

Land cover change detection in West Jilin using ETM+ images

Edward M. Osei, Jr., ZHOU Yun-xuan

College of Geo-exploration Science and Technology, Jilin University, Changchun 130026, Jilin, China

Abstract: In order to assess the information content and accuracy of Landsat ETM+ digital images in land cover change detection, change-detection techniques of image differencing, normalized difference vegetation index, principal components analysis and tasseled-cap transformation were applied to yield 13 images. These images were thresholded into change and no change areas. The thresholded images were then checked in terms of various accuracies. The experiment results show that kappa coefficients of the 13 images range from 48.05 ~ 78.09. Different images do detect different types of changes. Images associated with changes in the near-infrared-reflectance or greenness detects crop-type changes and changes between vegetative and non-vegetative features. A unique means of using only Landsat imagery without reference data for the assessment of change in arid land are presented. Images of 12th June, 2000 and 2nd June, 2002 are used to validate the means. Analyses of standard accuracy and spatial agreement are performed to compare the new images (hereafter called "change images") representing the change between the two dates. Spatial agreement evaluates the conformity in the classified "change pixels" and "no-change pixels" at the same location on different change images and comprehensively examines the different techniques. This method would enable authorities to monitor land degradation efficiently and accurately.

Key words: remote sensing; landcover change; change detection; accuracy assessment

Introduction

This paper describes a methodology for processing Landsat 7 Enhanced Thematic Mapper Plus (ETM+) satellite imagery for the detection and mapping of land cover changes and the methodology for comparing change detection techniques using error matrix and standard accuracy assessment procedures. Images of 2000 and 2002 from Tongyu County in western Jilin are used to validate the procedures. Both of the images were radiometrically corrected for atmospheric attenuation and geometrically rectified with respect to projection and datum to fit base maps.

Tongyu covers about an area of 8 433.67 km², located in the western part of Jilin Province. Four change detection techniques were compared for their effectiveness including ① Spectral Image Differencing (SID); ② Tasseled Cap Image Differencing

(TCID); ③ Principal Component Analysis (PCA) and ④ Vegetation Index (NDVI). SID was performed on five raw bands (bands 2, 3, 4, 5 and 7) and altogether 13 new images (change images) were produced.

Tasseled Cap change in Greenness (ΔG) was found to be most accurate for detecting areas affected by change followed by PC2 (PCA 2), SID4 (band 4), SID3 (band 3), SID2 (band 2) and NDVI. The change image produced from ΔG showed overall and Kappa accuracies of 90.63 percent and 78.09 percent respectively.

A visual interpretation technique to generate reference points from color composite Landsat images, for selecting Kappa-optimizing thresholds and for assessment of classification accuracy is described. The goal is to determine the most accurate and efficient

method to detect change in the arid area and to facilitate the transfer of this technology to the local NGOs.

1 Study area

The study area is Tongyu located in the west of Jilin Province, China (Fig. 1). It has an area of 8 433.67 km² and lies between 44°30' N and 45°30' N latitude and between 123°10' E and 124°30' E longitude, with elevation ranging from 150 m to 270 m. Research area lies in interleaving distribution section of low-lying waterlogged saline-alkalized land and sand land blown by wind in mid-west of Songnen plain. The western part of Jilin belongs to middle humid and middle arid area, and is also the interleaving section of agriculture and animal husbandry. Thus, this part shows itself obvious marginal and transitional character, and has characteristics of unstable natural ecosystem, high sensitivity to outside interference, inconstancy and very fragile ecological environments. The study of land use change and its influence on ecological environment in the west of Jilin Province therefore is necessary and has important and typical meaning.

Two dates of Landsat 7 ETM+ imagery (2000, 2002) for World Wide Reference System path 120, row 29 were acquired. The Landsat ETM+ images

have an approximate spatial resolution of 30 m. The standard false-color composites of the two Landsat TM images are shown in Fig. 2.

These images have been geometrically and radiometrically calibrated/slaved onto a master image, and the same contrast stretch was applied to all two for visual display. Because of the radiometric calibration, the brightnesses and colors of the images have the same spectral reflectances if they have the same DN values.

2 Method of analysis

2.1 Pre-processing

Two Landsat 7 ETM+ images dated 12th June, 2000 and 2nd June, 2002 were used for the analysis. To reduce the effects of atmospheric conditions, radiance values were converted to ground reflectance through a procedure developed by Irish (2000). Twenty-nine ground control points (GCPs) digitized from the 1:25 000-scale topographic map were used to rectify 12th June, 2000 Landsat 7 ETM+ image to an Albers Conical Equal Area map projection (root-mean-square error: RMSE = 0.09 pixel/2.7m). The 2002 image was registered using 50 GCPs obtained from the rectified 2000 image (RMSE = 0.20 pixel/6 m). Both RMSES are within acceptable limits for change-detection analysis. RMSE errors less than 0.5 pixel in sparsely vegetated areas have been shown to retain very high accuracy (greater than 97 percent) in the change-detection analysis (Townshend *et al.*, 1992). The images were resampled to a 30-m pixel size using the nearest-neighbor resampling technique to retain radiometric integrity.

Several binary masks were applied to the ETM+ images to eliminate contaminated areas (clouds and their shadows) and irrelevant areas. A cloud mask was created by screen digitizing clouds and their shadows. A polygon boundary file was rasterized to map projection and then resampled to 30 × 30 pixels, producing a

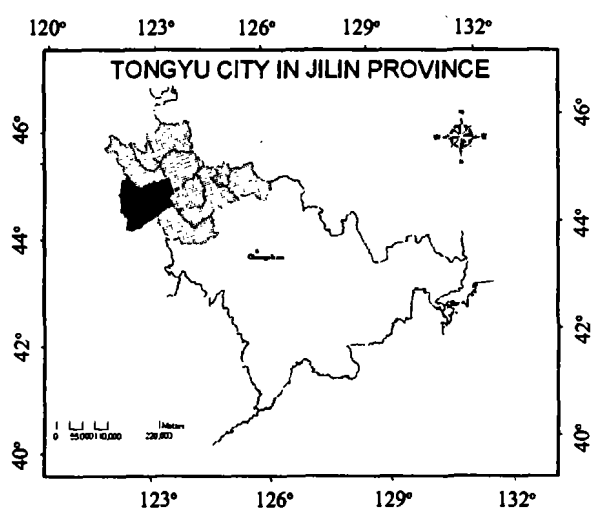


Fig. 1 Study area

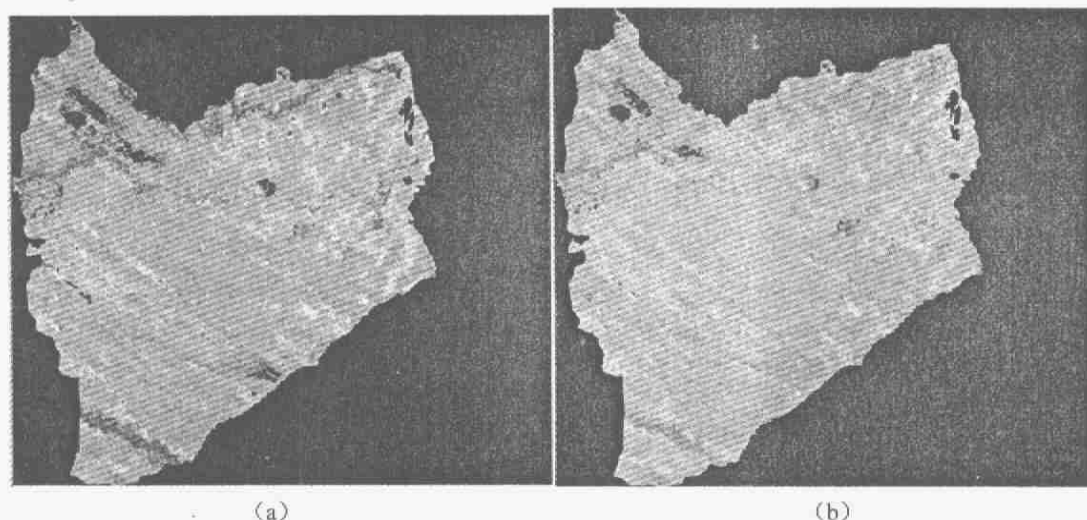


Fig. 2 Colour composites of Landsat TM Bands 7, 4, 3 RGB acquired in (a) 2000 and (b) 2002

binary mask of Tongyu. The mask was applied to each of the rectified images. Thus only land within Tongyu was allowed.

The mask also maintained a consistent amount of hectare in the image, which was important for computing the change in land cover between dates and in quantitative analysis.

2.2 Response of different bands of landsat TM data

Four different change-detection techniques including Spectral Image Differencing (SID), Tasseled Cap Image Differencing (TCID), Principal Component Analysis (PCA) and Vegetation Index (NDVI) were employed. SID was performed on five bands (band 2: green, band 3: red band 4: near-infrared, band 5: mid-infrared and band 7: mid-infrared). Tasseled Cap and PCA used all bands except band 6. Altogether, thirteen change images were generated using these four techniques.

2.2.1 Spectral Image Differencing (SID)

Spectral image differencing involves subtracting a pixel's digital number (DN) value on one date from the corresponding pixel DN on the second date. The subtraction results in positive and negative values in areas of surface reflectance change and zero values in areas

of no change. Using 8-bit Landsat ETM+ data, the potential range of difference values is -255 to $+255$, the process is expressed mathematically as

$$\Delta x_{ijk} = x(1)_{ijk} - x(2)_{ijk}$$

where Δx_{ijk} is the change pixel value, $x(1)$ is the value at time 1, $x(2)$ is the value at time 2, $i = 1 \cdots nl$ number of lines, $j = 1 \cdots nc$ number of columns, and k is a single band, e.g. band 3.

The resulting difference image distribution has pixels of no change, minor surface change, and noise (i. e. atmospheric and other non-surface radiance characteristics that weren't successfully corrected in the image calibration procedure) distributed around the mean, while pixels of significant surface change are distributed in the histogram tails. As with many of the change detection techniques investigated, a crucial component of this technique is the selection of a threshold value between change and no-change pixels. Numerous techniques have been used in selecting a change threshold. For this investigation 1.0 standard deviation of the mean was chosen.

2.2.2 Tasseled Cap Image Differencing (TCID)

The tasseled cap transformation defines a new coordinate system in which characteristics of the remotely sensed data can be more readily viewed (Kauth and

Thomas 1976; Crist 1983; Crist and Cicone, 1984; Crist and Kauth, 1986). All three functions of tasseled cap transformation — “brightness” “greenness” and “wetness” were employed, and were computed as follows (Huang *et al.*, 2002) (Table 1):

The images showing change in brightness (ΔB), greenness (ΔG) and wetness (ΔW) were produced by subtracting the function for 2000 from that of 2002.

The resulting difference images were then thresholded.

Table 1 employed and computed brightness, greenness and wetness

	Band1	Band2	Band3	Band4	Band5	Band7
Brightness	0.35612057	0.39722874	0.39040367	0.69658643	0.22862755	0.15959082
Greenness	-0.33438846	-0.35444216	-0.45557981	0.69660177	-0.02421353	-0.26298637
Wetness	0.26261884	0.21406704	0.09260517	0.06560172	-0.76286850	-0.53884970

2.2.3 Principal component analysis

The principal component transformation was performed on merged data sets (2000 and 2002) using ETM+ bands (1, 2, 3, 4, 5 and 7) from each date (Duvernoy and Leger, 1980). The basic premise for the PCA with merged data in change detection is that one or more of the new PCA bands contain information that can be directly related to change (Byrne *et al.*, 1980). Muchoney and Haack (1994) demonstrated that multitemporal SPOT spectral information related to hardwood defoliation by gypsy moths was confined to a single PCA band.

Fung and LeDrew (1987) have shown that the standardized PCA (using correlation matrix) performed better than the unstandardized PCA (using covariance matrix). Our study did not show any significant difference between them, hence we considered only the unstandardized PCA.

The eigenvalues and eigenvectors of the 12 by 12 covariance matrix of the twelve-dimensional merged TM data of 2000 and 2002 were computed (Table 2). The first, second, and third principal components accounted for 98.07 percent, 0.98 percent, and 0.63 percent of the variance, respectively and accounting for 99.68 percent. Components that represent change typically show an absence of correlation among bands between dates (Byrne *et al.*, 1980). The component that best highlights the change of interest is chosen for

thresholding, using visual interpretation of component images and analysis of the eigenvector matrix. The second (PC2), seventh (PC7), eighth (PCS) and twelfth (PC12) components are associated with changes. In PC2, the 2000 spectral bands are all positive in loadings. A reverse pattern is found in the 2002 bands. PC7, PCS and PC12 all have their loadings for 2000 being a reverse to that of 2002.

2.2.4 Normalized difference vegetation index

A Normalized Difference Vegetation Index (NDVI) has been used for several years to measure plant growth and vegetation cover from Landsat Thematic Mapper (TM) imagery. The principle underlying NDVI is that TM band 3 is the red light portion of the spectrum where chlorophyll causes high absorption of incoming sunlight, whereas TM band 4 is in the near infrared portion of the spectrum where a plant's mesophyll leaf structure highly reflects the sunlight. Healthy vegetation has a relatively low red light reflectance but a relatively high near-infrared reflectance and, hence, high NDVI.

NDVI is a ratio of reflectance bands, $NDVI = (IR - R) / (IR + R)$, where IR is the near infrared band (band 4 in ETM+ 7) and R is the visible red band (band 3 in ETM+ 7). NDVI values range from -1 to +1. The difference image was created by subtracting 2000 NDVI from 2002 NDVI, so that:

$$NDVID = NDVI_{2002} - NDVI_{2000}$$

Table 2 Unstandardized principal components of Multidate ETM+ data

	Components											
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
2000 TM1	0.39	0.19	-0.08	0.59	0.23	0.13	-0.36	0.40	0.27	-0.16	-0.02	0.01
TM2	0.36	0.37	-0.20	0.13	-0.06	-0.27	-0.19	-0.24	-0.63	0.33	0.02	0.01
TM3	0.36	0.54	-0.19	-0.38	0.19	-0.11	0.35	-0.19	0.39	-0.21	0.01	-0.01
TM4	0.32	0.21	0.67	-0.03	-0.61	0.15	-0.03	-0.01	0.07	-0.04	-0.03	-0.02
TM5	0.09	0.13	0.17	-0.18	0.31	0.50	0.33	0.43	-0.31	0.27	0.28	0.21
TM6	0.03	0.05	0.03	-0.08	0.14	0.18	0.11	0.15	-0.14	0.10	-0.72	-0.60
2002TM1	0.37	-0.38	-0.14	0.36	-0.05	0.31	0.42	-0.44	0.16	0.27	-0.01	-0.01
TM2	0.35	-0.33	-0.27	-0.09	-0.26	-0.09	0.24	0.30	-0.36	-0.58	0.02	-0.02
TM3	0.35	-0.30	-0.25	-0.53	-0.13	0.08	-0.44	0.17	0.24	0.38	-0.01	0.02
TM4	0.31	-0.34	0.51	-0.05	0.48	-0.53	0.06	0.01	0.00	0.06	-0.02	0.03
TM5	0.09	-0.08	0.14	-0.17	0.30	0.41	-0.39	-0.45	-0.19	-0.38	0.25	-0.28
TM6	0.03	-0.02	0.03	-0.08	0.11	0.18	-0.12	-0.17	-0.10	-0.18	-0.58	0.72
Eigenvalue	14948.87	148.78	95.89	24.50	12.50	7.82	1.90	0.90	0.82	0.48	0.09	0.07
% Variance	98.0729	0.9761	0.6291	0.1607	0.0820	0.0513	0.0124	0.0059	0.0054	0.0031	0.0006	0.0005
Cumulative	98.0729	99.0490	99.6781	99.8389	99.9208	99.9721	99.9846	99.9905	99.9958	99.9990	99.9996	100.0000

2.3 Thresholding and accuracy assessment

The histograms of all the change images produced showed nearly normal distributions. Fig. 2 shows an example of SID (band 4). Values near the mean indicate that they have similar spectral values on both dates, and therefore have experienced no disturbances. The values that are at both ends of the tails of the histogram indicate areas where spectral values decreased or increased and therefore changed.

The following discussion illustrates the method of determining threshold boundaries between change and no-change pixels. Threshold images were produced by adding or subtracting 1.0 standard deviation times from the mean and receding the image. Threshold images are binary images in which a value of 0.0 or 1.0 represents no-change or change, respectively. The change images produced were compared with the reference data (discussed in the following paragraph).

2.4 Classifying the change images

Cohen *et al.* (1998) selected a random sample of points from a classified image and displayed them on each date of raw TM, RGB color composite imagery. Each point was then labeled as change or no change by visual interpretation of the images, and used as therefor reference for accuracy assessment. They found the result-

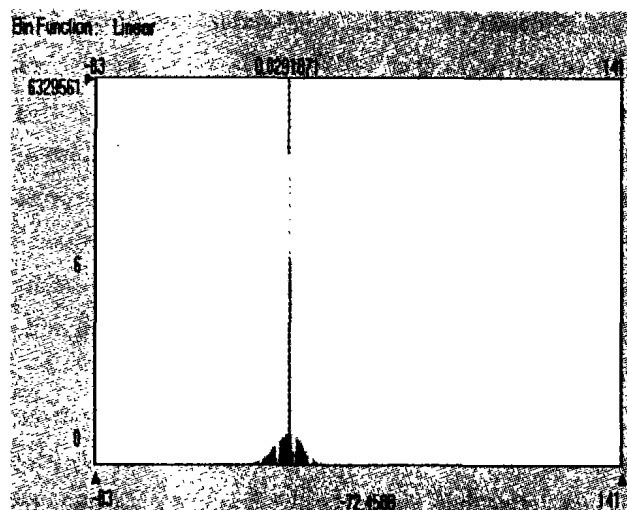


Fig. 2 SID4 Histogram with Mean=0.029 and SD=8.196

ing error matrix to be not significantly different than one prepared with an independent vector database derived from aerial photography interpretation and ground truth methods.

For each change image, an error matrix was developed using a sample of visually interpreted points as reference against the values of the change image. To assure an adequate distribution of sample points to each change class, each 8-bit (0~255) change image was recoded into 32 classes with each class corresponding to 8 original digital values (0~7, 8~15, ... ,

248~255). This 32-class temporary file was then used to generate a stratified random sample of points to be interpreted for use as reference in the thresholding procedure. A 3×3 moving window was used to select sample points in which all the surrounding pixels were of the same class (9 out of 9 majority), thus avoiding edge effects in interpretation. Five sample points were generated from each of the 32 classes in the temporary file ($n=160$).

In the absence of existing historical reference data for the study area, the visual interpretation method reported by Cohen *et al.* (1998) was the only option for developing reference data for error matrices.

3 Results

For accuracy assessment, this study uses several measures of accuracy, including producer's accuracy, user's accuracy, conditional kappa, overall accuracy and kappa (Fung and LeDrew, 1988; Congalton *et al.*, 1983; Congalton, 1991). Table 3 illustrates a typical error matrix generated from thresholding the SID4 (differenced image of ETM+ band 4) at 1.0 standard deviation of the mean.

The user's accuracy is the measure of error of commission which is 83.33 percent.

The producer's accuracy is the measure of error of omission which is 76.09 percent.

The overall accuracy is the measure of the accuracy of the entire image without any indication of the accuracy of individual categories which is 88.75 percent.

The average accuracy is an average of the accuracy of individual categories. Because the individual categories can be the user's or the producer's accuracy, it can be computed in both ways accordingly. The user's and producer's average accuracy are 87.01 percent and 84.97 percent respectively. In contrast to the overall accuracy, it is biased towards the category with a small number of samples.

Table 3 Error matrix of thresholded SID4 at 1.0 standard deviation from mean

		SID4		
		Reference Data		Total
Image Data	No-change	No-change	Change	
	Change	107	11	118
	Total	7	35	42
		114	46	160
User's Accuracy		90.68	83.33	
Producer's Accuracy		93.86	76.09	
Conditional Kappa ($\times 100$)		67.58	76.61	
Average Accuracy (User's)				87.01
Average Accuracy (Producer's)				84.97
Combined Accuracy (User's)				87.88
Combined Accuracy (Producer's)				86.86
Overall Accuracy				88.75
Kappa ($\times 100$)				71.81

The combined accuracy is the average of the overall accuracy and average accuracy. It can also be computed as either the user's accuracy (87.88 percent) or the producer's accuracy (86.86 percent). It has been used to dampen the inherent biases of the overall average accuracy (Nelson, 1983).

The Kappa coefficient of agreement (K) was developed by Cohen (1960). It is a measure of the actual agreement (indicated by the diagonal elements of the matrix) minus chance agreement (indicated by the product of row and column marginals). It uses all cells in the matrix and takes into account both the commission and omission errors (Rosenfield and Fritzpatrick-Lins, 1986). A Kappa coefficient measures how a classification performs as compared to the reference data.

The kappa coefficient of agreement is computed

$$\text{as } K = \frac{M \sum_{i=1}^r x_{ii} - \sum_{i=1}^r x_{i+} x_{+i}}{M^2 - \sum_{i=1}^r x_{i+} x_{+i}}$$

where r is the number of rows in the error matrix,

x_{ij} is the number of observations in row i and column j , x_{i+} and x_{+i} are thus the marginal totals or row i and column i respectively, and M is the total number of observations. The Kappa value is 0.718 1 for SID4.

The test statistics for a significant difference between two independent Kappas for different assessment (e.g., comparing the results of different techniques) is

$$Z = \frac{K_1 - K_2}{[V(K_1) + V(K_2)]^{1/2}}$$

where $V(K_1)$ is the approximate large sample variance of K and Z is the standard normal deviate (Cohen, 1960). If Z exceeds 1.96, then the difference is significant at the 95 percent probability level.

Table 4 compares the accuracies and Kappa in change images produced by different change-detection techniques. Among the thirteen change images, Tasseled Cap ΔG performed best in detecting areas of change with overall and Kappa accuracies of 90.63 percent and 78.09 percent, respectively. Following Tasseled Cap ΔG were PC2 and SID4 (band 4) with overall accuracies of 89.38 percent and 88.75 percent respectively and Kappa accuracies of 74.85 percent and 71.81 percent, respectively. SID7 (band 7) showed almost the same performance in accuracy compared to the NDVI. Among the PCA, PC2 showed the highest accuracy. The others PC7, PC8 and PC12 did not do

well in detecting change. Tasseled Cap ΔB and ΔW , the weighted average of six ETM bands (excluding band 6), showed the same accuracy.

The results indicate the effectiveness of using all bands of TM data. Accuracies were improved when all bands were used together in the algorithm.

3.1 Evaluation of spatial agreement between change images

Accuracy assessment is a common method to evaluate change images; however, it does not exactly explain how two change images produced from different techniques differ from each other. Spatial agreements between change images were examined to comprehensively evaluate change images produced from different techniques.

Table 5 illustrates the correlation among the thirteen unthresholded change images. The differences images generated from the spectral bands and change in brightness ΔB are highly correlated. There is also high correlation between differences images generated from the spectral bands. Apart from the PC2 which has correlation with change in greenness (ΔG), the PC images and other images are relatively low. Change in NDVI has some correlation with change in greenness ΔG .

To examine the differences among error matrices produced from the thresholded images, pairwise sig-

Table 4 Accuracy indices of the 13 images

	No Change			Change			Overall Accuracy	Average Accuracy		Combined Accuracy		Kappa / $\times 100$	Variance
	U	P	K	U	P	K		U	P	U	P		
SID 2	90.52	92.11	67.02	79.55	76.09	71.29	87.50	85.03	84.10	86.27	85.80	69.09	0.003634615
SID 3	92.04	91.23	72.30	78.72	80.43	70.14	88.13	85.38	85.83	86.75	86.98	71.20	0.003420769
SID 4	90.68	93.86	67.58	83.33	76.09	76.61	88.75	87.01	84.97	87.88	86.86	71.81	0.003488563
SID 5	86.07	92.92	52.56	78.95	63.83	70.19	84.38	82.51	78.38	83.44	81.38	60.11	0.004093480
SID 7	89.38	88.60	63.06	72.34	73.91	61.18	84.38	80.86	81.25	82.62	82.81	62.11	0.003876333
NDVID	90.35	90.35	66.44	76.09	76.09	66.44	86.25	83.22	83.22	84.73	84.73	66.44	0.003735165
PC 2	92.79	91.96	75.98	81.63	83.33	73.76	89.38	87.21	87.65	88.29	88.51	74.85	0.003052676
PC 7	85.09	86.61	50.29	67.39	64.58	53.42	80.00	76.24	75.60	78.12	77.80	51.81	0.003832323
PC 8	87.16	83.33	55.33	62.75	69.57	47.71	79.38	74.95	76.45	77.16	77.91	51.24	0.003731434
PC 12	82.24	83.02	47.39	66.04	64.81	48.74	76.88	74.14	73.92	75.51	75.40	48.05	0.003422412
? G	95.37	91.15	84.24	80.77	89.36	72.77	90.63	88.07	90.26	89.35	90.44	78.09	0.002715403
? B	85.95	92.04	52.17	76.92	63.83	67.32	83.75	81.44	77.93	82.59	80.84	58.79	0.004092543
? W	88.14	92.04	59.61	78.57	70.21	69.66	85.63	83.35	81.12	84.49	83.37	64.24	0.003896457

U—User; P—Producer; K—Conditional Kappa

Table 5 Correlation matrix of the eleven images

	SID4	SID7	NDVID	PC2	PC7	PC8	PC12	ΔG	ΔB	ΔW
SID3	0.7612	0.8166	-0.3704	-0.9795	-0.1039	0.0323	0.0006	-0.8508	0.9610	0.7834
SID4		0.6017	0.2688	-0.8265	0.0150	0.0023	0.0014	-0.3353	0.8985	0.6419
SID7			-0.3277	-0.8118	-0.2924	-0.2843	0.3266	-0.6863	0.7703	0.3825
NDVID				0.2593	0.2057	-0.0605	0.0387	0.7202	-0.1358	-0.2150
PC2					-0.0000	-0.0000	0.0000	0.7767	-0.9753	-0.7730
PC7						0.0000	0.0000	0.0167	0.0001	0.3696
PC8							0.0000	0.0061	-0.0109	0.2175
PC12								-0.0110	0.0020	-0.0278
ΔG									-0.7146	-0.7283
ΔB										0.8111

Table 6 Results of test of agreement between error matrices produced from the 13 thresholded images

	SID3	SID4	SID5	SID7	NDVID	PC2	PC7	PC8	PC12	ΔG	ΔB	ΔW
SID2	-0.2516	-0.3224	1.0211	0.8055	0.3087	-0.7049	1.9998	-5.9695	2.5041	-1.1292	1.1718	0.5582
SID3		-0.0731	1.2793	1.0646	0.5631	-0.4538	2.2772	2.3606	2.7984	-0.8789	1.4322	0.8133
SID4			1.3434	1.1305	0.6319	-0.3763	2.3377	2.4210	2.8577	-0.7970	1.4955	0.8803
SID5				-0.2235	-0.7150	-1.7437	0.9328	1.0032	1.3911	-2.1783	0.1464	-0.4623
SID7					-0.4964	-1.5311	1.1731	1.2462	1.6451	-1.9682	0.3719	7.0445
NDVID						-1.0213	1.6818	1.7591	2.1732	-1.4503	0.8647	0.2511
PC2							2.7773	2.8670	3.3305	-0.4258	1.9005	1.2725
PC7								0.0655	0.4409	-3.2476	-0.7841	-1.4147
PC8									0.3766	-3.3439	-0.8535	-1.4892
PC12										-3.8336	-1.2384	-1.8927
ΔG											2.3390	1.7023
ΔB												-0.6105

nificance testing of Kappa test are performed. As presented in Table 6, the ΔG is significantly different from the other ten images. It has the highest Kappa value of 0.780 9. In contrast, the PC12 is significantly different from the other images but with the lowest Kappa value of 0.480 5.

The spectral differencing (SIDs) and NDVI have no significant difference in terms of the accuracy of classification. Their Kappa values range from 0.621 1 (SID7) to 0.718 1 (SID4).

However it should be noted that each image may consist of different information content despite their differences or similarities in accuracy. While there is no significant differences in terms of accuracy of the two error matrices of SIDS and SID4, the land-cover changes they reveal may be entirely different. Comparison is meaningless unless the ability of each individual image to detect specific land-cover change is investigated.

4 Discussion and conclusion

Among the individual bands of TM data used, the near infrared band was effective in detecting change in arid areas. In SID, band 4 shows the highest accuracy (overall accuracy 88.75 percent and Kappa 71.81 percent) followed by band 3 (overall accuracy 88.13 percent and Kappa 71.20 percent) and band 2 (overall accuracy 87.50 percent and Kappa 69.09 percent). A study conducted by Ridd and Liu (1998) showed that band 3 and band 2 were effective in detecting changes at a construction sites and farmlands in an urban environment. Miller *et al.* (1983) and Patel *et al.* (1985) found muddy water showing higher reflectance for band 3 (red). Yamagata and Akiyama (1988) also used band 3 to estimate paddy damage caused by flooding using multitemporal Landsat data.

Among the different change-detection techniques tested, AG performed best with overall accuracy of

90.63 percent and Kappa of 78.09 percent. PCA and SID (bands 2, 3, and 4) also showed high accuracies. SID (bands 5 and 7) and TCBID (ΔW and ΔB) did not perform well.

SID, NDVID and TCBID applied in this study were image differencing. Image differencing is a relatively simple and easy technique. Despite its simplicity, SID has been found effective in many studies (e.g. Ridd and Liu, 1998; Macleod and Congalton, 1998; Muchoney and Haack, 1994). The other technique, PCA, employ many bands together in order to extract changes.

These methods have also been found useful in different change-detection studies (e.g. Michalek *et al.*, 1993; Lambin and Strahler, 1994a; Lambin and Strahler, 1994b; Muchoney and Haack, 1994; Yamagata and Akiyama, 1988; Fung and LeDrew 1987). It is important that change-detection techniques should address the changes occurring in a variety of land uses.

The application of multitemporal Landsat ETM+ data to detect areas affected by change in an arid area consisting of different land uses showed that change in Tasseled Cap Greenness was effective in detecting affected areas. Tasseled Cap Greenness performed the best followed by Principal Component Analysis (PC2; using all bands except 6 (and Spectral Image Differencing (SID; band 4). Because the detection of areas affected by change in a large area based on field-work is often a difficult task, the results of this study enhance the understanding of the practical applicability of automated change detection using multitemporal satellite data in overcoming such difficulties.

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