

COMPARISON OF CLASSIFICATION METHODS FOR MSS DATA BY AN
APPLICATION OF DETAILED DIGITAL LAND-USE DATA
(10 M-SQ. RESOLUTION) PREPARED BY JAPANESE
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Abstract: Changing its sampling sizes of training area along a slope from very small to 100 percent fit-size of the overall test field on a cell-to-cell basis, with or without the prior probabilities of identification class, application of fine resolution digital land-use data makes it possible to assess classification accuracies of precisely resampled MSS data, as ground verification. Systematic comparisons by the use of recent Kappa coefficient of agreement for a whole scene, were employed in this study in terms of the supervised distribution-dependent classification methods of discriminant analyses in order to apply a befitting practical method with proper training area size suitable for individual analyses in actual scenes.

Introduction

Although many new classification methods have been proposed in statistical field adoptable to remote sensing such as distribution-free and/or robust ones (Ohashi, 1985), applicability scrutinies of the usual procedures in remote sensing under the consistent and coherent conditions appear to be few through actual comparisons. For instance, in the COMPENDEX database, only 10 theses were found, despite the vital importance of practical analyses, during the period from 1984 to 1987 with key words of classif*, remote, sensing, and accura*, taking those intersections where '*' means the rest remaining letters. Two papers out of them, however have different single clear focuses unaccompanied with training representativity standpoint (Csillag, 1986; Belward and de Hoyos, 1987), while the others deal with TM-MSS comparisons, and so forth. Systematic actual comparisons of available established methods in the first place, thus, would be highly of importance.

On the other hand, to collect test field verification data for post classification evaluation requires vast elaboration not only for site-specific approach, but also for panchromatic or color aerial photograph-read in terms of securing sufficient number for post classification assessment. Governments at national and local levels, however, often prepare basic references for their own needs such as urban planning, estimation of the future residential demand and so forth, in the shape of recent computer readable tapes.

This research therefore utilized the governmental public file of land-use, originally for the Survey on the Trend of Housing Land Use prepared by Geographical Survey Institute(GSI) in collaboration with Economic Affairs Bureau, both in Ministry of Construction, Japan (Miyazaki and Tsukahara, 1987). Among the three candidate areas of Tokyo, Nagoya, and Osaka, the authors chose the first because of her relatively large flat area presence suitable for avoiding unnecessary diffused reflectance caused by geographical features. The data area size is just the same with that of Metropolitan Rearrangement Act(Shutoken Seibi Ho).

The analytical flow in this study is shown in Figure 1.

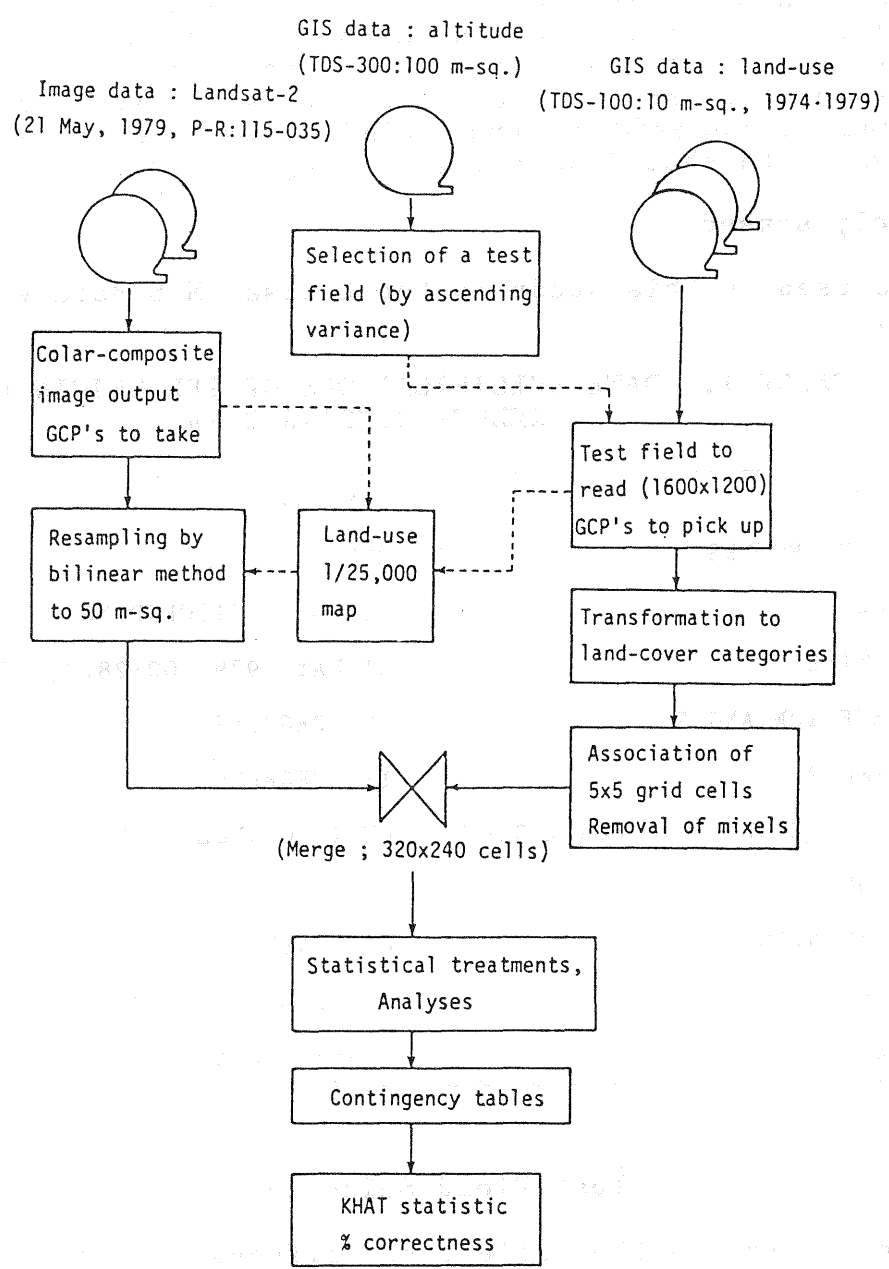


FIGURE 1. DATA PROCESSING FLOW OF THE ANALYSIS

Specifications of the Data Used

Ground verification

Detailed digital land-use data were assembled according to a standardized procedure by GSI. Its outlines concerning land-use file preparation, are that photo-interpretation results from color aerial photographs are tinted by color pencils to polyester transparent base, overlaid on a 1/10,000 base map, followed by drum scanner digitization and computer compilation. The mixels which show non-registered noise colors are inferred from the surrounding four-cell majority (Geographical Survey Institute, 1984).

Coordinates adopted in those files are 'pseud' or 'quasi' UTM, named Plane Rectangular Coordinates, with re-settlement of the origin (Japan Cartographers Association, 1985) to avoid cracks of well-aquainted maps and municipal jurisdictional boundaries for practical purposes (Okudaira, 1982). Thus resampling fitness to Landsat data should be relatively agreeable.

Remotely sensed

The data used in this study is the Landsat MSS data which is in Table 1.

TABLE 1. DATA SPECIFICATIONS OF THE ORIGINAL REMOTE SENSING DATA

PLATFORM	LANDSAT-2
TYPE OF DETECTORS	MSS
PATH-ROW	115-35 / DESCENDING
DATE & TIME	21 MAY 1979, 00:28.3(GMT)
SUN ELEVATION ANGLE	58 DEGREES
SUN AZIMUTH	111 DEGREES
METHOD OF GEOMETRICAL CORRECTION	CUBIC CONVOLUTION W/ GCP PRECISION
GAIN MODE	LOW
DATA TRANSMISSION	CONDENSED
DATA FORM	CCT/BIL (SUPER STRUCTURE)
OBTAINED BY	NASDA (JAPANESE AGENT)

Test Field Selection

In order to reduce the effect of diffused sun-ray reflection caused by geographical features, the authors utilized TDS-300, which has altitude informations on a 100 meter-square basis in metropolitan Tokyo. The variances were calculated by re-arranged

unit area of 160 x 120 grid cells (a cell has 100m-sq. resolution) while the original has 40 x 30, which is applied later to collating with Landsat image data. Ascending sort of the variance should give the order of flatness. With consideration of diverse land-use categories in suburban regions that accord us to analyze land-use complex in a practical sense in crowded Japan and Asian expanding squatter peripherals, the authors selected in-and-around Kawaguchi City on the northern outskirts of Tokyo among the top ten candidates. The resulting digital land-use sub-data have 1600 x 1200 grid cell size in 1979 (cell codes : 1216, 1217, 1218, 1219, 1316, 1317, 1318, 1319, 1416, 1417, 1418, 1419, 1516, 1517, 1518, 1519; 16km x 12km), read-off from TDS-100 land-use file with 10 m-sq. resolution, corresponding to the time cross-section of the Landsat data in 1979 (Figures 2 & 3).

Transformation from Land-use to Land-cover

Since the digital land-use file has been designed for governmental socio-economic plannings, it does not perfectly fit the operational taxonomy units (ground categories) for spectral analyses. Table 2 shows the conversion in this research. The reason why the authors left low density residential area independently in Table 2 was that in urban-suburban environment the role of small woods in garden is assumed to be a precious presence with a diverse number of bird species maintained (Tanaka and Chiba, 1986).

TABLE 2. TRANSFORMATION FROM LAND-USE TO LAND-COVER

TO: (LAND-COVER)	FROM: (LAND-USE)
FARM & GRASSLAND	AGRICULTURAL FIELD EXCEPT PADDIES OPEN SPACE AFTER LAND CONSTRUCTION
BARREN	LAND UNDER CONSTRUCTION
DEVELOPED AREA	INDUSTRIAL AREA RESIDENTIAL AREA FOR CROWDED HOUSES LESS THAN THREE STORIES RESIDENTIAL AREA FOR HIGHER STORIES COMMERCIAL & BUSINESS AREA ROAD AREA FOR OTHER PUBLIC FACILITIES
FOREST	FOREST & WASTELAND (BAMBOO BRAKE, GOLF COURSE, GRASSLAND, ABANDONED CULTIVATED LAND, ETC.)
PADDY FIELD	PADDY FIELD
RESIDENTIAL AREA	RESIDENTIAL AREA FOR ORDINARY HOUSES LESS THAN THREE STORIES PARK, GREEN SPACE OTHERS (DEFENSIVE FACILITIES, US BASES, BASE REMAINDER, ROYAL FACILITY, & OTHERS)
WATER SURFACE	RIVER, LAKE, AND OTHER WATER BODY SEA

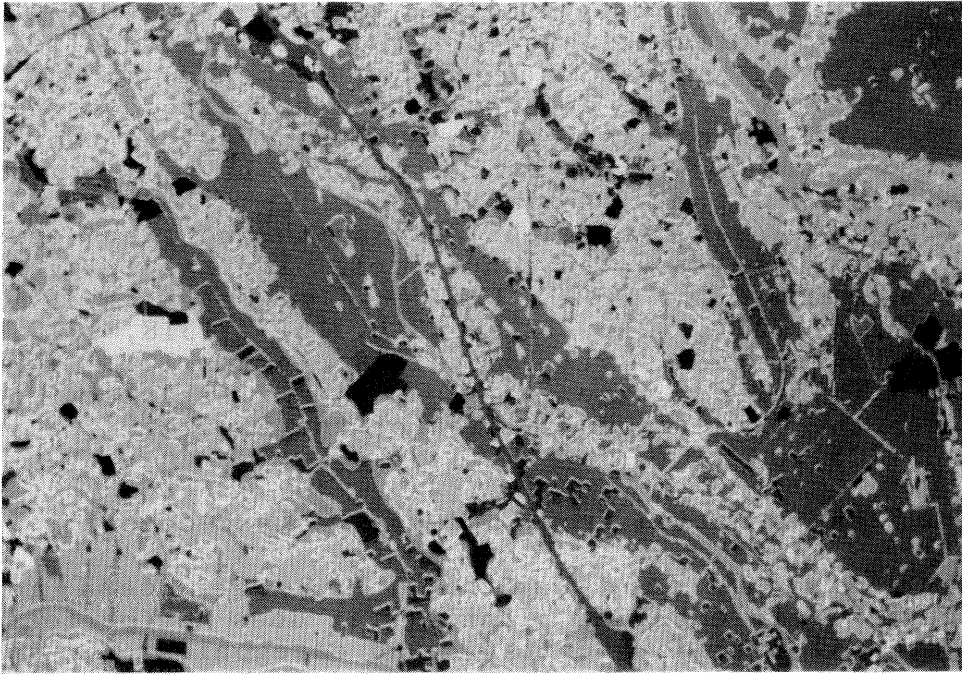


FIGURE 2. PARTIAL VIEW OF THE DETAILED DIGITAL LAND-USE DATA
IN THE TRAINING FIELD
(1000 x 768 GRID CELLS OUT OF 1600 x 1200; 1979)



FIGURE 3. COLOR-COMPOSITE IMAGE OF THE LANDSAT MSS DATA
(1000 PIXEL x 768 LINE; 21 MAY 1979)

Association of 5 x 5 Grid Cells of Digital Land-use File

Pixel-to-pixel evaluation requires exactly the same cell size. The 10 x 10 m ground data were associated with coarsened cell of 50 x 50 m. If some of the cells contain different land-use types, they are deleted when the greater cells have variance unequal to zero (nominal scale converted to numeric; Figure 4).

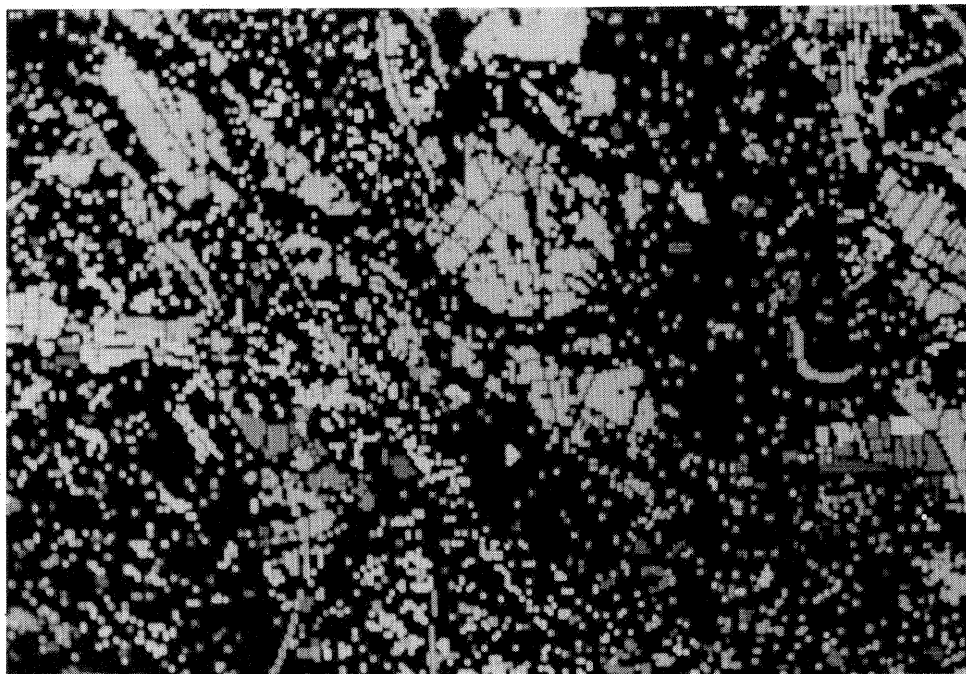


FIGURE 4. GRID CELL ASSOCIATION (320 x 240)

Geometrical Correction and Resampling

This procedure is a key central kernel of this research to make the following processes meaningful for pixel-to-pixel assessment. Forty-five GCP's were picked up from both the ground and Landsat data, and the coordinate values were written into 1/25,000 conventional land-use maps.

Bi-linear and affine regression equations were both calculated but while the latter had a little worse (bigger) mean square error for the image V, the former's XY item could not reject null hypothesis with 0.05 two-sided level. Therefore affine transformation method was adopted. Applying the method, six points had high Cook's D influence statistic (SAS Institute, 1985), and they were re-examined on the land-use maps. Two points with little confidence were deleted, and again regression was employed. The final equations with largely reduced MSE's were:

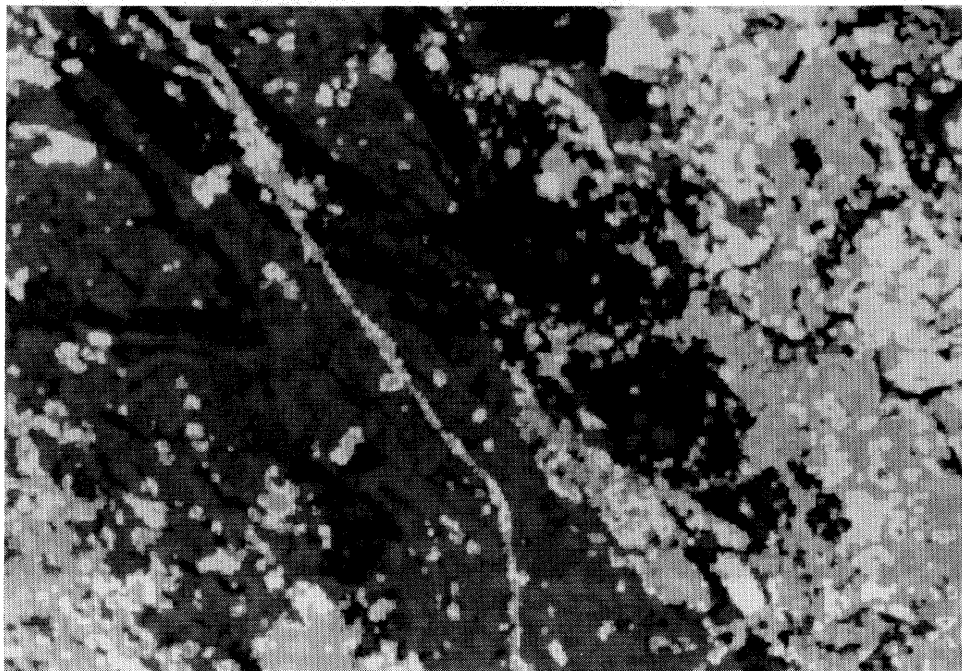
$$\begin{aligned} u &= 0.17329 X + 0.033392 Y + 106.53, & r\text{-sq.} &= 0.9995 \\ & (276.1) & (40.34) & (136.7) \\ v &= -0.033576 X + 0.17170 Y + 107.87, & r\text{-sq.} &= 0.9995 \\ & (-69.51) & (269.5) & (179.8) \end{aligned}$$

(Coordinate origins were the upper-left edge of the sub-scenes. The Landsat sub-image origin is from line-pixel, 1501-801 of

the original.)

Bi-linear interpolation method was applied based on the above equation since the original data had been already processed by cubic convolution(Table 2).

It took 45 minute and 8.13 second CPU time by optimum parameters of FORTRAN/E2 in HITAC M-680H with fourfold DO loops resulting 1.344×10^{10} time grid generation(Figure 5: the outcome).



**FIGURE 5. RESAMPLED IMAGE DATA BY BI-LINEAR INTERPOLATION
(320 x 240; NOTE THE VIEW RANGE UNEQUAL TO FIG. 4.)**

Descriptive Statistic

Integration after resampling enables us easily to obtain various statistics by each identification class(land-cover category) as shown in Table 3, and Figure 6.

Notice that the 'barren' class of band-6 and band-7 was not identified with normal distribution. The values and distributions of water surface data show great anomalies especially in band 6 and 7, which normally close to zero.

The reasons for the above is inferred due to the conversion from administrative land-use to land-cover categories, whereas the former does not represent spectral features as inseparable original unit(right side descriptions in Table 2).

This problem is argued in 'Discussion' later.

Slope of Training Area Sizes

TABLE 3. DESCRIPTIVE STATISTIC

BAND	N	MEAN	SD	MIN	MAX	SKEWNESS	KURTOSIS	PROB> D:NORMAL
----- OVERALL SCENE (TEST FIELD) -----								
4	14768	28.73	2.684	22	51	1.0380	2.8559	-
5	14768	30.17	4.647	20	63	1.0157	1.8691	-
6	14768	38.92	6.140	21	66	0.2938	-0.3389	-
7	14768	29.13	7.823	9	66	0.4005	-0.5036	-
----- ID CLASS=FARM & GRASSLAND -----								
4	3398	27.85	2.432	22	39	0.7807	0.3731	< 0.01
5	3398	28.82	4.334	21	50	0.9494	0.6167	< 0.01
6	3398	43.72	4.317	27	60	0.2097	0.6467	< 0.01
7	3398	36.33	5.289	13	59	0.0752	0.7639	< 0.01
----- ID CLASS=BARREN -----								
4	175	30.15	2.492	25	39	0.9382	0.8244	< 0.01
5	175	33.85	5.717	25	57	1.1293	1.3257	< 0.01
6	175	43.92	6.408	28	64	0.0278	-0.0173	> 0.15
7	175	33.82	6.872	17	52	-0.0654	-0.1310	0.134
----- ID CLASS=DEVELOPED AREA -----								
4	1903	32.34	2.814	24	49	0.5575	1.7460	< 0.01
5	1903	36.49	4.650	22	58	0.4163	1.1219	< 0.01
6	1903	43.85	4.017	30	59	0.0811	0.6662	< 0.01
7	1903	33.67	4.332	17	51	0.0481	1.1027	< 0.01
----- ID CLASS=FOREST -----								
4	273	26.26	1.672	22	35	1.1556	3.6679	< 0.01
5	273	25.29	2.779	20	43	1.5311	6.0492	< 0.01
6	273	47.08	3.455	36	59	-0.0210	1.2251	< 0.01
7	273	44.01	4.227	31	57	0.2091	0.5457	< 0.01
----- ID CLASS=PADDY FIELD -----								
4	8084	28.15	1.820	22	38	-0.0888	0.2291	< 0.01
5	8084	29.16	3.050	21	44	0.1479	0.4789	< 0.01
6	8084	34.99	3.944	23	63	0.6429	2.0648	< 0.01
7	8084	23.93	4.772	11	56	1.0523	2.5329	< 0.01
----- ID CLASS=RESIDENTIAL AREA -----								
4	566	31.22	3.338	25	51	1.7109	6.5654	< 0.01
5	566	34.24	5.540	24	63	0.8841	2.5167	< 0.01
6	566	45.23	4.412	34	66	0.8624	2.9849	< 0.01
7	566	36.47	5.754	21	66	0.6091	2.0978	< 0.01
----- ID CLASS=WATER SURFACE -----								
4	369	28.34	1.305	25	32	0.3649	-0.1808	< 0.01
5	369	27.71	2.659	21	39	0.7343	1.1037	< 0.01
6	369	37.23	7.428	21	56	-0.1758	-0.5500	< 0.01
7	369	28.91	8.758	9	52	-0.1771	-0.6475	< 0.01

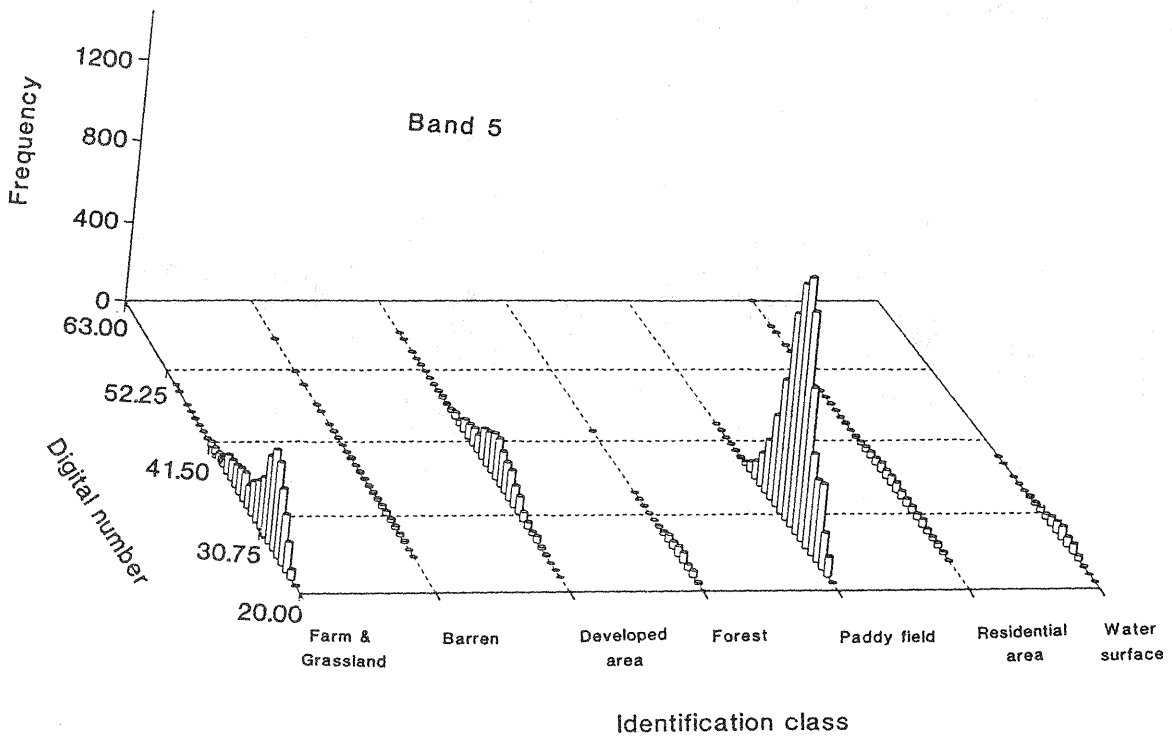
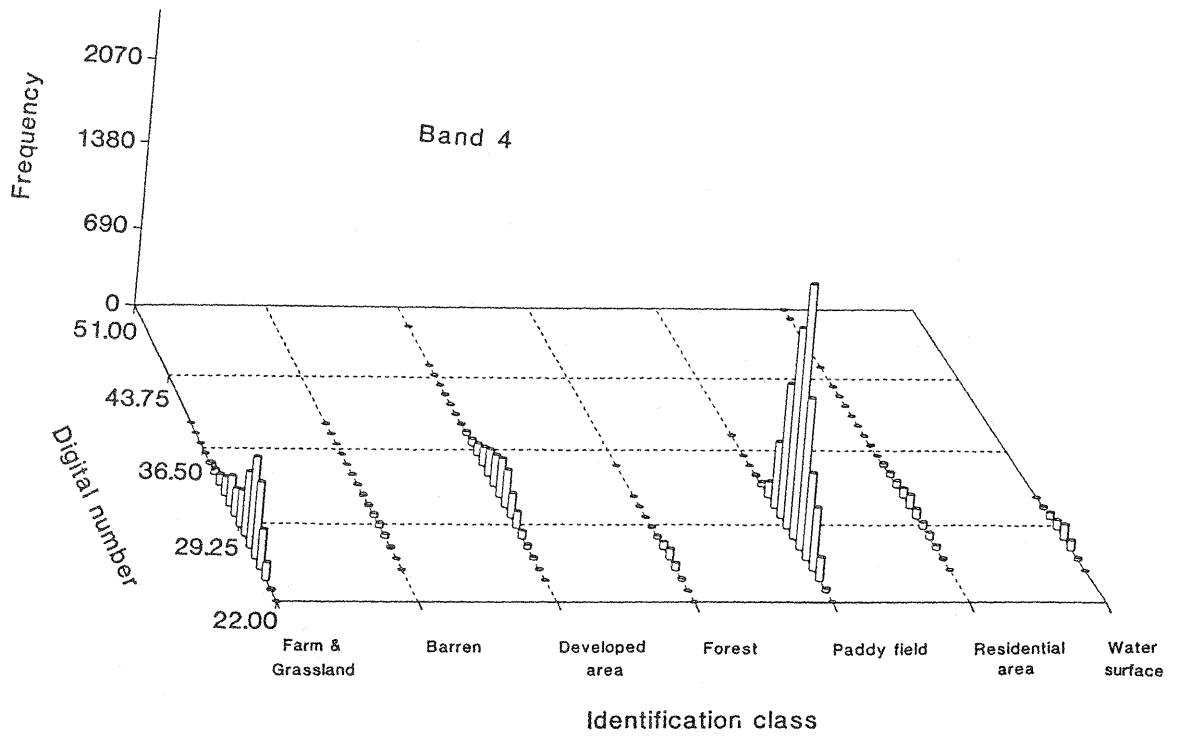


FIGURE 6. COINCIDENT SPECTRAL HISTOGRAMS

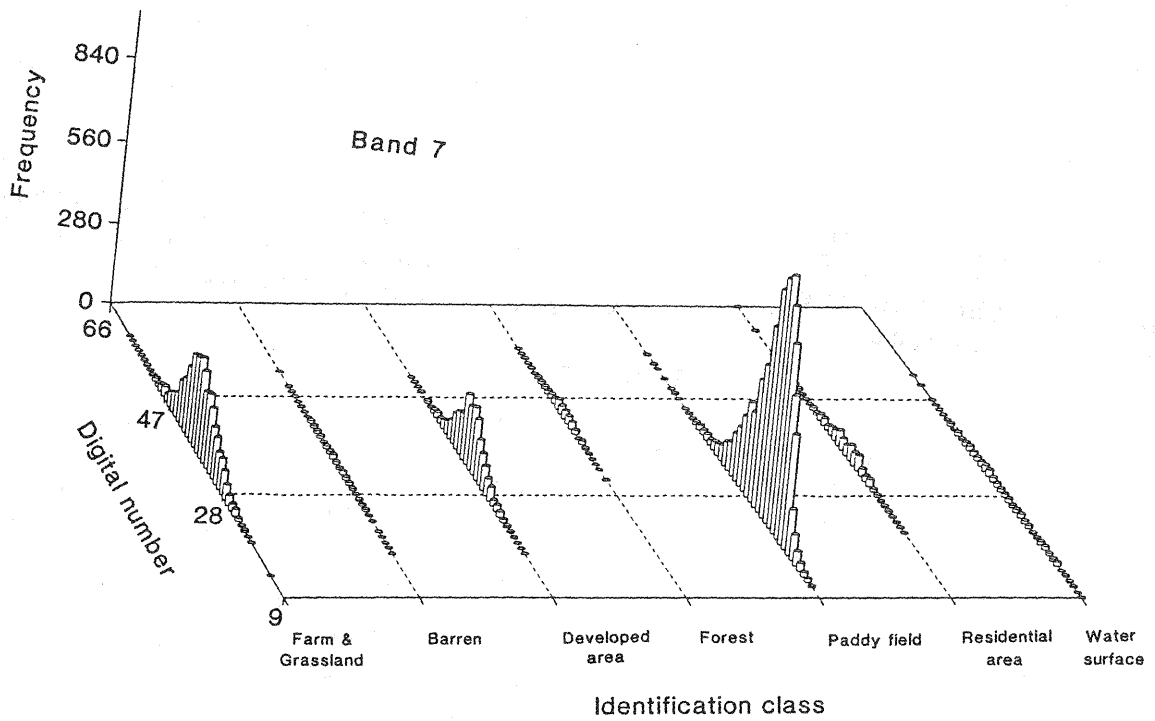
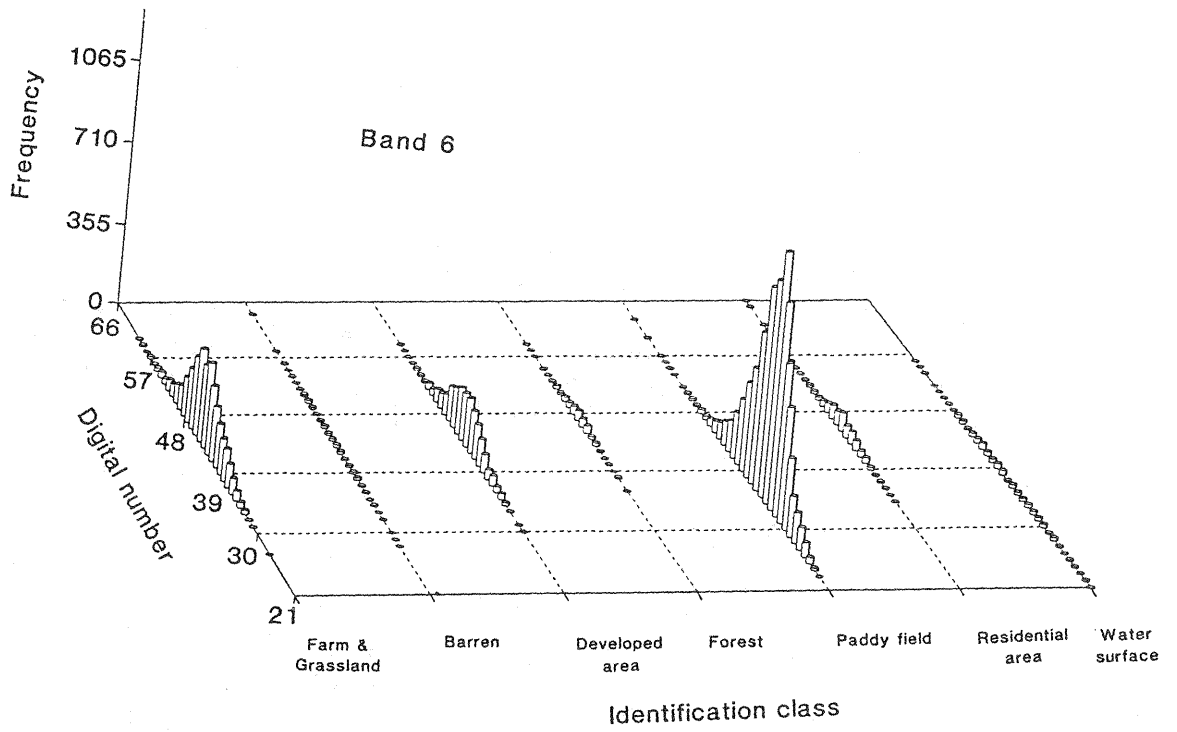


FIGURE 6. COINCIDENT SPECTRAL HISTOGRAMS
(CONTINUED)

The sizes are 25, 50, 75, and 100 percent of the whole scene test area respectively. The datasets for analysis were made by deletion(or keeping) of every other/every fourth record.

Classification Methods

Eight supervised discriminant analyses were carried out. Their abbreviations henceforth are expressed as follows,

- IP: application of Individual within-class matrices with Proportional prior probabilities using all four bands
- IE: application of Individual within-class matrices with Equal prior probabilities using all four bands
- PP: application of a Pooled covariance matrix with Proportional prior probabilities using all four bands
- PE: application of a Pooled covariance matrix with Equal prior probabilities using all four bands
- OIP: Ordination by principal component analysis --> IP using the two principal components as specified below
- OIE: Ordination by principal component analysis --> IE using the two principal components as specified below
- OPP: Ordination by principal component analysis --> PP using the two principal components as specified below
- OPE: Ordination by principal component analysis --> PE using the two principal components as specified below.

The ordination methods adopted here have several anticipated advantages of reducing both parameter estimation number(from 18 to 7) and redundant noise which could be contained in data. This procedure should have a trade-off relation with the ordinary all-band plain usage.

Two principal components indicated 96.36 percent of cumulative contribution(52.92% for the first, 43.44% for the second), therefore the two axes selected out of four. Please note that a pooled correlation matrix was used in the calculation.

Results

Kappa coefficients of agreement (Rosenfield and Fitzpatrick-Lins, 1986; Congalton and Mead, 1983; Congalton, Oderwald and Mead, 1983; Hudson and Ramm, 1987) for a whole scene were calculated by each method and training size besides conventional percent correctness(Table 4). The 'test' row means post classification results against the overall test field. For example, 'IP test 25%' expresses that the IP calibration data was derived from the 25% training area in the whole test field, and then, post classification accuracy for the rest 75% of the data computed. The 'train' row shows calibration result only, based on the discriminant function generated.

The columns in the Table 4 show the comparisons under the same sampling size of training area while the rows give training area size shift by the same classification method.

Comparison of the methods

TABLE 4. SUMMARY OF Khat STATISTIC BY EACH METHOD

TEST: POST CLASSIFICATION RESULT AGAINST
THE OVERALL TEST FIELD
 TRAIN: CALIBRATION RESULT BASED ON DISCRIMINANT
FUNCTION GENERATED ONLY
 % CORRECT.: PERCENT OF THE SUM OF DIAGONAL VALUES TO
TOTAL NUMBER OF CELL COUNTS IN
CONTINGENCY TABLE

		TRAINING AREA SIZE (TOTAL OBSERVATION NUMBER = 14768 IN THE TEST FIELD)			
		25 %	50 %	75 %	100 %
IP	TEST	0.6176 (76.92%)	NA	NA	-
	TRAINING	0.6028 (76.03%)	NA	NA	0.6168 (76.77%)
IE	TEST	0.5041 (66.05%)	0.4963 (65.32%)	0.4887 (64.62%)	-
	TRAINING	0.4975 (65.63%)	NA	0.4911 (64.76%)	0.4900 (64.80%)
PP	TEST	0.6029 (76.16%)	NA	NA	-
	TRAINING	0.5838 (75.05%)	NA	NA	0.6058 (76.27%)
PE	TEST	0.4544 (61.25%)	0.4625 (62.02%)	0.4609 (61.90%)	-
	TRAINING	0.4476 (60.89%)	NA	0.4650 (62.16%)	0.4607 (61.84%)
OIP	TEST	0.5999 (76.20%)	NA	NA	-
	TRAINING	0.5819 (75.16%)	NA	NA	0.6038 (76.29%)
OIE	TEST	0.5003 (66.37%)	0.4955 (65.87%)	0.4822 (64.63%)	-
	TRAINING	0.4813 (65.03%)	NA	0.4879 (65.01%)	0.4858 (64.98%)
OPP	TEST	0.5947 (75.89%)	NA	NA	-
	TRAINING	0.5760 (74.81%)	NA	NA	0.5998 (76.07%)
OPE	TEST	0.4355 (59.78%)	0.4388 (60.10%)	0.4396 (60.20%)	-
	TRAINING	0.4155 (58.50%)	NA	0.4454 (60.58%)	0.4388 (60.12%)

Table 5 shows the order of accuracy based on the KHAT values in Table 4. The remarkable thing is that there is a large accuracy gap between the methods with prior land-use probabilities, and without them by ca. 15 percent (based on % correct) when the values in Table 4 also referred, where the former assume a postiori probabilities.

The usefulness of those prior values were thus confirmed in actual analysis here. It would be worthwhile computing discriminant analysis twice, with equal prior probabilities first, and then with the culculated rough a postiori ratio, using recent 32-bit low cost super personal computer free of computation charges.

The accuracy orders of the matrix-calculation method in the second place, dividing the above two groups, show distinct results. The ordination methods look different behavior between the two groups. It would be reasoned that the contradiction in the ordination procedure between the first pooled treatment of principal component analysis and the following individual calculation of matrices in the OI_x series. Other aspect of this issue is to be dealt later, in 'Comparison of KHAT and % correctness'.

TABLE 5. ACCURACY ORDER OF METHODS BY TRAINIG SIZE(KHAT)

25 %	TEST	IP > PP > OIP > OPP >> IE > OIE > PE > OPE
	TRAIN	IP > PP > OIP > OPP >> IE > OIE > PE > OPE
50 %	TEST	(N. A.) IE > OIE > PE > OPE
75 %	TEST	(N. A.) IE > OIE > PE > OPE
	TRAIN	(N. A.) IE > OIE > PE > OPE
100 %	TRAIN	IP > PP > OIP > OPP >> IE > OIE > PE > OPE

Comparison of training sizes

Apparent trend is attributed to the size sensitibility difference that calculation of individual matrices could be worsened when very large sampling size taken, while pooled covariance matrix ones was not necessarily affected. Fujimura et al.(1978) pointed out that there is a tendency of that category of smaller variance mis-classified into larger one. Further split of the sizes could find the optimum trainig size for individual matrix methods which have usually better classification accuracy than that of the pooled(Table 5).

Comparison of KHAT and % correctness

Table 6 re-sorts Table 5 by % correctness. While the Table 6 shows a little fluctuation of order in 25 % row, structural discrepancies, however, lies between them. The behavior of the ordination methods in the order queue would be regarded as a key. Further investigation should be executed to anatomize this

dynamics which was beyond the author's command this time. However, two general trends could be pointed out that the ordination methods are apt to ignore minority categories of small sampling number, which suggests that the original spectral information contains little redundancy or noise, and that % correctness evaluation also underestimates the small sampling size minorities which conceal themselves among other big diagonals. An extreme example was a post classification result of OPP method with 25 % training area size that encompasses none of 'barren', 'low-densed residential area & parks', and 'water surface', with accuracy outcome of 75.89 percent.

TABLE 6. ACCURACY ORDER OF METHODS BY TRAINING SIZE (% CORRECTNESS)

25 %	TEST	IP > OIP > PP > OPP >>	OIE > IE > PE > OPE
	TRAIN	IP > OIP > PP > OPP >>	IE > OIE > PE > OPE
50 %	TEST	(N. A.)	OIE > IE > PE > OPE
75 %	TEST	(N. A.)	OIE > IE > PE > OPE
	TRAIN	(N. A.)	OIE > IE > PE > OPE
100 %	TRAIN	IP > OIP > PP > OPP >>	OIE > IE > PE > OPE

Discussion

Spectral perturbation potential in the original ground data

As shown in Table 2, the original ground data is not perfectly suitable for spectral analyses. For example, collecting several band-7 digital numbers of dark-displayed areas in figure 3, they showed no anomalies (mean values: Sayama and Tama lakes=9.0, oblique shadow of a cloud=15.1, the sea=4.4, and the big paddy fields=18.3). It means that the values of 'water surface' in Table 3 are not actually of water, because of the fact that GSI counts all stuff inside of a river bank as water body, even when the water level of an urban river is low and scarce.

According to the detailed descriptions of land-use category definition of the file (Geographic Survey Institute, 1984), a lot of such distinct discrepancies can be easily found. If there should be some renewal of the definition criteria of land-use, in coincidental respect of land-cover spectral features, many useful and practical research methodologies would blossom into reality such as to precisely estimate the mixel effect and to determine empirically the optimum spatial resolution (Ioka and Koda, 1986; Arai, 1985), combining the very fine and reliable ground data of new taxonomy.

Data deterioration caused by interpolation

This study used the image data transformed twice. Firstly by the retailer (RESTEC; cubic convolution), and secondly by

ourselves (bi-linear). However, the authors should assume that there be the little effect on the comparisons by any classification method that used the same data of the same conditions.

Conclusions

Profitability of the very orthodox methodology employed in this study is confirmed in terms of deriving systematic sets of outcomes based on actual scrutinies of classification methods based on ground verification. Re-defined fine resolution ground data involving land-cover spectral features, therefore, are proven to be highly useful.

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Last but never in the least, Prof. S. Murai had been kind enough to suggest papers in a good match which were very useful to avoid terminology confusions of GIS, long-before the authors applied to ISPRS.

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