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A Comparative Study of Wetland Change Detection Techniques Using Post-Classification Comparison and Image Differencing on Landsat-5 TM Data[1]

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랜셋-5號 TM 데이타를 利用한 區分后 比較 및 映像對差의 濕地帶 變化 探知 技法에 關한 比較研究[1]

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ABSTRACT

The extensive Snake River floodplain in Northwest United States has experienced major changes in water channels and vegetation types due to floodings. To detect the change of wetland cover-types for the period of 1985 and 1988, post-classification comparison and image differencing change detection techniques were evaluated using Landsat-5 TM digital data. Differenced infrared-band images indicated better accuracy indices than any visible-band images. A thresholding technique was applied to identify the change and no-change categories from the transformed images produced by image differencing. The problems in using different accuracy indices, including the Kappa coefficient of agreement, overall accuracy, producer's accuracy, user's accuracy, and average accuracy(based on both the producer's and user's accuracy approaches) in determining an optimal threshold level, were examined.

Key words : Wetland change detection, post-classification comparison, image differencing, and Kappa coefficient of agreement.

要 約

美西部의 광대한 Snake江 범람평원은 홍수로 인하여 水路 및 植生型의 빈번한 변화 및 침해를 받아왔다. 1985년과 1988년 기간 동안의 습지대 식생형의 변화를 탐지하기 위하여, 원격탐사의 변화탐지 技法 중 區分后 比較 및 映像對差法 등을 Landsat-5호 TM 디지탈 데이타를 이용하여 비교·고찰하였다. 對差된 赤外線帶 영상들이 可視帶 영상들보다 나은 정확도 指標를 보였으며, 閾技法을 적용하여, 영상대차법에 의하여 변형된 영상들로부터 變化와 無變化를 구분하였다. 또한, 여러 정확도 지표들 중, 카파 一致係數, 총정확도, 생산자 정확도, 이용자 정확도 및 평균정확도(생산자 및 이용자 정확도 등에 근거한) 등을 이용하여 最適閾領域을 결정함에 있어서의 문제점들을 고찰하였다.

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INTRODUCTION

Remote sensing has become an important tool in wetland management, providing much of the required data base information and monitoring capability. During the past two decades, legislation requiring wetland classification and inventory, concerns for wetland losses, the need for habitat evaluation, and the increased availability of aircraft and satellite data have rapidly expanded remote sensing research and technology related to wetlands. Use of remotely sensed data for wetland inventory and mapping is now common in government agencies, although research continues for improved methodology and new sensors (Christensen, 1987).

One of the most important applications of digital remote sensing data is the recording of land use/cover changes through time. Remote sensing-based change detection utilizes multiple-date imagery to identify both temporal and spatial changes. Different dates of Landsat MSS (Multispectral Scanner) and TM (Thematic Mapper) satellite imagery have been used to detect and monitor suburban sprawl, deforestation, crop development, etc. (Nelson, 1983 ; Adeniyi, 1985). Relatively few investigations have applied satellite digital data to wetland change detection (Howarth and Wickware, 1981 ; Frick, 1984).

Although a number of change detection techinques using Landsat digital data are now available, the remote sensing specialist and the resource manager need to know how and when to apply such techniques in an operational monitoring program. The purpose of this paper is to outline the procedures that could be practically followed and the information to be expected from each step in the process in a long-term operational monitoring program for remote areas. Previous works by Griffiths (1988) and Howarth and Wickware (1981), which demonstrated what can be achieved in studying change using image differencing and post-classification comparison change detection, is used to illustrate this monitoring process.

MATERIALS AND METHODS

Study Area

The 500-year floodplain adjacent to the leveed reaches of the Snake River in the Jackson Hole, Wyoming area was selected since it has numerous and diverse wetlands. The study area occupies a corridor of up to approximately three miles (five km) in width and 14 miles (23 km) in length extending from Wilson Bridge to Route 189 Bridge crossing on the south end of Jackson Hole. This area has experienced frequent floodings even with its well-developed dike systems (USACE, 1989). Throughout the period of 1985 to 1988, both river channel and vegetation changes were sufficient to be readily recorded by Landsat imagery.

Data Sources

From the available Landsat data, two Landsat-5 TM images dated on 15 August 1985 (Scene-ID Y5053217370X0) and 23 August 1988 (Scene-ID Y5163617381X0) of path 38 and row 30 were selected for the wetland change detection analysis and their digital-floppy disk products were purchased from the Earth Observation Satellite Company (EOSAT). A TM digital-floppy disk product (subscene) covers an area represented by 512×512 pixels, or about $12 \times 15 km (= 180 km^2)$. Both images are cloud-free and were collected at near-anniversary dates. The analyses of these data were carried out using a commercial image analysis system marketed by the Earth Resources Data Analysis System, Inc. (ERDAS) and an ARC/INFO Geographic Information System (GIS) marketed by the Environmental Systems Research Institute, Inc. (ESRI). The software systems include various data manipulation procedures and pattern-recognition-oriented algorithms. The hardware systems are IBM-486/25 general purpose computers.

Data Preprocessing

Atmospheric Effects Correction. The "radiometric rectification" technique (Hall et al., 1991) was used for this study to radiometrically rectify the 1985 subject image to the 1988 reference image. This correction procedure is relatively simple and useful when reliable atmospheric optical depth data or calibration coefficients are not available.

From the tests of this technique, Hall et al. (1991) concluded that radiometric rectification performed well, removing the effects of relative atmospheric differences to within one percent absolute reflectance.

Image-to-Image Registration. Image registration was applied using the translation and rotation alignment process by which two images of like geometries and of the same set of objects are positioned coincident with respect to one another so that corresponding elements of the same ground area appear in the same place on the registered images.

The 1985 image was registered using nearest-neighbor interpolation to the 1988 image for the further analysis of change detection algorithms.

Geometric Rectification. The next step in the analysis of these satellite-collected data sets was to rectify the images to map coordinates. The Universal Transverse Mercator (UTM) System was chosen as the geographical reference system because: its metric system of coordinates fits nicely with the metric pixel size of the Landsat data and the UTM coordinate system of the USGS 7.5-minute topographic maps used; and, the task of analyzing the numerical data was much easier to deal with on the computer (Ness, 1988).

Sampling Scheme

The 204 sample points randomly selected and well-distributed (Jensen, 1986) were cross-checked with aerial photography and some of them were ground-truthed during the summer of 1991 (Ulliman, 1992). These cross-checked sample points were used for the accuracy evaluation of the classified wetland cover-type maps and the binary images representing change and no-change in the analysis phase. Among 204 random points, 27 points (13.2%) revealed changes throughout the period of 1985 to 1988.

Image Analysis

Since the primary objective of this study is to determine wetland change patterns in the study area, enhancement techniques were explored which would lead to change detection. Two image processing methods were employed: Post-Classification Comparison and Image Differencing.

However, thermal data (TM band-6) for the two dates were excluded for the study, since they may lead to misinterpretation or spurious classification unless considerable caution is exercised. Indiscriminate use of the thermal data as an adjunct to the visible near-infrared data appears to be undesirable because of many possibilities for misinterpretation and the fact that the thermal "signature" is not a direct indicator or surface type (Price, 1981).

Post-Classification Comparison. This is the most obvious method of change detection which requires the comparison of independently classified images. By properly coding the classification results for 1985 and 1988, change maps, which show a complete matrix of changes, can be produced. In addition, any subset of changes which may be of interest can be observed by selective grouping of the classification. 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 the two dates (Singh, 1989).

However, if the land cover classification generated from a single date of Landsat data is considered, 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% accuracy might have only a $0.80 \times 0.80 \times 100 = 64\%$ correct joint classification rate. 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".

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

$$Dx^k_{ij} = x^k_{ij}(t_2) - x^k_{ij}(t_1) + C$$

where : x^k_{ij}=pixel value for band k ; i and j are line and pixel numbers in the image ; t_1=first date ; t_2= second date ; and, C=a constant, set equal to 112 for the study, to provide positive digital numbers.

The image differencing procedure, most widely used technique for change detection, 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 (Singh, 1989).

A critical element of the image differencing method is deciding where to place the threshold boundaries between change and no-change pixels in the histogram (Singh, 1989). Often a standard deviation from the mean is selected and tested empirically to determine if changes were accurately monitored (Jensen, 1986). Fung and LeDrew (1988) examined the effect of using different accuracy indices in determining the optimal threshold levels for digital land-cover change detection. They found that the best accuracy index among five (0.8, 0.9, 1.0, 1.1, and 1.2) was 0.9 for a differenced image of MSS band-4 between 1981 and 1984 images, and 1.0 and 1.1 for the ratioed or higher-order principal component images.

Varied accuracy indices were examined in this study for the image differencing change detection techinque to decide where to place the threshold boundaries between change and no-change pixels. The histograms of differenced change data sets were examined and the mean and standard deviation values for each data set were calculated. Threshold values of $\pm$ T standard deviations from the mean were iteratively selected to separate the change from no-change pixels. The T value was chosen as 1.0 in the first iteration. In the subsequent iterations, it was increased or decreased with an interval of 0.1 at each stage until a T value with highest accuracy for the thresholded data set was found. The thresholded images are binary images in which values of 0 and 1 represent no-change and change, respectively.

Accuracy Assessment

The thresholded images produced by image differencing at each iteration were verified with the reference sample data. Error matrices were produced and analyzed. Table 1 illustrates a typical error matrix generated from thresholding the D4 (differenced image of TM band-4) at a T value of 1.0.

From the error matrix, the following accuracy indices are generated :

(1) The producer's accuracy is the number of correctly classified samples of a particular category divided by the total number of reference samples for that category. It is a measure of the error of omission (Story and Congalton, 1986). The producer's accuracy for the change category is thus 13/27 or 48.1% (Table 1).

(2) The user's accuracy is the number of correctly classified samples of a particular category divided by the total number of samples being classified as that category. It measures the error of commission. The user's accuracy for the change category is 13/29 or 44.8% (Table 1), which is a little lower than its producer's accuracy.

(3) The overall accuracy is the total number of correctly classified samples (diagonal elements in the

Table 1. Error Matrix of Differenced TM Band-4 Image (D4) Thresholded at 1.0 Standard Deviation from Mean Threshold Level

		Reference Data		
		No-change	Change	Total
Classified Data	No-change	161	14	175
	Change	16	13	29
	Total	177	27	204
Producer's accuracy		91.0	48.1	
User's accuracy		92.0	44.8	
Average accuracy (producer's)				69.6
Average accuracy (user's)				68.4
Overall accuracy				85.29
Kappa (x 100)				37.92

matrix) divided by the total number of samples. It is 174/204 or 85.29% (Table 1).

(4) The average accuracy is an average of the accuracies in the individual categories. Becaese 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 68.4% and 69.6%, respectively.

(5) The Kappa coefficient of agreement ($\hat{K}$) is a measure of the actual agreement (indicated by the diagonal elements in the matrix) minus chance agreement (indicated by the product of row and column marginals). It uses all elements in the matrix and takes into account both the commission and omission errors (Rosenfield and Fitzpatrick-Lins, 1986).

the Kappa coefficient of agreement is computed as :

$$\hat{K} = \frac{N \sum_{i=1}^{n} x_{ii} - \sum_{i=1}^{n} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{n} (x_{i+} * x_{+i})}$$

where, n is the number of rows in the error matrix, x_{ii} is the number of observations in row i and column i (i.e., the diagonal elements), + represents summation over the index, x_{i+} and x_{+i} are thus the marginal totals of row i and column i, respectively, and N is the total number of observations (Congalton, 1991). The Kappa value is 0.3792 for the D4 image at the 1.0 threshold level (Table 1).

(6) The test statistic for a significant difference between two independent Kappas for different accuracy assessments (e.g., comparing the results of different techniques) is :

$$Z = \frac{\hat{K}_1 - \hat{K}_2}{\sqrt{V(\hat{K}_1) + V(\hat{K}_2)}}$$

where $V(\hat{K}_1)$ is the approximate large sample variance of $\hat{K}_1$, and Z is the standard normal deviate (Cohen, 1960).

These accuracy indices are computed at each iteration. Table 6 presents the changing pattern of these indices as the threshold level changes at each 0.1 increment in thresholding the images.

RESULTS AND DISCUSSION

Post-Classification Comparison

A supervised classification approach was applied to both the 1985 and 1988 images, independently. Table 2 shows the classification scheme, the areal extent of each wetland cover-type category, and each change trend between the two dates in the study area.

Two independently classified images presented rather conspicuous differences in each category between the two dates. Table 2 shows that there were losses in forest types and agricultural land, and increases in grassland, shrubland, and water cover, possibly, due to floodings. Much concern is given to the conversion of agricultural land to the grassland

Table 2. TM Data Classification Scheme, Areal Extent of Each Wetland Cover-Type, and Change Trend between 1985 and 1988

Class	Number of Hectares		
	1985	1988	Trend
Water	468.09	596.97	+128.88
R3USI (Cobble/Gravel)	457.02	227.61	−229.41
PEM1 (Emergent Grasses)	216.72	662.76	+446.04
Bare Soil	6.84	4.41	−2.43
MG (Riparian Grassland)	788.85	1170.27	+381.42
MGf (Agricultural)	1060.47	720.90	−339.57
Scrub/Shrub	188.19	390.33	+202.14
MFC (Cottonwoods)	1655.10	1124.37	−530.73
Other Hardwoods	70.20	9.99	−60.21
Conifers	17.73	21.60	+3.87
Total	4929.21	4929.21	0.00

and the shrubland.

The overall classification accuracies are 73.0% and 73.5% for 1985 and 1988 images, respectively (Table 3). For further accuracy comparison of the two dates, producer's accuracy, user's accuracy, average accuracy, and Kappa coefficient of agreement are shown in Table 3.

Both overall accuracies and Kappa values are quite close between the two classified images and they show no significant difference in classification accuracy at the 95% probability level with a Z-statistic of 0.2492. Major confusions in classification occurred among scrub/shrub, grassland, and agricultural land, while the Scrub/Shrub category indicated the lowest average accuracy in both images. The Cobble/Gravel(R3US1) category was classified with the highest average accuracy in 1985, while the Other Hardwoods categoty was the highest in 1988.

To estimate the correct joint classification rate between the two dates for the change detection analysis, the classified image of 1985 was subtracted from that of 1988 and the differenced image was

Table 3. Error Matrix of Classified 1985 and 1988 TM Images and Their Accuracy Indices for 204 Random Sample Points

1985 : Classified Data	Reference Data 1	2	3	4	5	6	7	8	9	10	Total
1. Water	11	1	3		1		1	1			18
2. R3US1		18	1	1	1		1				22
3. PEM1			6								6
4. Bare Soil				1	1						2
5. MG	1				29	2	3				35
6. MGf					9	33	2	1	1	1	47
7. Scrub/Shrub			2				4				6
8. Cottonwoods			7		6		6	43	2		64
9. Other Hardwoods									3		3
10. Conifers										1	1
Total	12	19	19	2	47	35	17	45	6	2	204
Producer's accuracy	92	95	32	50	62	94	24	96	50	50	
User's accuracy	61	82	100	50	83	70	67	67	100	100	
Average accuracy	77	89	66	50	73	82	46	82	75	75	
Overall accuracy											73.04
Kappa(x 100)											67.55

1988 : Classified Data	Reference Data 1	2	3	4	5	6	7	8	9	10	Total
1. Water	10	6	2		1		3				22
2. R3US1		10		1							11
3. PEM1		6	16		1		1	2			26
4. Bare Soil				1							1
5. MG					37	3	2	1	1		44
6. MGf					2	24	4				30
7. Scrub/Shrub					3	3	10	3			19
8. Cottonwoods		1	2		2	1	2	36		1	45
9. Other Hardwoods									5		5
10. Conifers										1	1
Total	10	23	20	2	46	31	22	42	6	2	204
Producer's accuracy	100	43	80	50	80	77	45	86	83	50	
User's accuracy	45	91	62	100	84	80	53	80	100	100	
Average accuracy	73	67	71	75	82	79	49	83	92	75	
Overall accuracy											73.53
Kappa(x 100)											68.82

Refer to classification scheme in Table 2 for class symbols.

Table 4. Error Matrix of Differenced Image between 1985 and 1988 Classification Maps

		Reference Data		
		No-change	Change	Total
Classified Data	No-change	105	12	117
	Change	72	15	87
	Total	177	27	204
Producer's accuracy		59.3	55.6	
User's accuracy		89.7	17.2	
Average accuracy (producer's)				57.5
Average accuracy (user's)				53.5
Overall accuracy				58.82
Kappa (x 100)				7.66

recoded with a binary digit of 0(no-change) and 1(change) (Table 4).

The differenced binary image presented poor correct joint classification accuracies except for the no-change category in user's accuracy, and was compared with other thresholded images produced by the image differencing change detection technique (Table 9).

Image Differencing

The 1985 image was subtracted from the 1988 image and their six differenced images, one for each band, were thresholded using 1.0 standard deviation from the mean for the first iteration to delineate change and no-change pixels (Table 5).

The three differenced visible bands (D1, D2, and D3) provided lower accuracies compared with the other three infrared bands. The D4 image indicated the highest accuracy among six images at the 1.0 threshold level. Among various accuracy indices, Kappa coefficient of agreement was used as the standard measure for accuracy because all elements in the error matrix are considered (Fung and LeDrew, 1988).

Of the six differenced bands, the three infrared bands showing higher accuracies were further evaluated at the various threshold boundary levels with an increment of 0.1. For the differenced band-4 image (Table 6), a 1.0 standard deviation from the mean revealed highest Kappa coefficient of agreement again.

As the T value increases (i.e., the threshold values are selected further away from the mean), the user's accuracy of the no-change category decreases. In other words, the error of commission increases. In contrast, the producer's accuracy increases as the error of omission approaches zero when nearly the entire histogram is classified as no-change. Owing to the fact that the thresholded data compose the binary images, a reversed pattern is formed for the change category. The user's accuracy increases while the producer's accuracy decreases when the T value increases.

This inverse relationship between the user's accuracy and the producer's accuracy of individual categories indicates the importance of considering both accuracy indices (Story and Congalton, 1986). For instance, at a T value of 0.8, the producer's accu-

Table 5. The Accuracy Indices of the Six Differenced Images Using 1.0 Standard Deviation from the Mean As a Threshold Boundary Level

Differ. Image	$\hat{K}$	Overall	Producer's		User's		Average	
			No-change	Change	No-change	Change	Producer's	User's
D1	26.1	83.8	91.5	33.3	90.0	37.5	62.4	63.8
D2	27.1	84.3	92.1	33.3	90.1	39.1	62.7	64.6
D3	27.4	83.3	90.4	37.0	90.4	37.0	63.7	63.7
D4	37.9	85.3	91.0	48.1	92.0	44.8	69.6	68.4
D5	30.7	83.8	90.4	40.7	90.9	39.3	65.6	65.1
D7	31.7	84.3	91.0	40.7	91.0	40.7	65.9	65.9

Underlined items represent the higher three accuracies.

Table 6. The Accuracy Indices of the Differenced Band-4 Image Using Five Different Threshold Boundary Levels

Level (T)	$\hat{K}$	Overall	Producer's No-change	Producer's Change	User's No-change	User's Change	Average Producer's	Average User's
0.8	35.0	80.4	83.1	<u>63.0</u>	<u>93.6</u>	36.2	<u>73.1</u>	64.9
0.9	35.5	83.3	88.1	51.9	92.3	40.0	70.0	66.2
<u>1.0</u>	<u>37.9</u>	85.3	91.0	48.1	92.0	44.8	69.6	68.4
1.1	36.2	<u>86.3</u>	93.2	40.7	91.2	<u>47.8</u>	67.0	<u>69.5</u>
1.2	27.9	85.8	<u>94.4</u>	29.6	89.8	44.4	62.0	67.1

Underlined items represent the highest accuracy.

racy for the change category is 63.0% but the user's accuracy for this one is only 36.2%.

A similar inverse relationship also exists between the same accuracy indices of the two categories. While the producer's accuracy at a T value of 1.2 is 94.4% for the no-change category, the same index for the change category is less than 30%. These two inverse relationship should be borne in mind when the accuracy indices of the other differenced images are discussed.

The differenced images of TM bands 5 and 7 were also further thresholded with various T values of 0.1 increment, and a 1.2 standard deviation from the mean showed highest Kappa coefficient of agreement in both images(Tables 7 and 8).

The five accuracy indices, namely Kappa, overall accuracy, producer's accuracy, user's accuracy, and average accuracy(both producer's and user's) exhibit a common property. As the T value increases, most of the accuracy indices also increase towards a maximum at a certain threshold level, after which they then decrease. In both images, D5 and D7, the average user's accuracy tended to generate the highest accuracy at a larger threshold level.

Because only the Kappa can take into account all of the elements in the error matrices, the optimum threshold levels are thus selected based on the highest Kappas of the thresholded images. The differences among the three thresholded infrared-band images are now compared with the post-classification comparison change detection approach.

Table 7. The Accuracy Indices of the Differenced Band-5 Image Using Five Different Threshold Boundary Levels

Level (T)	$\hat{K}$	Overall	Producer's No-change	Producer's Change	User's No-change	User's Change	Average Producer's	Average User's
0.9	28.7	82.8	89.3	<u>40.7</u>	90.8	36.7	65.0	63.8
1.0	30.7	83.8	90.4	<u>40.7</u>	90.9	39.3	65.6	65.1
1.1	32.8	84.8	91.5	<u>40.7</u>	91.0	42.3	66.1	66.7
<u>1.2</u>	<u>38.7</u>	<u>87.3</u>	94.4	<u>40.7</u>	<u>91.3</u>	52.4	<u>67.6</u>	<u>71.9</u>
1.3	31.6	<u>87.3</u>	<u>96.0</u>	29.6	89.9	<u>53.3</u>	62.8	71.6

Underlined items represent the highest accuracy.

Table 8. The Accuracy Indices of the Differenced Band-7 Image Using Five Different Threshold Boundary Levels

Level (T)	$\hat{K}$	Overall	Producer's No-change	Producer's Change	User's No-change	User's Change	Average Producer's	Average User's
1.0	31.7	84.3	91.0	<u>40.7</u>	<u>91.0</u>	40.7	65.9	65.9
1.1	32.8	85.8	93.2	37.0	90.7	45.5	65.1	68.1
<u>1.2</u>	<u>39.2</u>	<u>88.2</u>	96.0	37.0	90.9	58.8	<u>66.5</u>	74.9
1.3	35.5	87.7	96.0	33.3	90.4	56.2	64.7	73.3
1.4	34.4	<u>88.2</u>	<u>97.2</u>	29.6	90.1	<u>61.5</u>	63.4	<u>75.8</u>

Underlined items represent the highest accuracy.

Table 9. The Comparison of Accuracy Indices Among the Best Four Differenced Images

Image	$\hat{K}$	Overall	Producer's		User's		Average	
			No-change	Change	No-change	Change	Producer's	User's
D4(1.0)	37.9	85.3	91.0	48.1	92.0	44.8	69.6	68.4
D5(1.2)	38.7	87.3	94.4	40.7	91.3	52.4	67.6	71.9
D7(1.2)	39.2	88.2	96.0	37.0	90.9	58.8	66.5	74.9
PC-COMP	7.7	58.8	59.3	55.6	89.7	17.2	57.5	53.5

Parenthesis represents the threshold boundary level.
PC-COMP represents the post-classification comparison technique.
Underlined items represent the highest accuracy.

Table 10. The Results of Test of Agreement between Error Matrices Produced from One Differenced and Three Thresholded Images, Based on the Highest Kappa Values at the 95% Probability Level

	Z-Statistic		
	D7(1.2)	PC-COMP	D5(1.2)
D4(1.0)	-0.0981 (NS)	-2.8513 (S)	-0.0617 (NS)
D7(1.2)		-2.7975 (S)	-0.0362 (NS)
PC-COMP			-2.8062 (S)

NS – not significant.
S – significant.
$Z_{0.025}=1.96$.

Comparison Among the Images

Table 9 illustrates the comparison among the four change images with different accuracy indices.

An important thing to notice is the threshold level where the images reached highest accuracy, especially in the differenced band-7 image, where a T of 1.2 indicated the highest kappa value among all thresholded images, while the band-4 differenced image showed highest accuracy at the 1.0 threshold boundary level(Tavle 5).

To examine the differences among error matrices produced from the thresholded images and a differenced image of the two classification maps, pairwise significance testing of Kappas' test statistics were performed(Table 10).

As shown in Table 10, PC-COMP is significantly different from the other three images at the 95% probability level. It has the lowest Kappa value of 0.0766(Table 9). The three thresholded infrared-band images have no significant difference in terms of the accuracy of classification with 0(no-change) and 1(change). Their Kappa values range from 0.3792(D4) to 0.3924(D7)(Table 9).

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 difference in terms of the accuracy of the two error matrices of D4(1.0) and D7(1.2), the wetland cover-type changes they reveal may be different.

CONCLUSION

For this study, two general classes of change detection techniques, including post-classification comparison and image differencing, were evaluated to detect wetland cover-type change in the Jackson Hole, Wyoming area between 1985 and 1988 using Landsat-5 TM imagery. It was revealed that the three differenced infrared-band images were more appropriate for wetland change detection than the three visible-band images in the study area. Also we examined the use of different accuracy indices to determine optimal threshold levels for change detection images. Differenced band-7 image represented highest accuracy with a 1.2 standard deviation from the mean as a threshold boundary level.

While significance testing may provide valuable information concerning the differences in accuracies between the error matrices produced from different images, it is also important to scrutinize the ability of each image to detect specific wetland-cover changes.

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