研 究 速 報

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A Study on Modeling of Spatial Land-Use Prediction

土地利用変化の空間予測の方法に関する研究

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1. Introduction

Land-use mapping could be categorirized 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 prediction models that have been integrated from the Markov 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.

2. 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 nonclass members. Likewise, each type of land-use change that was

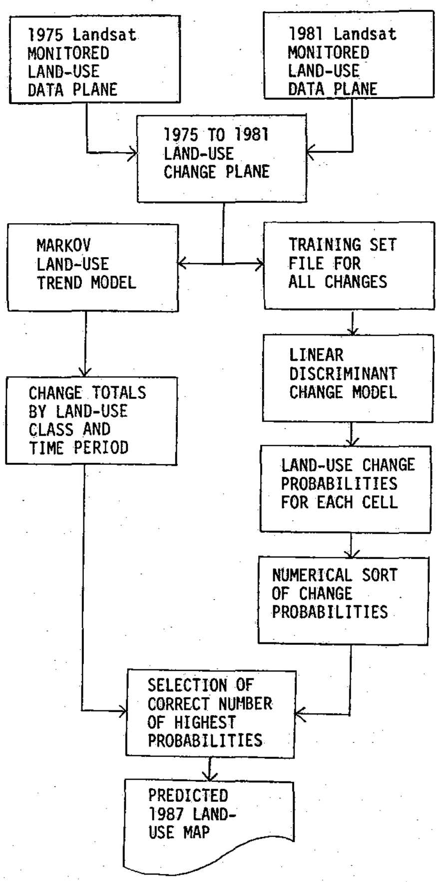

Fig.1 Combination of Markov and Linear Discriminant Model for Improved Spatial-Change Prediction

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

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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 carrying along their respective rows and colums in CheJoo area. The sorted pixels can be reassembled 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.

3. 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 '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.

Table 1　Stepwise discriminant function

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

One CheJoo scene is composed of 434 line×755 column with 100 m×100 m pixel resolution, and all changing pixels by type were systematically sampled from the center of five-by five array of picture elements 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 of change-type were as following.

Landsat image	Physiographic
1) '75 MSS-4	9) Topographic elevation
2) '75 MSS-5	10) Topographic slope
3) '75 MSS-6	11) Topographic aspect
4) '75 MSS-7	
5) '81 MSS-4	
6) '81 MSS-5	
7) '81 MSS-6	
8) '81 MSS-7	

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

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 discriminant analysis was as shown in the Table 1.

Where F values for each variable

If variable j has been entered

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

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

If variable j has not been entered

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

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 (remaining) 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

$$C_{ki}=(n-g)\sum_{j=1}^{r}\bar{x}_{ki}a_{ij}$$

$$C_{ko}=-\frac{1}{2}\sum_{i=1}^{r}C_{ki}\bar{x}_{ki}$$

where

$i=1, 2, \cdots\cdots, r$

$k=1, 2, \cdots\cdots, g$

When the number of variables entered is determined,

for $l=1, 2, \cdots\cdots, t$

$m=1, 2, \cdots\cdots, g$

$k=1, 2, \cdots\cdots, n_1$

Value of the m^{th} 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 $p=[p_{i,j}]$ 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 matrix 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 initial state was '75—'81 change-type matrix as the Table 3.

Selecting correct numbers of pixels which have highst 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 prediction by the model of future changes in land-use on a pixel to pixel or spatial basis for CheJoo Island area was as the Table 2.

4. Prediction of '87 Land-use

Applying the equation $[P_{rn}]=[P_r]\cdot[P]$ 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.

5. Concluding Remarks

Only physiographic variables were used to struc-

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
Perrenial 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	
Others			(Average)
Total	327670	233538	47.0

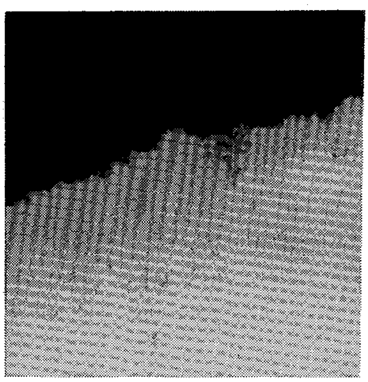

Fig. 2 '75 observed land-use map CheJoo City area intentionally extracted for display of urban sprawl Sea ; black points, Urban ; grey points, others ; white points

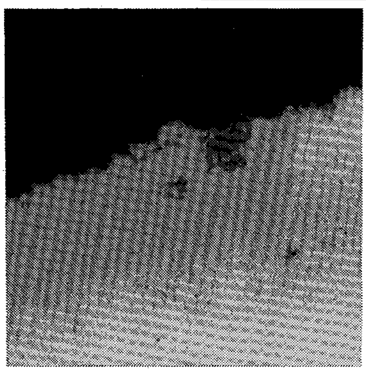

Fig. 3 '81 observed land-use map

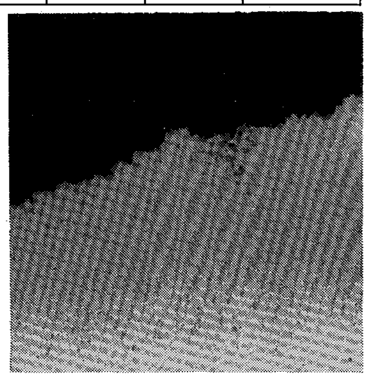

Fig. 4 '81 predicted land-use map

Table 3 '75—'81 change-type matrix

FROM	TO BARR	BROA	CROP	DENS	OPEN	PAST	PERR	PADD	SEA	SPAR	URBA	ROW TOTAL
BARR				268		489				151		908
BROA			1358		1314	1539	1429				239	5879
CROP		2199			5175	788	3521	1125			672	13480
DENS	337					852				442		1631
OPEN		2083	4763			5412	2698				920	15876
PAST	3018	2235	2215	3429	8216		1409			2092	2147	24761
PERR		1046	1528		1375	505		112			2001	6567
PADD	783	3581		1952	814	743					456	8329
SEA												
SPAR	375			322		1851						2548
URBA		141	175		306	1046	369	87				2124

Table 4 '75—'87 change-type matrix

FROM	TO BARR	BROA	CROP	DENS	OPEN	PAST	PERR	PADD	SEA	SPAR	URBA	ROW TOTAL
BARR	137	44	44	87	162	250	28			114	42	908
BROA	188	776	884	213	1366	755	707	147		130	713	5879
CROP	96	1461	3489	109	1851	3051	1676	88		67	1592	13480
DENS	169	77	76	273	283	503	48			128	74	1631
OPEN	660	1756	1669	749	4787	1484	2218	481		457	1615	15876
PAST	1016	1806	3486	1155	1954	9617	2891	297		1431	1108	24761
PERR	62	619	912	70	1302	1828	1273	209		43	249	6567
PADD	99	1062	1050	113	2041	1361	1583	330		69	621	8329
SEA												
SPAR	292	167	166	367	614	370	105			306	161	2548
URBA	127	230	341	145	543	188	199	21		88	242	2124

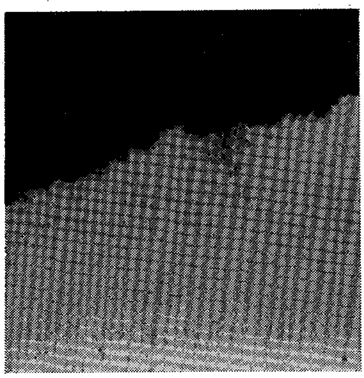

Fig. 5 '87 Predicted land-use map

ture 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, 79 m×57 m 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.

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