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Change of Coastal Ocean According to Kwang Yang Bay Development based on Landsat TM Images

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This study presents an investigation of the changes that have occurred in the coastal ocean area of Kwangyang Bay located in the South Coastal region of Korea using remote sensing data based on Landsat Thematic Mapper (TM) multispectral digital data from 1988 and 1996. The coastal changes were detected using the digital histogram method and vector trace method. All the images were preprocessed, i.e. geometrically corrected, before the training set selection. When comparing the histograms of 7-band TM data, it was found that the band 5 image exhibited two critical Digital Number(DN) peaks, thereby indicating new coastal water and coastal land data. Based on this information, the coastal ocean area of the band 5 image was calculated using the vector tracing method supported by a CAD program. The result shows that the coastal ocean area decreased by about 5 % between 1988 to 1994. Accordingly, this gives a strong indication that the continuing land development will have a serious impact on the ecosystem of Kwangyang Bay.

Key words : Kwangyang Bay, Landsat Thematic Mapper, histogram method, geometric correction, Digital Number, CAD program, coastal ecological area

1. Introduction

The need for better monitoring and modelling of the marine environment has increased dramatically in recent years, in particular, along coastal boundaries and shelf regions where human activities are extensive and pollution has a more significant impact. Kwangyang Bay, located on the south coast of Korea has been undergoing continuous development due to the construction of Kwangyang Harbor and coastal development projects (Fig. 1). As a result of this development, the coastal ocean has become polluted and its area reduced. However, it is very hard to identify and estimate the ongoing impact of the bay development process and the coastal area loss using just a map or observation. Remote sensing techniques are now widely used for coastal area change estimations. Modern satellite remote sensing began in 1972 when the United States launched its first Earth Resources Technology Satellite(ERTS, later renamed Landsat). Since then, numerous satellite images of the Earth's surface have been acquired by agencies and industries worldwide. Among these images, NOAA AVHRR satellite images are commonly used for monitoring and forecasting coastal environments. However, since these satellite images have a low resolution (1 km × 1 km), it is very hard to monitor coastal changes of a small area, such as a small bay or channel like Kwangyang Bay in Korea. When comparing satellite images, the Landsat TM images play a vital role in monitoring environmental and global changes. For example, the Environmental Protection Agency's North American Landscape Characterization studied the North American continent(Lunetta et al., 1993). The Landsat TM provides information about surface geology, soil types, and cultural features. Satellite imagery of Landsat TM has been used for a variety of environmental studies, for example, determining vegetation(Tucker, 1979, Lillesand, 1994). Yuan(1998) reported on Landsat MSS data that can be applied to geological mapping, which is also very similar to Landsat TM data. The specific difference between these two types of image is the resolution. Johnny et. al(1993) monitored and modelled marine coastal environments using remote sensing data based on NOAA and SAR. and showed that remote sensing data could be applied to water quality and coastal environmental change problems. Ryan et. al(1991) demonstrated that shoreline features can be extracted from remote sensing data with the use of neural nets and image processing. Qari(1991) also successfully applied Landsat TM data to geological studies in the Al-Khabt Area, in the Southern Arabian Shield. Therefore, it has been established that remote sensing techniques provide a feasible means of monitoring many land and ocean conditions.

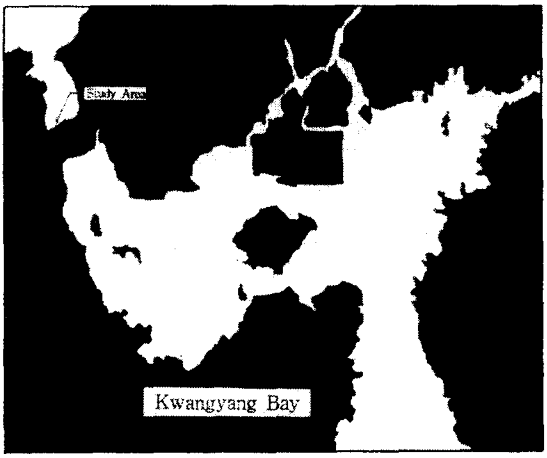


Fig. 1. Study area of Kwangyang Bay(black represents land and white is ocean.

Accordingly, this paper is primarily concerned with the application of a remote sensing technique based on Landsat TM images including 7 bands in the identification of coastal ocean area loss caused by the Kwangyang Development project from 1988 to 1994.

2. Data and Method

The data were Landsat TM image data from April 1988 and June 1994 and a map of the coastal ocean(N152-6-04, N152-6-03) with a scale of 1/50,000. The remote sensing data, based on 7-band images with 7 different wave lengths, were used as described in Table 1.

Rectification and restoration techniques were applied to the image data to correct any distorted or degraded data in order to create a more faithful representation of the original scene. This typically involved the initial processing of the raw image data to correct any geometric distortions.

Table 1. Thematic Mapper Spectral Bands Based on Landsat Satellite

Band	Wavelength (μm)	Resolution (m)	Nominal Spectral Location	Principal Application
1	0.45 – 0.52	30	Blue	Designed for water body penetration, making it useful for coastal water mapping. Also useful for soil/vegetation discrimination, forest-type mapping, and cultural feature identification
2	0.52 – 0.60	30	Green	Designed to measure green reflectance peak of vegetation for vegetation discrimination and vigor assessment. Also useful for cultural feature identification
3	0.63 – 0.69	30	Red	Designed to sense in a chlorophyll absorption region aiding in plant species differentiation. Also useful for culture feature identification.
4	0.76 – 0.90	30	Near infarred	Useful for determining vegetation types, vigor, and biomass content for delineating waterbodies and for soil moisture discrimination.
5	1.55 – 1.75	30	Mid-infarred	Indicator of vegetation moisture content and soil moisture. Also useful for differentiation of snow from clouds.
6	10.4 – 12.5	120	Thermal infarred	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping applications.
7	2.08 – 2.35	30	Mid-infarred	Useful for discrimination of mineral and rock types. Also sensitive to vegetation moisture content.

The governing equation of the transformation is an affined transformation as follows ;

$$x' = a + bx + cy \quad (1)$$

$$y' = d + ex + fy \quad (2)$$

where a, b, c, d, e, f are the integers, x and y are the coordinates.

Gray-level thresholding was used to segment the 7-band images into two classes, water and land. To identify a good image for the separation of land and ocean, the brightness variations of each band were checked based on a histogram of the DN and number of pixels. This is an enhancement technique called level slicing, where the DNs distributed along the x axis of an image histogram are divided into a series of analyst-specified intervals or slices. All the DNs falling within a given interval in the input image are then displayed at a single DN in the output image. Consequently, if different slices are established, the output image also contains different gray levels.

The result looks something like a simple map or simple color figure, except that the areas between the boundaries are occupied by pixels displayed at the same DN. This technique is used extensively in the display of thermal infrared images in order to show discrete temperature ranges coded by the gray level or color.

3. Results and Discussion

In order to take advantage of and make good use of remote sensing data, it is important to be able to extract meaningful information from the imagery. Since targets can be a point, line, or area feature, they can have any form, from a bus in a parking lot or plane on a runway, to a bridge or roadway, to a large expanse of water or a field. As such, the target must be distinguishable; it must contrast with other features surrounding it in the image. Recognizing targets is the key to interpretation and information extraction. Observing the differences between targets and their backgrounds involves comparing different targets based on any, or all, of the visual elements of tone, shape, size, pattern, texture, shadow, and association.

Most of the interpretation and identification of targets in remote sensing imagery is performed manually or visually, i.e. by a human interpreter. In many cases this is done using images that are displayed in a pictorial or photograph-type format, independent of the type of sensor used to collect the data and how the data were collected. The most common application is land-cover / land-use change analysis using two-date images taken of the same target land features. The features in the raw image on each date are classified into land-cover / land-use categories through supervised or unsupervised classification. The classification then assigns the same unique and distinct identifier to each class on both dates.

In the above case, the data is in analog format. As discussed in data & method, the remote sensing images of Landsat TM can also be represented in a computer as arrays of pixels, with each pixel corresponding to a digital number(DN), representing the brightness level of that pixel in the image.

To interpret and identify certain targets in Kwangyang Bay and the coastal ocean between April 1988 and June 1994, the DN numbers of the targets were checked using a histogram of the remote sensing data. The histogram displayed the distributions of the DNs of the target regions. The use of human analysis as the interpretation method is very useful in distinguishing land and ocean, where visual interpretation is used to classify homogeneous groups of pixels that represent various features or land cover classes of interest. In contrast, digital image classification uses the spectral information represented by the digital numbers in one or more spectral bands, and then attempts to classify each individual pixel based on this information. This type of classification is a kind of spectral pattern recognition. In this case, the objective is to assign all the pixels in an image to a particular class or theme (e.g. water, coniferous forest, deciduous forest, corn, wheat, etc.). The resulting classified image is comprised of a mosaic of pixels, each of which belongs to a specific theme, and is essentially a thematic "map" of the original image.

Fig. 2 shows the histogram of bands 1, 2, and 3 in 1988, and Fig. 3 shows bands 5, 6, and 7 in 1988. In these figures, the horizontal line is the color number and the vertical line is the frequency of each color number, i.e. the DN, where a high peak means many DNs of that color.

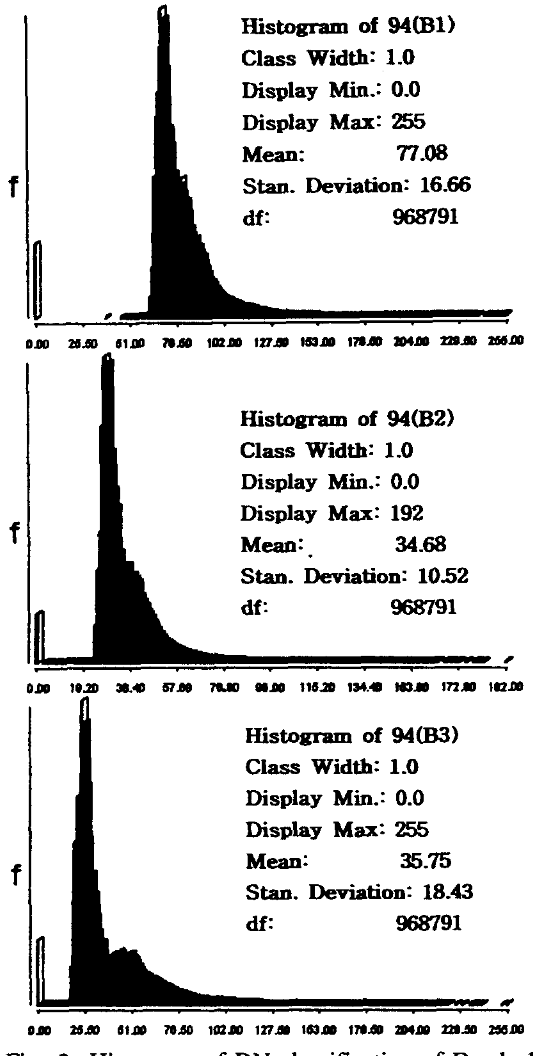


Fig. 2. Histogram of DN classification of Bands 1, 2, and 3 in 1988.

In these figures, the histogram modes had either one or two peaks, which indicates that the colors representing Kwangyang Bay and the ocean have one or two different characteristics. According to Lee & Kang (1999), the color characteristics of land and ocean are different since the ocean color generally has a low color number (Digital Number (DN)), that is, less than 60 based on only a small portion of the available range of digital values (commonly 256 levels). In Figs. 2 & 3, bands 4, 5, and 6 exhibited two-mode histograms, that is, two peaks. In particular, bands 4 and 5 had two dominant peaks. Accordingly, these figures made it easy to classify the water and land regions in the bay. This type of classification is termed spectral pattern recognition where the objective is to assign all pixels in the image to particular classes or themes (e.g. water, forest, land etc.). Finally, the resulting classified image is comprised of a mosaic of pixels, each of which belong to a particular theme, and is essentially a thematic map of the original image.

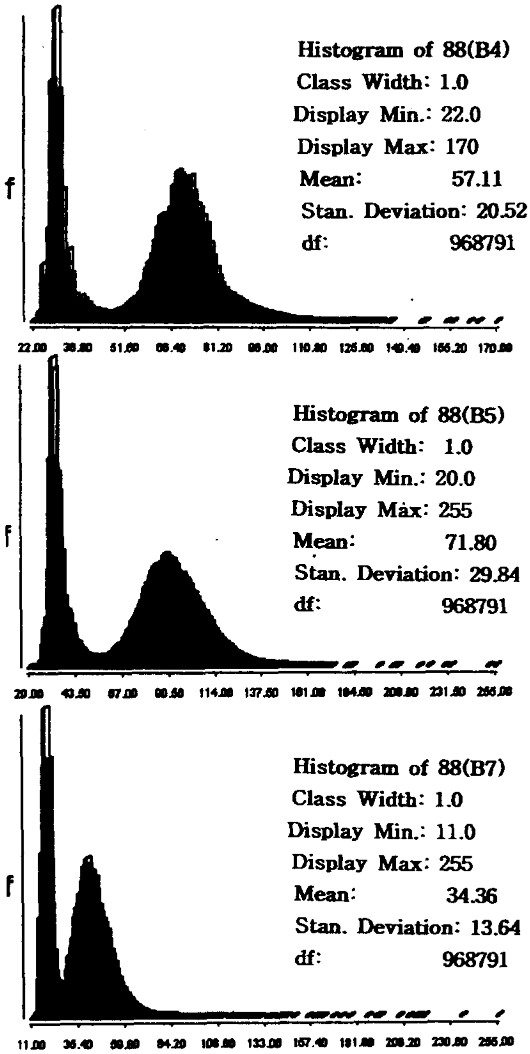


Fig. 3. Histogram of DN classification of Bands 4, 5, and 6 in 1988.

Fig. 4 shows the histogram of bands 1, 2, and

3 in 1994, and Fig. 5 shows bands 4, 5, and 7 in the same year. In these figures, bands 4, 5, and 7 exhibited two of the same critical peaks as in Fig. 3. As in the histograms of 1988, bands 4 and 5 included the dominant peaks of the histogram. When comparing Figs. 2 and 3, band 5 was better than band 4 in classifying the land and ocean since the tilt of the band 4 histogram had low color numbers. Fig. 6 shows the histogram of band 6 in 1984 and 1994, respectively. Band 6 exhibited different pixel sizes compared to the other bands, Therefore, it was not effective for measuring a small area.

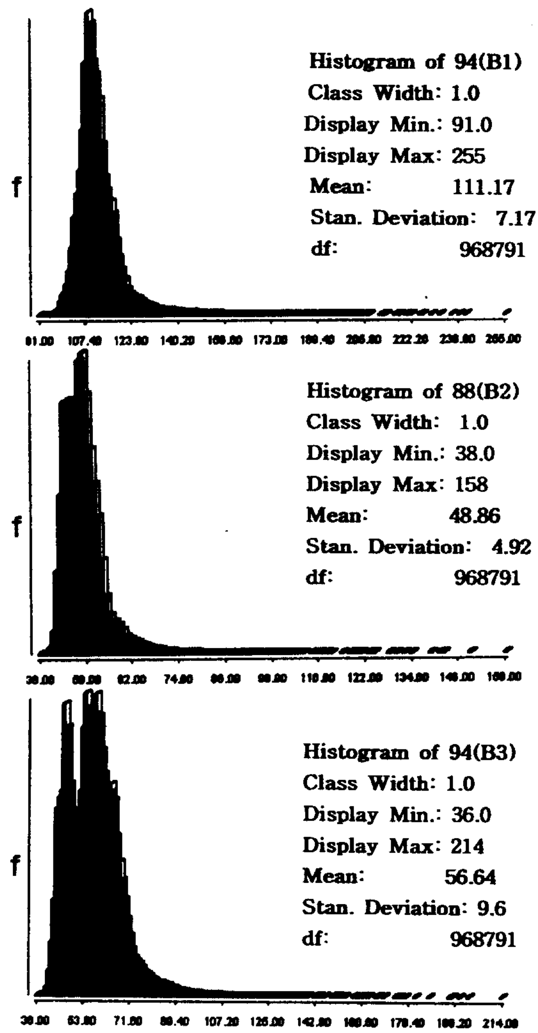


Fig. 4. Histogram of DN classification of Bands 1, 2, and 3 in 1994.

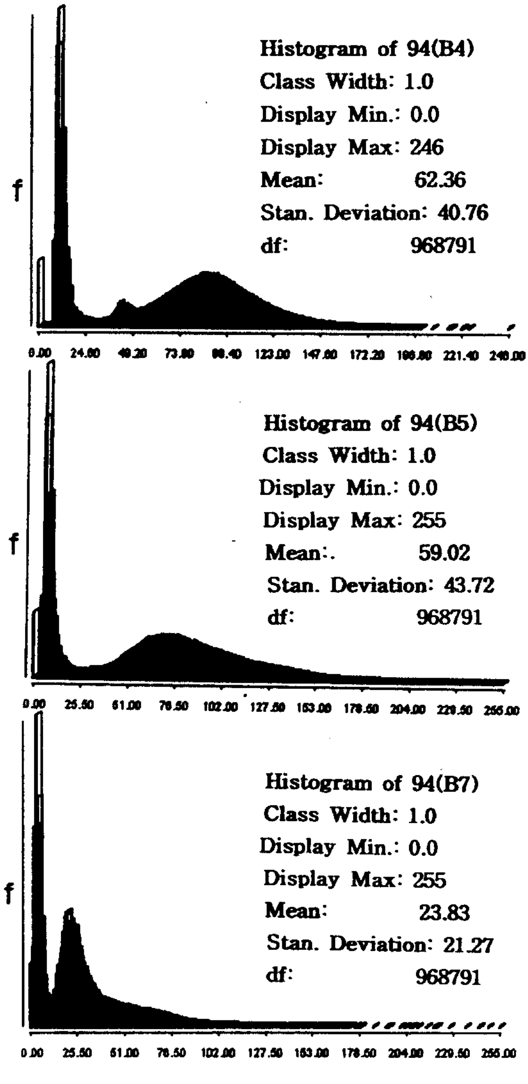


Fig. 5. Histogram of DN classification of Bands 4, 5, and 6 in 1994.

Finally, the band 5 remote sensing data of Landsat TM was selected for measuring the coastal area of the bay. This result also agrees with the previous studies of Lee & Kang (1999). Figures 7 and 8 show the colors of the land and coastal ocean of Kwangyang Bay. In these figures, red represents the land regions and blue the ocean or water, as displayed by IDRISI GIS software. To check the DN of the band 5 images of 1988 and 1994, the images were traced using the cursor inquiry mode of IDRSI. The results of the DN distribution in 1988 and 1994 are shown in Table 2.

Table 2. DN distributions of land and ocean in 1988 and 1994, respectively

Area / Year	Land	Ocean
1988	46 ~ 160	35 ~ 45
1994	20 ~ 150	0 ~ 10

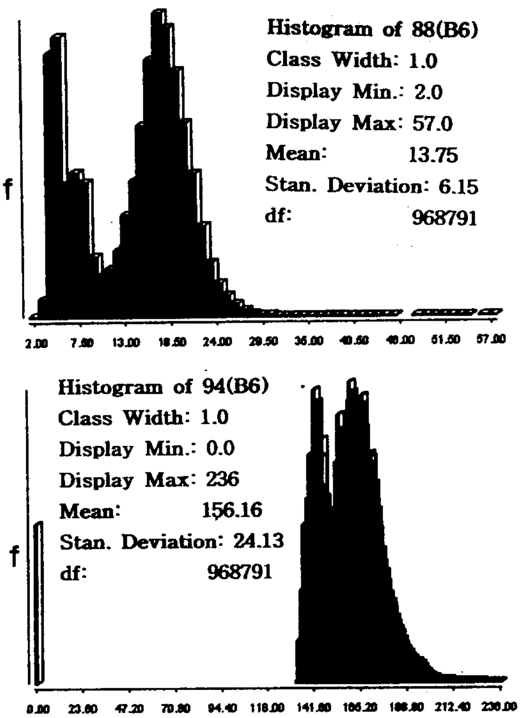


Fig. 6. Histogram of DN classification of Band 6 in 1988 and 1994.

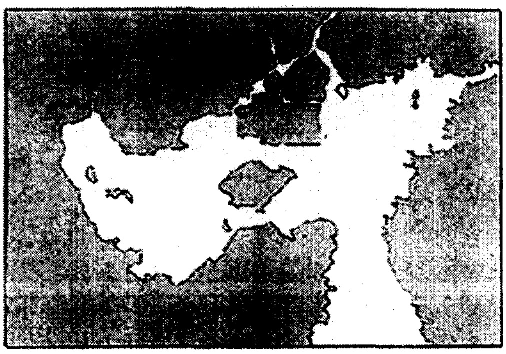
However, this table is slightly confusing since the ocean and land can only be distinguished using the numbers in the table, thereby indicating limitation of using remote sensing data based on a general unsupervised method. Accordingly, vector data was instead drawn from the master data of the remote sensing data using the Microstation CAD program. To create vector data, the coastal line was traced using the trace technique supported by the program. This is a type of supervised classification method. In supervised classification, the analyst identifies homogeneous representative samples of the different surface cover types (information classes) of interest in the image. These samples are then referred to as training areas. The selection of appropriate training areas is thus based on the analyst's familiarity with the geographical area and their knowledge of the actual surface cover types in the image. As a result, the analyst supervises the categorization of a set of specific classes. In the remote sensing data used in the current study, the images had two classes, the ocean and land. As such, it was very easy to trace and identify the water and land in the image, and thus impact of the expanded construction of Kwangyang Bay in 1994.

Fig. 7. Landsat TM image of Band 5 in 1988.

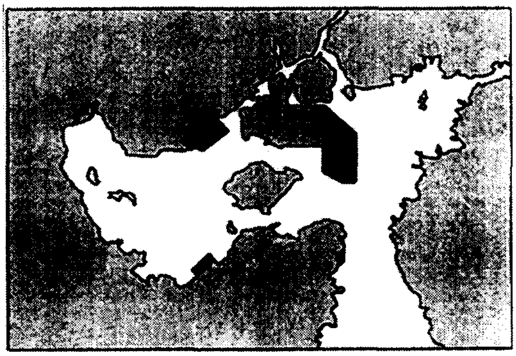
Fig. 8. Landsat TM image of Band 5 in 1994.

Fig. 9 shows the vector data based on the Landsat TM remote sensing image. Fig. 9(a) is the vector data of 1988 and Fig. 9(b) is that of 1994. Table 3 and the thick line in Fig. 9(b) presents the area changes due to the construction of Kwangyang Bay since 1988.

In Table 3, the total area of coastal ocean was 255.4km^2 in 1988 and 241.96km^2 in 1994, respectively. This means that during these 6 years, the coastal ocean area decreased by about 13.44km^2, which is almost 5.26% of the total ocean area. Since this is a substantial change, it is thus very likely that ecological changes and eventually marine ecological changes will also occur.



(1998)



(1994)

Fig. 9. Area presentation of Kwangyang Bay between 1988 and 1994 using Vector Trace Method. The dark black represents the area that changed between 1988 and 1994.

Table 3. Coastal ocean area change from 1988 to 1994

Area / Year	Total Coastal Ocean Area of Kwangyang Bay Based on Landsat TM data	Changed Area between 1988 and 1994
1988	255.4 km^2	13.44km^2 (5.26%)
1994	241.96 km^2	

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References

[1] Johannessen, J. A., Roed, L.P., Johannessen, O.M. Evensen, G., Hackett, B., Pettersson, L.H., Haugan, P.M. Sandven, S and R. Shuchman(1993), Monitoring and Modelling of the Marine Coastal Environment, American Society for Photogrammetry and Remote Sensing, 59(3), 351~361.

[2] Lathrop, Jr., Ricahard G.(1992), Landsat Thematic Mapper Monitoring of Turbid Inland Water Quality, American Society for Photogrammetry and Remote Sensing, 58(4), 465~470.

[3] Lee, B.-G. and I.-J, Kang(1999) : Image Classification Characteristics of Cheju and Its Coastal Ocean Using Remote Sensing Techniquies Based On Landsat TM Image, Bull. of The Mar. Res. Inst., Cheju Nat'l Univ.,V. 23, 151~159.

[4] Lillesand, T.M, and R.W. Kiefer(1994), Remote Sensing and Image Interpretation, John Wiley & Sons, Inc, p. 750.

[5] Lunetta,R.S., Lyon, J.G., Sturdevant, J.A., Dwyer, J.L., Elvidge, C.D., Fenstermaker, L.K., Yuan, D., Hoffer, S.R., Weerackoon, R., 1993. North American Landsacpe Characterization(NALC) Research Plan. EPA/600/R-93/135. U.S. Environmental Protection Agency.

[6] Price, K.P., Pyke, D.A. and L. Mendes(1992), Shrub Dieback in a Semiarid Ecosystem : The Integration of Remote Sensing and Geo graphic Information Systems for Detecting Vegetation Change, American Society for Photogrammetry and Remote Sensing, 58(4), 455~463.

[7] Qari, Mohammed Yousef H.T.(1991), Application of Landsat TM Data to Geological Studies, Al-Khabt Area, Southern Arabian Shield, American Society for Photogrammetry and Remote Sensing, 57(4), 421~429.

[8] Ryan, T.W., Sementilli, P.J., Yuen, P. and

B.R. Hunt(1991), Extraction of Shoreline Features by Neural Nets and Image Processing, American Society for Photogrammetry and Remote Sensing, 57(7), 947~955.

[9] Tucker, C.J.,1979. Red and Photographic infrared linear combinations for monitoring vegetation. Remote Sensing Environment, 8, 127~150.

[10] Yuan, D., Lucas, J.R., Holland, D.E., 1998. A Landsat MSS times series model and its application in geological mapping, 53. 39~53.