Reprinted from

Eighth International Symposium

Machine Processing of

Remotely Sensed Data

with special emphasis on

Crop Inventory and Monitoring

July 7-9, 1982

Proceedings

Purdue University
The Laboratory for Applications of Remote Sensing
West Lafayette, Indiana 47907 USA

RENEWAL OF LAND USE DATA BASE WITH THE AID OF REMOTE SENSING

H. SHIMODA, K. FUKUE, T. SAKATA

Tokai University
Tokyo, Japan

I. ABSTRACT

A project to establish National Land Information System containing landforms, geological features, land uses, water resources and so on was started on 1974 by The National Land Agency of Japan and an initial Numerical National Land Information(NNLI) was provided. The grid coordinate system of the initial NNLI is being utilized now, however land use data should be renewed periodically. Since land use data in NNLI were obtained by manual interpretation of topographical maps and aerial photographs, renewal of the data using the same method required extensive man-power.

This paper describes feasibility studies on renewal of the land use data in NNLI using remote sensing data and digital processing techniques, which resolves the above problems faced in carring out the renewal of NNLI. Several kinds of approaches can be considered for the renewal of land use data base. We chose a method in which overal object areas are classified without manual selection of training areas. In this study, LANDSAT data were used for change detection and high altitude infrared color aerial photographs were used for classification.

As a results of this study, the following conclutions were obtained. 1)The renewal system of NNLI, which utilizes remote sensing data(LANDSAT/airborn data) and digital processing techniques, was established. The method used in this system is more timely and economically than conventional interpretation method. 2)maximum likelihood classification algorithm can not achieve sufficient classification accuracy for land use(not land cover) classification. 3)Histgram matching algorithm is highly useful for land use classification, although it consumes more times than maximum likelihood algorithm.

II. INTRODUCTION

A project to establish National Land Information system containing landforms, geological features, land uses, water resources and so on was started on 1974 by The National Land Agency of Japan and an initial Numerical National Land Information(NNLI) was provided. The grid coordinate system of the initial NNLI is being utilized now, however some of these data should be renewed periodically. Especialy, land use data should be renewed in shorter interval(several years) than other kinds of data such as landforms. Since land use data in NNLI were obtained by manual interpretation of topographical maps and aerial photographs, renewal of data using the same method requires extensive man-power.

Remote sensing technique can collect global land cover information timely. Satellites such as LANDSAT series especialy provide repetitive coverage with the advantages of a synoptic overview. Thus remote sensing techniques provide the method to resolve the above problems faced in carring out the renewal of NNLI.

This paper describes feasibility studies on renewal of the land use data in NNLI using remote sensing data and digital processing techniques, which was carried out under contract with The National Land Ajency of Japan.

As the first generation NNLI represents the landuse at about 1972, LANDSAT MSS data can be used for change detection. However, the resolution of LANDSAT MSS is too large to use for classification of land use for NNLI which has about 10m ground resolution. Hence, high altitude aerial photographs were used for classification.

III. STUDY AREA AND IMAGE DATA

The study area is Sendai and its suburb(long. 142 52'30"E-143 00'00"E, lati. 38 15'N-38 20'N) which covers approximately 101km^2. Recentry, industrial developments and urban growth are active in this area.

The smallest unit of NNLI for data collection and strage is 10x10m^2 UTM grid cell. Land use categories in NNLI are fifteen and are shown in Table 1. Figure 5 shows the land use map of study area created from the NNLI which almost corresponds to the state at 1971.

Two LANDSAT data covering the study area, dated on Novenber 26, 1972 and December 14,1979, were used for this study. For classification of land use, high altitude infrared color photographs (9in.x9in.) were acquired on October 20, 1979 with 12,000m altitude. The scale of this image is 1 to 80,000.

IV. CHANGE DETECTION WITH LANDSAT DATA

A. PREPROCESSING

The preprocessings needed for the change detection are divided into four stages, i.e. destriping, geometric correction, normalization and smoothing. The destriping was firstly applied for two LANDSAT images by means of histgram equalization algorithm.

Secondly, each LANDSAT image is geometrically corrected using system correction with the aid of ground control points within the mean accuracy of one pixel using UTM projection. Resampled pixel size is 50x50m^2 using a nearest neighbour algorithm, so that rectified image of the study area contained 800x800 pixels.

The normalization means a linear transformation which coincids mean and standard deviations of LANDSAT data acquired at 1979 to those acquired at 1972. The reson of this normalization is to remove ascertain changes such as detector responce differences and different atmospheric effects between the two images. Lastry, a smoothing was applied to both images using 3x3 pixels window in order to decrease misregistration effects between two images.

B. CHANGE DETECTION

There are several algorithms[1,2] for change detection such as subtraction, ratioing and so on. In this study, subtraction(eq.1) was used, because the purpose of this change detection is only to eliminate change regions for training area selection.

$$D = \bigcup (x_{1j}-x_{2j} * T_j) \quad \text{..... (1)}$$

D : change region=1, no=0

$\bigcup$: logical sum operator

x_{ij}: pixel value of MSS band "j"

i=1 (Nov. 26,1972)

i=2 (Dec. 14,1979)

T_j : threshold value for MSS band "j"

Results of change detection is shown in Figure 3.

V. NON-PARAMETRIC LAND USE CLASSIFICATION WITH AERIAL PHOTOGRAPHS

A. PREPROCESSING

The three components(G,R,IR) of the infrared color photographs were digitized throuth rotating drum digitizer with the resolution of 100x100m^2 which corresponds about 8x8m^2 on the ground. A shading correction was first performed to the digitized data using a low-pass filter[3]. Next, the image was rectified with 10x10m^2 ground resolutions corresponding to the grid cell of the NNLI using nearest neighbor resampling.

B. CLASSIFICATION

Training areas for land use categories were selected from no-changed regions in NNLI. As feature vectors for classification, spectral data(G,R,IR) extracted from the training areas were first examined.

The separability(Mahalanobis' distance) among these training classes was insufficient for classification. The major reasons of this bad separability are supposed as follows ;

1) Land use(not land cover) differences does not exactly correspond to spectral feature differences.
2) Training data do not exactly fit to a Gaussian distribution. (An example of crop fields is shown in Figure 1.)
3) Small areas less than 10 pixels were usually neglected in the manual interpretation.

In order to obtain sufficient classification accuracy, following three methods were employed. The first method is the utilization of texture features. Three parameters[4] according to eq.(2),(3) and (4) were calculated with 3x3 pixels window for infrared band data.

$$T_1 = \sum (x_i-\bar{x})^2 / 9 \quad \text{..... (2)}$$

$$T_2 = \sum |x_i-x_c| / 8 \quad \text{..... (3)}$$

where x_c is the value of the center pixel.

$$T_3 = \quad x_i - x_j \quad / \ 4 \qquad \text{..... (4)}$$

where i,j are adjacent pixels.

After the application of principal component analysis to these parameters, the first principal conponent, of which proportion is 92.5%, was used for classification as a feature vector(Figure 4).

The second method is the employment of a non-parametric classifier. Although land use classes have large variance and non-Gaussian nature, these classes have very distinctive shape of histgram. Consequentry, if the shape of histgrams can be utilized as a feature vector, it will increase the classification accuracy. From this point of view, we developed new classification algorithm called a histgram matching algorithm.

In the histgram matching algorithm, shape of histgrams with neighbor points including a unknown pixel is compared with each shape of training data and the unknown pixel is classified to the class which has the nearest hidtgram shape. Since 5x5 pixels window was used in this study as neighbor points, histgrams of training data were normalized into cumulative frequency of 25.0. The distance between a unkown pixel and each classes is defined by eq.(5).

$$D_{ij} = \quad H_i(x) \ - \ H_j(x-w)S(w) \qquad \text{..... (5)}$$

D_{ij}: distance between class i and pixel j
H_i : histgram of class i
H_j : histgram of neighbor points included a unknown pixel
S : smoothing function

$$S(w) = \begin{matrix} 1 & (w=-1,0,1) \\ 0 & (\text{else}) \end{matrix}$$

This algorithm time-consuming compared with maximum likelihood method, but has following advatages;
1) training data need not indicated a Gausiun distribution, because it is a non-parametric classifier.
2) Although training data have large variance, classification accuracy do not decrease.
3) Since smoothing is performed automaticaly in this procedure, the results are not so match influenced by noises and uniform regions can be extracted.

In this study, first and second principal components for spectral features (G,R,IR) and first pricipal component of texture features were used in land use classification. An example of a histgram of crop fields used in classification are shown in Figure 2.

The third method is a utilization of decision tree classifier. A change pattern in land use has a regurarity. For example, forests can change to urbon areas, while urbon areas do not change to forests. A decision tree was constructed based on this regularity of change patterns(Table 2). With the aid of this classifier, processing times largely decreased and classification accuracy has increased.

VI. RESULTS

The classified results is shown in Figure 6. A small misclassifications, e.g. noises near the boundaries were manually corrected pixel-by-pixel basis. Since three land use categories(sea water, seashore, plantations) do not appeare in this target area, the number of classification categories were twelve.

Table 3 represents percentages and change ratios of each land use categories between 1971 and 1979.

VII. CONCLUSIONS

AS a result of this study, the following conclusions were obtained.

1) The renewal system of NNLI, which utilizes remote sensing data(LANDSAT/airborn data) and digital processing techniques, was established. The presented renewal method is more economical than conventional manual interpretation method.

2) Conventional maximum likelihood classification algorithm can not acheve sufficient classification accuracy for land use(not land cover) classification.

3) Histgram matching algorithm is highly useful for land use classification, although it consumes more times than maximum likelihood algorithm.

VIII. REFERENCES

1. L.D.Miller,K.Nualchawee and C.Tom,"Analysis of the Dynamics of Shifting Cultivation in the Tropical Forests of Northern THailand Using Landscape Modeling and Classification of LANDSAT Imagery",Proc. 12th Inter. Sympo. on Remote Sensing of Environment(ERIM), p.1167-1185 (1981)

2. D.M.Carneggie,C.S.Holm,"Remote Sensing Techniques for Monitoring Impacts of Phosphate Mining in Southeastern Idaho" Proc. 2nd Annual Pecora Sympo. (1976)

3. K.Fukue,H.Shimoda and T.Sakata,"Radiometric Correction for Aerial Photography",Journal of the Society of Photographic Science and Technology of Japan,Vol.43,No.6 (1980)

4. S.Hsu,"Texture-Tone Analysis for Automated Land-Use Mapping",Photographic Engineering and Remote Sensing, Vol.44 p.1393-1404 (1978)

5. J.C.Coiner,R.C.Bruce,"Use of Change Detection in Assessing Development Plans : a Philippine Example",Proc. 12th Inter. Sympo. on Remote Sensing of Environment(ERIM), p.547-565 (1978)

6. P.Carter,"Urban Monitoring with LANDSAT Imagery", in Machine-Aided Image Analysis, 1978, edited by W.E.Gardner, The Institute of Physics,Beistol and London (1979)

7. E.Tsurumi,"Data Base of Land Information",Proc. Inter. Georgraphical Union/ Commission on Geographical Data Sensing and Processing (1980)

AUTHOR BIOGRAPHY

Kiyonari Fukue recieved the B.S. and M.S. degrees from the Tokai University of Kanagawa, Japan, in 1976 and 1978, respectively. From April 1978 to March 1981 he was a graduate student of doctor cource in the Department of Electro Photo-Optics Enginering, Tokai University. Currently, he is an assistant at the Institute of Research and Development, Tokai University. His research interests include digital image processing and system, especially in remote sensing.

Haruhisa Shimoda recieved the Ph.D. degree in solid state physics of Organic semiconductor from the University of Tokyo, Tokyo, Japan, in 1972. Since 1972, he has been an Assistant Professor of the Department of Electro Photo-Optics Enginering at the Tokai University, Kanagawa, Japan. He is currently engaged in field of digital image processing, a development of image processing system, and application of digital image processing to remote sensing.

Toshibumi Sakata recieved B.S. degree of Chemical Enginering from Chiba University. He took doctor in Enginering of Chemical Physics at the University of Tokyo and then joined to the Institute of Industrial Sciene there, as a research associate. He was a research scientist of Munich University during 1964 to 1966. In 1966 he moved to the Tokai University and he had a chair of professor in 1971. Presently he is the director of Tokai Research and Information Center, the Tokai University.

Table 1 Land Use Categories in NNLI.

1.	Paddy Fields
2.	Upland Fileds
3.	Orchards
4.	Tree Plantations
5.	Forests
6.	Waste Lands
7.	Highdensity Urvan Areas
8.	Residential Areas
9.	Transportation & Distribution District
10.	Others (open spaces)
11.	Lakes
12.	Rivers without constructions
13.	Rivers with constructions
14.	Seashore
15.	Sea water

Table 2 Change Patterns in Land Use.

from\to	1	2	3	5	6	7	8	9	10	11	12	13
1	*	a			a	a	a		a			
2		*			a	a	a		a			
3		a	*	a	a	a	a		a			
5		a	a	*	a	a	a		a			
6			a	a	*	a	a		a			
7						*						
8						a	*		a			
9								*				
10				a	a	a	a		*			
11										*		
12										a	*	a
13												*

Table 3 Area Percentage of Land Use Categories on 1971 and 1979.

	1971 (%)	1979 (%)	1971 -1979
1.	27.42	24.68	-2.74
2.	7.68	6.40	-1.28
3.	0.69	0.60	-0.09
4.	0.00	0.00	0.00
5.	16.55	14.07	-2.48
6.	0.37	1.90	1.53
7.	11.56	14.92	3.36
8.	18.09	20.60	2.51
9.	3.14	3.14	0.00
10.	11.27	10.46	-0.81
11.	0.45	0.46	0.01
12.	1.73	1.73	0.00
13.	1.05	1.04	-0.01
14.	0.00	0.00	0.00
15.	0.00	0.00	0.00

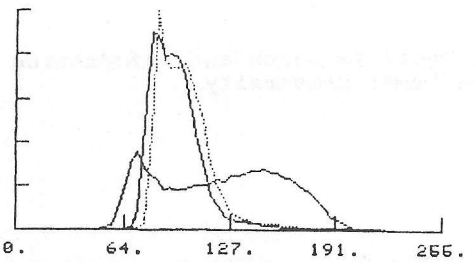

Fig. 1 Histgram of training data using spectral features for forests.

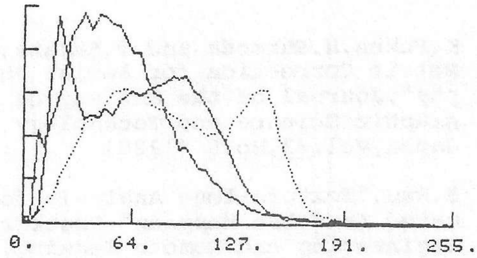

Fig. 2 Histgram of training data composed of first and second principal components from spectral data and a first principal component from texture data.

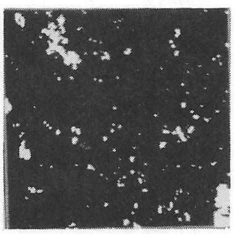

Fig. 3 Changed regions in land use according to subtraction between LANDSAT images on 1972 and 1979.

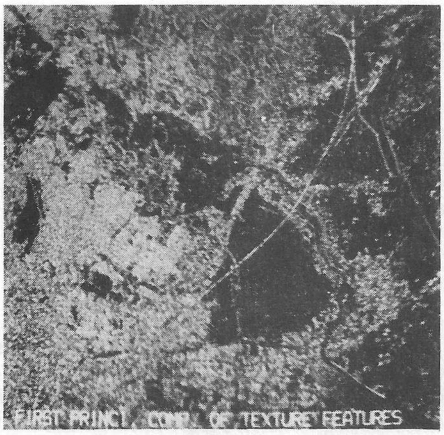

Fig. 4 The first principal component of texture information in the aerial photograph.

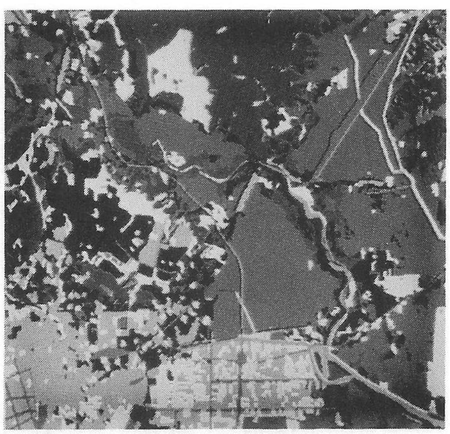

Fig. 5 Land use map on 1971 created from NNLI.

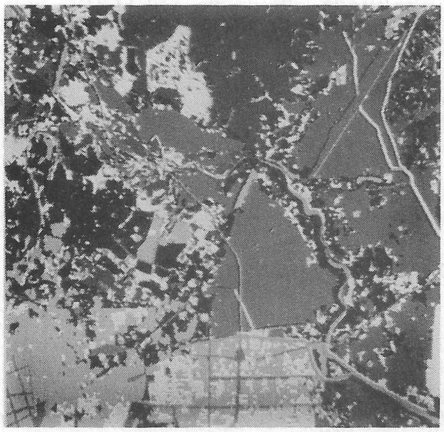

Fig. 6 The renewed result of land use NNLI data (1971-1979).