*, **43**, 1541–1552.

RIORDON, C. J., 1980, Non-urban to urban land cover change detection using Landsat data. Summary Report of the Colorado Agricultural Research Experiment Station. Fort Collins, Colorado U.S.A.

ROBINSON, J. W., 1979, A critical review of the change detection and urban classification literature. Technical memorandum CSC/TM-79/6235, Computer Sciences Corporation, Silver Springs, Maryland, U.S.A.

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

SHEPARD, J. R., 1964, A concept of change detection. *Photogrammetric Engineering*, **30**, 648–651.

SHORT, N. M., 1982, *The Landsat Tutorial Workbook*, NASA RP-1078 (Washington, D.C.: Government Printing Office).

SINGH, A., 1984, Tropical forest monitoring using digital Landsat data in northeastern India. Ph.D. thesis, University of Reading, Reading, England.

SINGH, A., 1986, Change detection in the tropical forest environment of northeastern India using Landsat. In *Remote Sensing and Tropical Land Management*, edited by M. J. Eden and J. T. Parry (London: John Wiley & Sons), pp. 237–254.

SINGH, A., and HARRISON, A., 1985, Standardized principal components. *International Journal of Remote Sensing*, **6**, 883–896.

STAUFFER, M. L., and MCKINNEY, R. L., 1978, Landsat image differencing as an automated land cover change detection technique, technical memorandum Rep CSC/TM-78/6215, Computer Sciences Corporation, Silver Springs, Maryland, U.S.A.

STOW, D. A., TINNEY, L. R., and ESTES, J. E., 1980, Deriving land use/land cover change statistics from Landsat: A study of prime agricultural land. *Proceedings of the 14th International Symposium on Remote Sensing of Environment held in Ann Arbor in 1980* (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 1227–1237.

SWAIN, P. H., and HAUSKA, H., 1977, The decision tree classifier: design and potential. *I.E.E.E. Transactions on Geoscience and Electronics*, **15**, 142–147.

SWAIN, P. H., 1978, Bayesian classification in a time-varying environment, *I.E.E.E. Transactions on Systems, Man and Cybernetics*, **8**, 879–883.

TODD, W. J., 1977, Urban and regional land use change detected by using Landsat data. *Journal of Research by the US Geological Survey*, **5**, 527–534.

TOLL, D. L., ROYAL, J. A., and DAVIS, J. B., 1980, Urban area up-date procedures using Landsat data. *Proceedings of the Fall Technical Meeting of the American Society of Photogrammetry held in Niagra Falls, Canada, in 1980* (Falls Church, Virginia: American Society of Photogrammetry), pp. RS-E1–17.

TOWNSHEND, J. R. G., GOFF, T. E., and TUCKER, C. J., 1985, Multitemporal dimensionality of images of the normalised difference vegetation index at Continental scales. *I.E.E.E. Transactions on Geoscience and Electronics*, **23**, 888–895.

TUCKER, C. J., 1979, Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, **8**, 127–150.

WEISMILLER, R. A., KRISTOF, S. J., SCHOLZ, D. K., ANUTA, P. E., and MOMEN, S. A., 1977, Change detection in coastal zone environments. *Photogrammetric Engineering and Remote Sensing*, **43**, 1533–1539.

WILLIAMS, D. L., and HOVER, G. F., 1976, Forest land management by satellite: Landsat-derived information as input to a forest inventory system. NASA intralab project 75-1, Goddard Space Flight Centre, Greenbelt, Maryland, U.S.A.

WILLIAMS, D. L., and STAUFFER, M. L., 1978, Monitoring gypsy moth defoliation by applying change detection techniques to Landsat imagery. *Proceedings of the Symposium on Remote Sensing for Vegetation Damage Assessment* (Falls Church, Virginia: American Society for Photogrammetry), pp. 221–229.

WILSON, J. R., BLACKMAN, C., and SPANN, G. W., 1976, Land use change detection using Landsat data. *Proceedings of the 5th Annual Remote Sensing of Earth Resources Conference held in Tullahama, Tennessee, in 1976* (Tennessee: University of Tennessee), pp. 79–91.

WOODWELL, G. M., HOBBIE, J. E., HOUGHTON, R. A., MELILLO, J. M., PETERSON, B. J., SHAVER, G. R., STONE, T. A. MOORE, B., and PARK, A. B., 1983, Deforestation measured by Landsat: step towards a method. Report No. DOE/EV/10468-1, USA Department of Energy, Washington, D.C., U.S.A.