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A Study on Modeling of Spatial Land-use Prediction

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ABSTRACT

The purpose of the study is to establish models of land use prediction system for development and management of land resources using remotely sensed data as well as ancillary data in the context of multi-disciplinary approach in the application to CheJoo Island.

The model adopts multi-date processing techniques and is a spatial/temporal land-use projection strategy emerged as a synthesis of the probability transition model and the discriminant-analysis model. A discriminant model is applied to all pixels in CheJoo landscape plane to predict the most likely change in land use. The probability transition model provides the number of these pixels that will convert to different land use in a given future time increment. The synthetic model predicts the future change in land use and its volume of pixels in the landscape plane.

I. INTRODUCTION

Land-use mapping could be categorized into 3 kinds in general.

1) Land-use status monitoring
2) Land-use change detection
3) Future land-use prediction

When the subject of land-use change detection is considered, the analysis eventually results out separately in a quantitative one and a spatial one. The same circumstances is concerned with that of land-use change prediction. Among while, a spatial land-use prediction strategy developed as a synthesis of the quantitative probability transition model and the discriminant analysis model.

This paper deals with the structure, testing and verification of the land-use trend model which provided the correct number of changing location in a particular time period and the linear discriminant model which provided next most likely changing type of each spatial location. Spatially registered Landsat digital imagery served as land-use status inputs.

II. CONCEPTUAL FRAMEWORK OF LAND-USE PREDICTION MODEL

A particular land use can be considered as a class in a classification system, and further, each class is defined by its similarity to other class members and some level of differentiation from non-class members. Likewise, type of land-use change that was observed between 1975 and 1981 was quantitatively defined by its associated landscape parameters for the Chejoo Island Area. It was assumed that they exhibited some similarity to other cells in the change class and differentiation from non-changed cells.

After stepwise discriminant analysis, the most optimal discriminant function is applied to all pixels in CheJoo Landscape plane to predict the next most likely change in land-use as shown in Fig. 1. The Markov trend model provides the number of these pixels that will convert to a different land use in a given future time increment. The discriminant model predicts the next change in land-use and its posterior probability for each pixel in the landscape. The actual change in a future time period can be determined by assembling all changes of each given type from all pixels predictions constituting the entire landscape. The group of pixels representing each type of change can be ordered by their posterior probability of occurrence. The correct number of transitions supplied by the Markov trend model can be selected on the basis of the highest posterior probability at the top of each of the ordered list of change type. Pixels with low probability can be assumed to be unchanged. The exact spatial location of each pixels is preserved by row and column, and a predicted map of the future distribution of each land use for a particular date can be displayed. The total modeling process can be iteratively performed to yield a time succession of spatial projections of future land-use maps.

III. COMPARISON BETWEEN OBSERVED '81 LAND-USE AND PREDICTED '81 LAND-USE

Both of '75 Land-use and '81 Land-use were mapped after spatial registration of Landsat images using 2 variable (X, Y coordinates) least square method (Fig. 2 '75 observed land-use map, Fig. 3

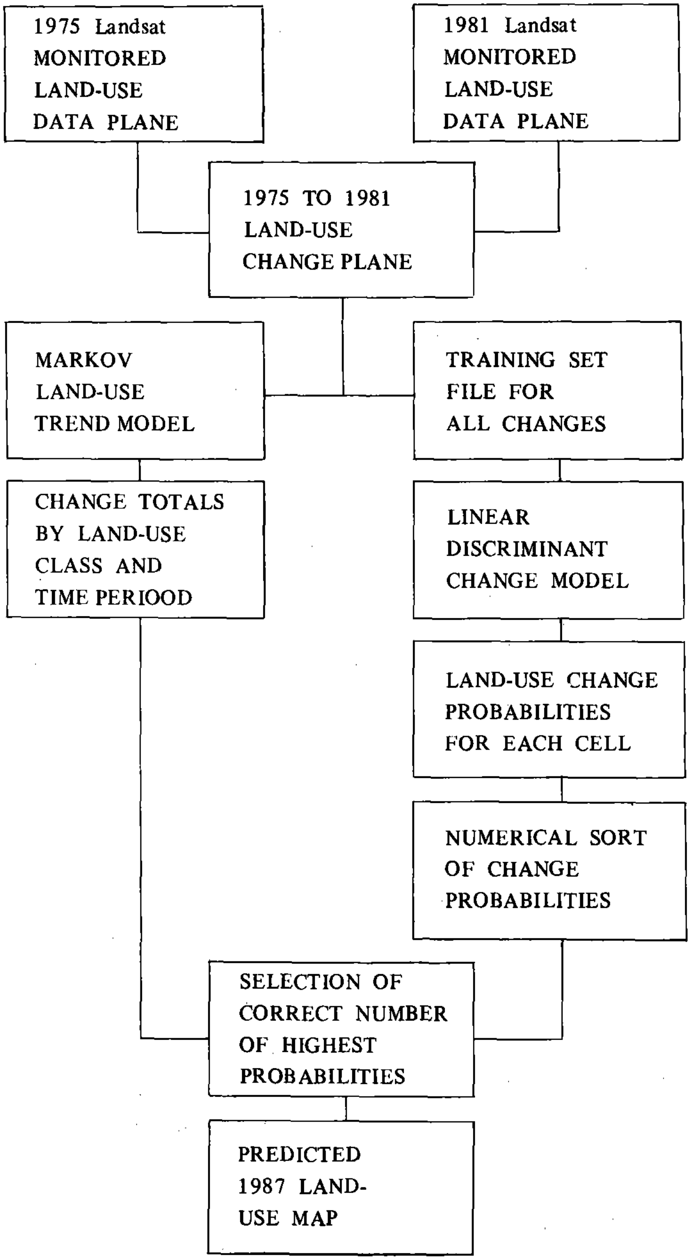

Fig. 1. Combination of Markov and Linear Discriminant Model for Improved Spatial-Change Prediction

'81 observed land-use map).

The ground truth for the reference of the discriminant function was land-use map published by Korea Institute of Geography in '73.

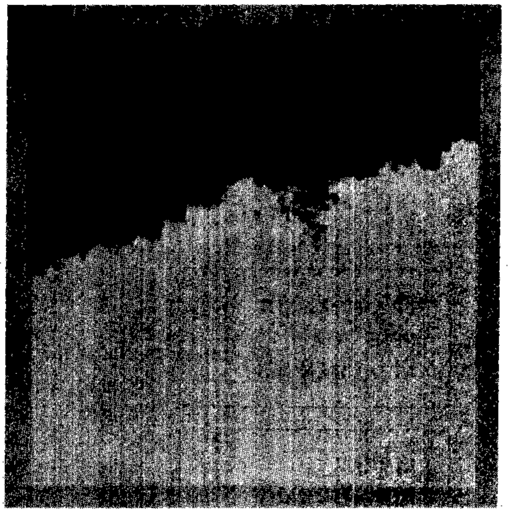

Fig. 2. '75 observed land-use map
CheJoo city area intentionally extracted for display of urdan sprawl.
sea ; black points
urban ; grey points
others ; white points

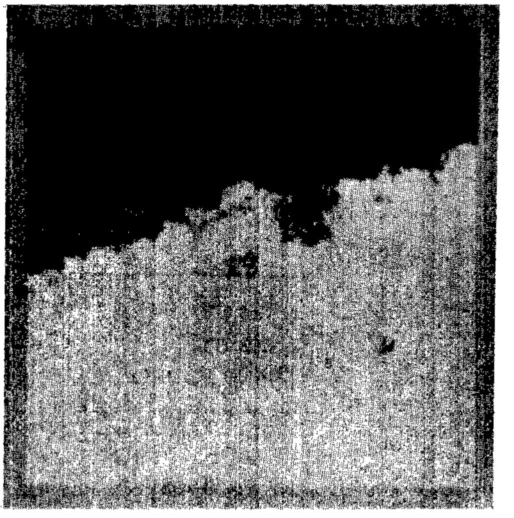

Fig. 3. '81 observed land-use map

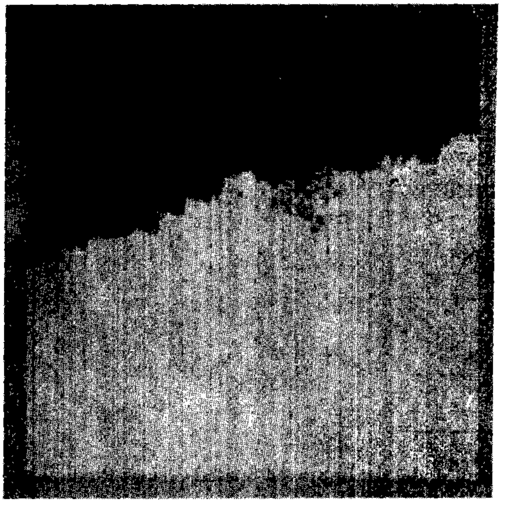

Fig. 4. '81 predicted land-use map

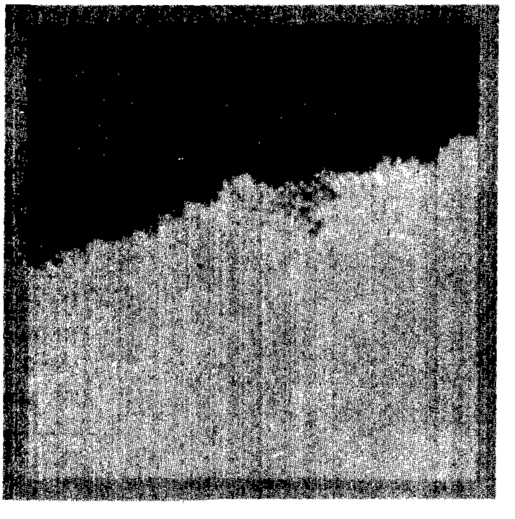

Fig. 5. '87 Predicted land-use map

One CheJoo scene is composed of 434 line x 755 column with 100m x 100m pixel resolution, and all changing pixels by type were systematically sampled by pixel to pixel basis excluding non-changing pixels and pixels of sea (which was logically excluded). Those of change-type were 51 classes as shown in Table 3 matrix.

The variables used for the linear discriminant function for mapping for change-type were as following.

Landsat image
1) '75 MSS-4
2) '75 MSS-5
3) '75 MSS-6
4) '75 MSS-7
5) '81 MSS-4
6) '81 MSS-5
7) '81 MSS-6
8) '81 MSS-7

Physiographic
9) Topographic elevation
10) Topographic slope
11) Topographic aspect

Topographic elevation data was digitized on the basis of 500m x 500m grid point of the local Transverse Mercatore topographic map (also published by KIG in '82), interpolated 100m x 100m and spatially registered to that of landsat composition.

Table 1. Stepwise discriminant function

STEP NUMBER	VARIABLE ENTERED	F VALUE TO ENTER	NUMBER OF INCLUDED VARIABLES	U-STATISTIC
1	'81 MSS-5	186.0271	1	0.2589
2	'81 MSS-6	164.2453	2	0.0734
3	'75 MSS-7	92.5556	3	0.0303
4	'75 MSS-5	80.6121	4	0.0135
5	'81 MSS-7	30.7630	5	0.0092
6	'75 MSS-6	24.0161	6	0.0067
7	'75 MSS-4	21.4499	7	0.0050
8	elevation	17.7216	8	0.0039
9	'81 MSS-4	15.0636	9	0.0032
10	aspect	1.8325	10	0.0031
11	slope	1.7840	11	0.0030

With F level of 0.01 for including a variable and F level of 0.005 for deleting a variable the stepwise result of multiple class linear discriminat analysis was as show in the Table 1.

F values for each variable

If variable j has been entered

$$F_j = \frac{a_{jj} - b_{jj}}{b_{jj}} \cdot \frac{n - r - g + 1}{g - 1}$$

with degrees of freedom $g - 1$ and $n - r - g + 1$

If variable j has not been entered

$$F_j = \frac{b_{jj} - a_{jj}}{a_{jj}} \cdot \frac{n - r - g}{g - 1}$$

with degrees of freedom $g - 1$ and $n - g - r$

Under the usual normality assumptions these are the likelihood ratio tests of the equality over all g classes of conditional distribution of variable j given the (remainning) entered variables.

Wilks λ to test equality of class means

$U = \mathrm{Det}(W_{11}) / \mathrm{Det}(T_{11})$

with degrees of freedom $(r, g - 1, \ n - g)$

In the later classification procedure, coefficients and constant terms of the classification functions

$$C_{ki} = (n - g) \sum_{j=1}^{r} X_{ki} A_{ij}$$

$$C_{ko} = \sum_{i=1}^{r} C_{ki} X_{ki}$$

Where

$i == 1, 2, \text{———}, r$

$j = 1, 2, \text{———}, g$

When the number of variables entered is determined,

for $\ell = 1, 2, \text{———}, t$

$m = 1, 2, \text{———}, g$

$k = 1, 2, \text{———}, n$

Value of the m classification function evaluated at case k of class l

$$S_{lmk} = C_{mo} + \sum_{j=1}^{r} C_{mj} X_{lkj}$$

Posterior probability of case k in class l having come from class m

$$P_{lmk} = \frac{P_m \exp(S_{lmk})}{\sum_{i=1}^{g} P_i \exp(S_{lik})}$$

Where p_m is the prior probability of class m.

Meanwhile elements of the probability transition matrix $p = [p_{ij}]$ not on the principal diagonal are transition probabilities (or proportions) for a given land-use to change in the given time interval. All rows in the matirx are stochastic vectors, that is, the entries sum to one across any row, or in dot notation.

$$P_i = \sum_{j=1}^{m} p_{i,j} = 1$$

In the transition proportion matrix of Markov chains, the vector of probabilities associated with states n stepts away from the initial state is $[p_{rn}] = [p_r] \cdot [p]^n$. In this study the intial state was '75 - '81 change-type matrix as the Table 3.

Selecting correct numbers of pixels which have highest posterior probabilities from the top of each of the ordered list of change-type, the '81 land-use map was projected by prediction model as the Fig. 4.

The accuracy of '81 prediction by the model of future changes in landuse on a pixel to pixel or spatial basis with '81 observation for CheJoo Island area was as the Table 2.

Table 2. '81 year Map Verification Accuracy

CLASSIFICATION	TOTAL POINTS	CORRECT POINTS	CORRECT POINTS (%)
Urban Area	11444	5264	46.0
Broad Leave Forest	10314	4043	39.2
Crop Field	30621	18403	60.1
Perennial Crop	19147	11220	58.6
Paddy Field	1781	499	28.0
Open/Waste Land	27274	7937	29.1
Pasture	51099	41288	80.8
Dense (Needle) Forest	26562	18328	69.0
Sparse (Needle) Forest	5470	1860	34.0
Barren	7781	1969	25.3
Sea	136177	132727	
			(Average)
TOTAL	327670	233538	47.0

Table 3. '75 - '81 change-type matrix

FROM	URBAN	BROAD	CROP	POSTURE	TO PADDY	OPEN	PERRAINAL	DENSE	SPARSE	BARREN	SEA	ROW TOTAL
URBAN	2313	174	260	109	987	529	2611					6983
BROAD		6387	2402	3224	457	2722	909					16101
CROP	366	977	20176	1605	699	3206	661					27690
PASTURE		1471	961	7366	329	808	181					11116
PADDY	330	612	7613	1058	4560	3036	1357					18590
OPEN	675	1325	3144	1557	1467	10483	7625					26276
PERRAINAL	4168	867	2015	669	3942	4070	35231	1567	1760	1942		56231
DENSE							666	17077	2381	287		20411
SPARSE							871		1084	344		2299
BARREN							755	235		1980		2970
SEA											139003	139003
COLUMN TOTAL	7852	11813	36571	15588	12441	24878	50867	18879	5225	4553	139003	327670

Table 4. '75 - '87 change-type matrix

FROM	URBAN	BROAD	CROP	POSTURE	TO PADDY	OPEN	PERRAINAL	DENSE	SPARSE	BARREN	SEA	ROW TOTAL
URBAN	2096	237	827	303	456	657	2407					6983
BROAD		6278	2677	2138	565	1720	2703					16101
CROP	614	2146	15742	2197	916	3078	3897					27690
PASTURE		990	1481	6144	317	1016	1168					11116
PADDY	501	820	5191	1407	5099	2083	3489					18590
OPEN	1056	1163	3927	1839	1298	8924	8069					26276
PERRAINAL	3605	1481	5116	1793	3624	4901	27380	2791	3363	2177		56231
DENSE							2172	15151	2404	684		20411
SPARSE							787		1377	135		2299
BARREN							753	228		1989		2970
SEA											139003	139003
COLUMN TOTAL	7872	12215	34961	15821	12275	22379	52845	18170	7144	4985	139003	327670

IV. PREDICTION OF '87 LAND-USE

Applying the equation $[\, p_{r2}\,] = [\, p_r\,] \cdot [\, p\,]^2$ to the '75 -'81 transition proportion matrix (which could be easily calculated, dividing each of row vector by the row total) the '75 -'87 transition matrix resulted out as the Table 4.

Selecting correct numbers of pixels as before, the '87 land-use was predicted as the Fig. 5 map at last.

V. CONCLUDING REMARKS

Only physiographic variables were used to structure the discriminant function in the pattern space in this research. Nevertheless, other variables such as those of transportation, socio-economic factors should be considered to enhance the final mapping accuracy.

Pixel resolution of Landsat, 79m x 57m is still coarse to the small-scaled environment of Asian country such as Korea where crop field, paddy field and even residential house is bordered inside one pixel. TM data of Landsat 5, SPOT data or air-craft MSS data is desired for land-use mapping. The methodology developed in this study can be applied to any discipline such as agriculture, forest, water resources, oceanography and so on.

REFERENCE

Tom, C. and Miller, L. D. 1978, Spatial Land-use Invetory, Modeling and Projection, NASA Technical Memorandum 79710, pp. 79-83.

Mastuoka, R. and Murai, S. 1978, Land-cover Classification using Multi-date Landsat Data, Proceedings of '78 annual Conference of Japan Society of Photogrammetry & Remote Sensing, pp. 135-138.

Lee, C. M. 1981, Computer Land Use Mapping with Landsat Digital Data, proceedings of the 2nd Asian Conference on Remote Sensing, Univ. of Utah, pp. C-4-1-13.

Kim, E. H. 1983, A Study on Methodology for Spatial Land-use Projection, Proceedings of '83 Autumn Conference of Japan Society of Photogrammentry & Remote Sensing, pp.69-70.