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Communication

Digital Change Detection by Post-classification Comparison of Multitemporal Remotely-Sensed Data

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Abstract : Natural and artificial land features are very dynamic, changing somewhat rapidly in our lifetime. It is important that such changes are inventoried accurately so that the physical and human processes at work can be more fully understood.

Change detection is a technique used to determine the change between two or more time periods of a particular object of study. Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution in the population of interest.

The purpose of this research is to detect environmental changes surrounding an area of Mountain Moscow, Idaho using Landsat Thematic Mapper (TM) images of (July 8, 1990 and July 20, 1991). For accurate classification, the Image enhancement process was performed for improving the image quality of each image. A SPOT image (Aug. 14, 1992) was used for image merging in this research. Supervised classification was performed using the maximum likelihood method. Accuracy assessments were done for each classification. Two images were compared on a pixel-by-pixel basis using the post-classification comparison method that is used for detecting the changes of the study area in this research. The 'from-to' change class information can be detected by post classification comparison using this method and we could find which class change to another.

Key Words : Change Detection, Post-classification, Multiteporal Remotely-sensed Data.

1. Introduction

In recent times, both biophysical and artificial features are changing rapidly. It is important that such changes can be inventoried accurately so that the physical and human processes at work can be more fully understood (Estes, 1992). For this purpose, the development of change detection methods using the remotely sensed data was used.

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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 (Singh, 1989). Many change detection methods have been developed and used for many applications. For example, there is post-classification comparison, image differencing, image ratioing, image regression, principal component analysis, and so on.

The important goal in change detection is to compare spatial representations of two points in time by controlling all variance caused by differences in variables of non-interest (i.e. variation in orbital and platform altitudes) and to measure change caused by differences in variables of interest. Currently, change detection relies primarily upon two types of techniques: map-to-map comparison and image-to-image comparison. Map-to-map comparison relies on the identification of differences between two maps of different dates. This type of comparison requires that the images (either digital or analog) from two different dates be classified by interest, and then compared with the maps to one another. In the past, the comparison was performed on a light table and was the only type of spatially referenced change detection possible. With the introduction of remote sensing and geographic information systems (GIS), map-to-map comparison can now be performed digitally, either by the area in each polygon type or on a pixel-by-pixel basis. The usefulness of map-to-map comparison is constrained by the assumptions and techniques used to produce maps of the same area at different times. Maps of the same area on different dates will vary for three reasons: one is due to different classification systems; another is due to different mapping techniques; and third is due to actual differences in land cover. Thus, change detection using maps or a GIS coverage alone is risky because changes between maps can be caused by factors other than differences in land cover or land use. A more powerful method of change detection incorporates the analyses of remotely sensed imagery and/or field examinations using GIS (Verbyla, 1990).

Post-classification comparison is used for change detection in this research. This is the most obvious method of change detection that needs comparison of the classification maps which are independently produced. An algorithm simply compares the two classification maps utilizing class pairs specified by the analyst and generates a map indicating areas of change. The 'from-to' change class information can be detected by comparing to another change detection methods which are not able to detect 'from-to' information (Jensen, 1996).

2. Material and Methodology

1) Study Area

The study area comprised Moscow city and Moscow mountain, including approximately 545.4 square kilometers (E-W width: 28.23km, N-S length: 19.32km). The study area is located within Latah County, Idaho, U.S.A. Its elevation ranges from 772m to 1495m and it is in the north temperate region.

The forest cover of the study area is predominantly conifer. The dominant tree species present are lodgepole pine (*Pinus contorta* Dougl.), ponderosa pine (*Pinus ponderosa* Dougl.), grand fir

(*Abies grandis* Lindl.), subalpine fir (*Abies lasiocarpa* Nutt.), western red-cedar (*Thuja plicata* Donn), Western hemlock (*Tsuga heterophylla* Sarg.), Douglas fir (*Pseudotsuga menziesii* Franco), Western larch (*Larix occidentalis* Nutt), and Engelmann spruce (*Picea engelmannii* Parry). Lower elevations support agricultural crops (wheat, barley, dry peas, and lentils) and pasturage.

The boundary universal transverse mercator (UTM) coordinates of the study area are upper left X: 496600E, Y: 5189600N and lower right X: 524800E, Y: 5170310, zone 11.

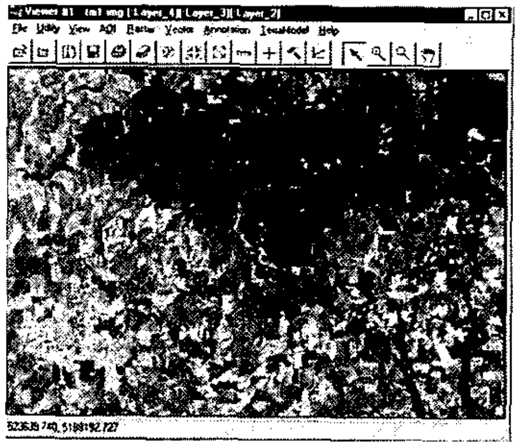
2) Materials

Landsat Thematic Mapper (TM) data were acquired on July 8, 1990 (Fig. 1a) and July 20, 1991 (Fig. 1b), and SPOT panchromatic (PAN) data were acquired on August 14, 1992 (Fig. 1c).

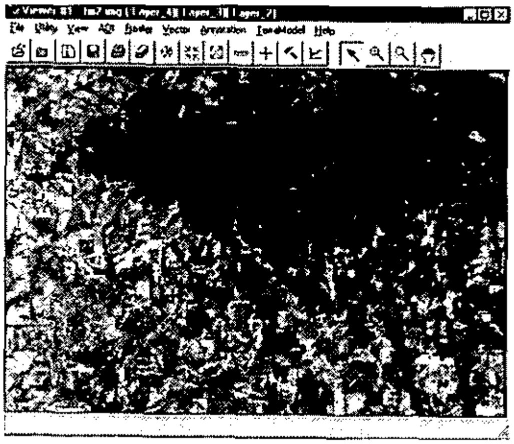
The multispectral data from July 1990 and 1991 were geocoded using geometric correction and its root mean squared error was 0.286 pixel. The geocoding process used a single set of control points to create a sensor-orbit-earth ellipsoid model to transform individual pixels to the UTM reference system. Also, the multispectral data were resampled from 30 meter to 10 meter spatial resolution using an intensity, hue and saturation (IHS) transformation based on the SPOT 10 meter panchromatic data (Fig. 2).

3) Classification

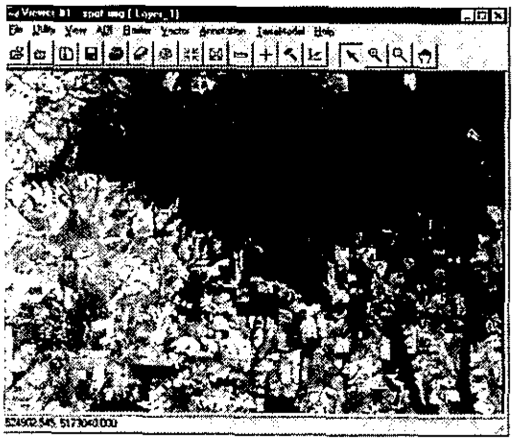
One of the criteria for evaluating the change detection technique was classification accuracy. First of all, supervised classification was used with the decision rule of maximum likelihood (Fig. 3). Even though we performed image enhancement, we could not classify in detail. We classified 6 classes (forest, water, barren land,



(a) Landsat TM image (Jul. 8, 90).

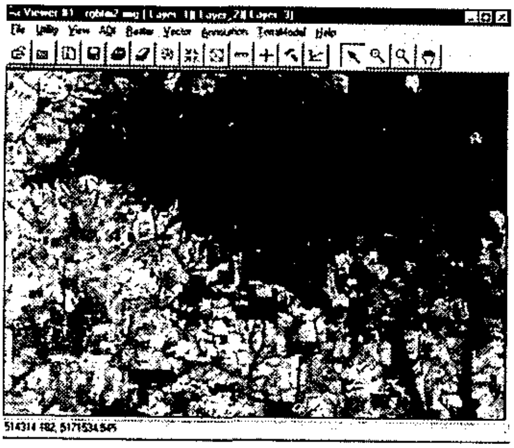


(b) Landsat TM image (Jul. 20, 91).

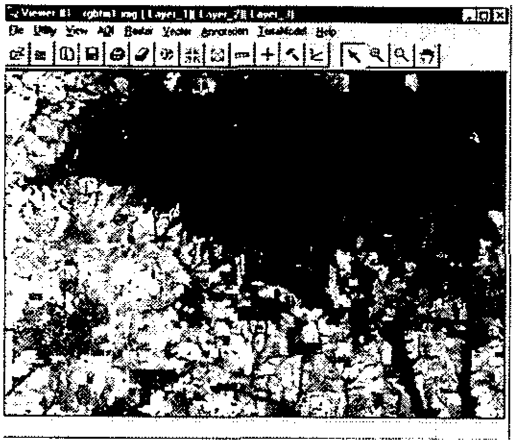


(c) SPOT panchromatic image (Aug. 14, 92).

Fig. 1. Remotely-sensed images of Moscow city and Moscow mountain.



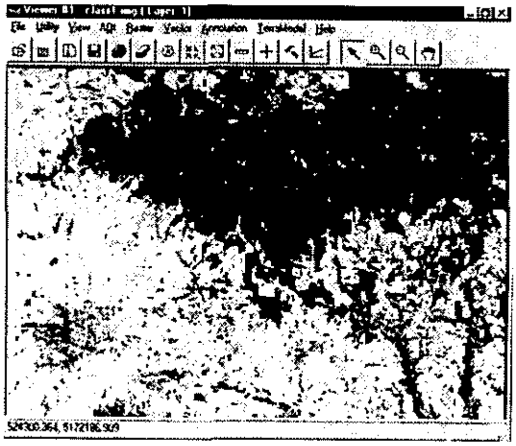
(a) TM image after image enhancing with Fig. 1a.



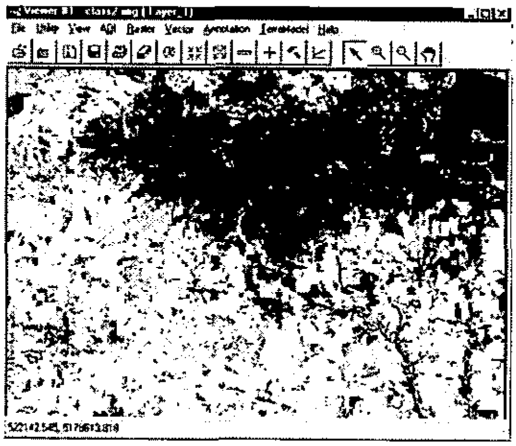
(b) TM image after image enhancing with Fig. 1b.

Fig. 2. Enhanced images

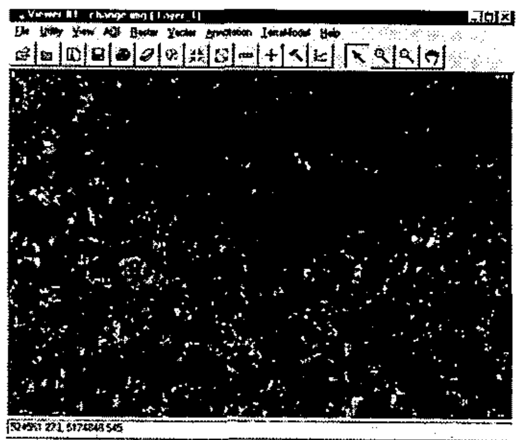
agricultural land, urban & barren land, and cloud & shadow) for 1990 TM image and 5 classes (forest, water, barren land, agricultural land, and urban & barren land) for 1991 TM image relatively. There was a little clouds in 1990 TM image data, so there was a cloud & shadow class. In 1991 TM image data, there was no cloud, there were just 5 classes. In classification maps, forest represented for dark green, water for blue, barren land for cyan, agricultural land for gold, urban & barren land for purple, and cloud & shadow for white. Accuracy assessment was performed



(a) Classified image with Fig. 2a.



(b) Classified image with Fig. 2b.



(c) Change detection image with (a) and (b).

Fig. 3. Classified and Change detection images

randomly on the entire image for each date error matrix for each classification is given in Table 1. Also, Kappa statistic (k-hat) was calculated for measuring the difference between the observed agreement (diagonal element) and the agreement that might be derived by total chance mapping of the maps (Campbell, 1996).

4) Post-classification Comparison

Based on the two classification maps, post-classification comparison was performed and we made a change detection map using this technique(Fig. 3). Using the map and matrix, I could analyze the changes of land cover in the study area.

3. Results and Discussion

Based on Table 1, classification accuracy was quite good for the next step after image enhancement. Overall accuracy was higher than

Table 1. Error matrix of TM data.

(a) Reference image(July 8, 1990)

Image to be Evaluated		F	W	B	A	U & B	C & S	Total	CA(%)	k-hat
	F	81	0	0	0	6	1	88	92.1	0.8824
	W	0	0	0	0	0	0	0	—	—
	B	0	0	6	0	2	0	8	75	0.7430
	A	0	0	1	142	1	0	144	98.6	0.9662
	U & B	2	0	0	1	13	0	16	81.3	0.7949
	C & S	0	0	0	0	0	0	0	—	—
	Total	83	0	7	143	22	1	256		
	PA(%)	97.6	—	85.7	99.3	59.1	100			

Overall classification accuracy : (242/256)x100 = 94.53

Overall k-hat : (0.9453-0.4319) / (1-0.4319) = 0.9037

(b) Reference image(July 20, 1991)

Image to be Evaluated		F	W	B	A	U & B	Total	CA(%)	k-hat(%)
	F	77	0	0	2	0	79	94.5	0.9209
	W	0	0	0	0	0	0	—	—
	B	0	0	7	0	0	7	100	1
	A	0	0	1	150	2	153	98.0	0.9513
	U & B	0	0	0	1	16	17	94.12	0.9368
	Total	77	0	8	153	18	256		
	PA(%)	100	—	87.5	98	88.8			

Overall classification accuracy : (250/256)x100 = 97.66

Overall k-hat : (0.9766-0.456) / (1-0.456) = 0.9570

Forest (dark green)	=	F	Water (blue)	=	W
Barren land (cyan)	=	B	Agricultural land (gold)	=	A
Urban and barren land (purple)	=	U & B	Cloud and shadow (white)	=	C & S
CA : consumer's accuracy		PA : producer's accuracy			

Table 2. Change summary in the study area.

Original Cover Type	Total Ha	Gain Ha	Gain Percent	Loss Ha	Loss Percent	Unchanged Ha	Unchanged percent
Forest	19880.10	1689.28	8.50	1895.1	9.53	17985.00	90.47
Water	14.39	4.87	33.84	2.62	18.21	11.77	81.79
Barren land	810.73	1194.61	147.35	328.06	40.46	482.67	59.54
Agricultural land	28727.87	4291.31	14.94	3359.84	11.70	25368.03	88.30
Urban & Barren	4801.01	2754.03	57.36	4159.98	86.65	641.03	13.35
Cloud & Shadow	147.41	0.00	0.00	147.41	100.00	0.00	0.00
Total	54381.51	9934.1	18.27	9893.01	18.19	44488.50	81.81

Table 3. Post-classification comparison in the study area (unit: ha)

		20-Jul-91				
		Forest	Water	Barren land	Agricultural land	Urban & Barren
8-Jul-90	Forest	17985	1.55	332.91	1614.98	0.00
	Water	0.46	11.77	0.00	0.00	2.16
	Barren land	0.00	0.00	482.67	40.27	288.02
	Agricultural land	91.89	0.00	850.90	25368.03	2445.04
	Urban & Barren	1470.92	0.92	10.8	2635.54	641.03
	Cloud & Shadow	126.01	2.40	0.00	18.81	0.52

90% and overall k-hat was also over 0.9, so we could proceed to change detection. Table 2 summarizes the land cover changes with the comparison of both classification coverages. Even though the interval was just one year, we can find much change in land cover. Table 3 summarizes the post-classification comparison where we can note which land cover change to another and also how much change. We also could find the change location using change detection map (Fig. 3).

In the study area, changes of barren land and urban & barren land were greater than other land cover types and the changes in forest and agricultural land were smaller than the others relatively. The changes of barren land were related to agricultural land and urban & barren land, and the changes of urban & barren land were related to forest and agricultural land. The changes of cloud and shadow were atmospheric problem, and changes indicated original land cover.

4. Conclusions

Classification accuracy was improved by image enhancement using an intensity, hue and saturation (IHS) transformation, but it was still difficult to classify urban and barren area. Based on the tables and map about change detection, we found many changes those are size, location, and the 'from-to' change class information using post-classification comparison technique even interval was just one year.

In further research, we will perform several change detection in same study area but different interval and different period, and then we can monitor the trend of changes of land cover and changing locations.

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