Reprinted from

Ninth International Symposium

Machine Processing of

Remotely Sensed Data

with special emphasis on

Natural Resources Evaluation

June 21-23, 1983

Proceedings

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

AN EFFECTIVE CLASSIFICATION METHOD AND AUTOMATED RESULT TESTING TECHNIQUES FOR DIFFERENTIATING CROP TYPES

G. CSORNAI, O. DALIA
Á. KOZICS-GOTHÁR, J. VÁMOSI

Földmérési Intézet/Remote Sensing Department
Budapest, Hungary

I. ABSTRACT

This paper decribes some evaluation techniques which might be useful in processing and classification of remotely sensed data. During the multispectral and multitemporal assessment and monitoring of agricultural fields the main goal is to achieve reliable, low cost methods and results that can be extrapolated with success. The histogram clustering methods can compete in speed with iterative methods. A very simple solution introduced. By using multitemporal Landsat data set vegetation types and the story of the growing stages can be examined with better results than using only a one date data. When monitoring agricultural area with bigger fields it is more effective in terms of speed /cost/ and reliability to use per field classification techniques to exploit the contextual information of images. With help of partitioning algorithm efforts were made to compensate the effects of in field inhomogeneities. There is a brief account on the usage of Bayes optimal decision rule in classification to facilitate and express users' actual interest in term of a loss matrix. A test technique of classification results is developed that gives a flexible tool and possibility for the user to assess result in term of loss instead of simple number or rate of misclassification.

II. INTRODUCTION

The increasing demand to get quick, valuable, low cost information on the different phenomena of the Earth surface is waiting for adequate response from remote sensing even in countries that are doing the first steps on the way, like Hungary. One of the most important application areas is the agriculture. There is real need to regularly assess and monitor vegetated areas. This task requires flexible, effective and reliable methods and technology to be developed.

In recent years a few projects were launched to find tools and methods to assess the status and developement of vegetation. These used different data and evaluation techniques. This presentation gives a brief account of some results achieved in one of these projects.

Parallel to finding effective methods for monitoring vegetation we have to develop evaluation methods adequate for computer. Toward a deeper understanding of underlying physical-agronomical nature of phenomena we are faced with the problems coming from usage of statistical models and techniques. When developing appropriate processing methods we aimed to get insight the dependence of results on actual data and conditions which is subject of thorough study in literature.[10]

As iterativ clustering methods generally use Euclidian or similar metrics we developed a histogram clustering algorithm which is faster and could avoid the dependence of results on the intensity range of actual data. To help users in achieving the maximum correctness or the minimum loss with classification, we adopted the idea of Bayes optimal decision technique and developed computer program.

Though usage of multitemporal data set and per-field techniques reduce the inhomogeneities of image that should be treated as noise in land use mapping we should generally treat these techniques as complement ones depending on the task to be solved.

The development of adjustable result test technique was motivated by the goal to ease the way toward deeper knowledge of classification methods.

III. STUDY AREA AND DATA SET

The study area is located at the eastern part of Hungary on the Great Plain. From an approximately 7oox7oo pixel /Landsat MSS/ area more than the half has proven to be very feasible for the purposes of monitoring the vegetation and agricultural fields with remote sensing methods. The terrain is flat and bears a relatively homogeneous soil body. Microclimate and other conditions make this area suitable for intensive agriculture. Besides we can find some important crops here within a limited area e.g. several types of corn, wheat, sunflower, sugar beet etc.

In the project we used a set of Landsat MSS data collected from an important period of the growing season in 1981. Only four scenes were partly cloud free: June 29 /t_A/, July 17 /t_B/, August 4 /t_C/, Sept 27 /t_D/. In addition to some mainly qualitative ground truth data recorded at farms, we used MKF-6 six band aerial photos that were taken during a mission on the 6th July. At last we selected six subscenes /S2 - S7/ that were representative enough to the whole area and used them during the training and test of classification result.

IV. METHOD

A. PREPROCESSING

As the first step we compiled a detailed land use and vegetation status map on the basis of the visually interpreted color composites of MKF-6 bands and ground truth data from farms. That data served as reference to training and classification. After selecting the neccessary subimages from Landsat CCT-s we removed strips from data.[1] After examining the geometrical correctness of subimages we made pixel size correction by a simple resampling using nearest neighbour interpolation. For the multitemporal analysis we registered the four date Landsat data set with the help of a computer program developed to facilitate to remove geometrical distortions.[2] Though this correction method can approximate distortion functions with two variable polinomials up to six degree we used only the linear mapping option with the control point set resulting a 0.4-0.5 pixel residual error in registration.

To ease further multitemporal analysis of this agricultural area we interleaved the registered MSS7 channels of the four dates data, creating a new pseudo image /referred as t_M/. This accumulates the information coming from vegetation in a certain period of the growing season and it has quite a different and broader meaning than it is of one Landsat MSS scene.

On the basis of compiled reference thematic map digital reference thematic map was generated and loaded to the computer. It is a one channel image where pixel values are codes correspond,to each thematic class,respectively. An example is shown in grey tone map representation on Figure 1.c.

B. TRAINING TO THE CLASSIFICATION

The previously selected representative six subimages served as input data to clustering. To achieve a relatively low cost training we tried to select the possible least amount of input data that were representative to classes of the total area. An iterative clustering program was developed in our department that based on ISODATA algorithm.[1,3,4] At the step of merging close clusters we used Swain-Fu distance. As this intercluster distance does not hold triangular inequality we added a hierarchical agglomerative merging procedure to avoid misleading results.[5,6] Euclidian and sum of absolute difference point to point distance was used.

Besides this iterative clustering method another algorithm based on multidimensional histogram was elaborated. Instead of hashing techniques the conventional box-type storage method was used. A requantization through lookup tables helps to exploit the inherent redundancy of pixel intensity data to minimize the neccessary memory. Once the histogram is built a direct method leads to find local maxima. The definition of local maximum is again very simple and is based on the frequency of the tested cell and its closest neighbours in all dimensions.[7] To avoid peaks originating from noise, histogram passed through a filter. Smoothing is then applied to merge too close peaks. This algorithm requires approximately 1-2 times more memory than the iterative method but 3 times faster. As a cluster assignment lookup table is used this rate of speeds increases for bigger amount of subimage data.

It was shown that it is more effective to use per-field classification techniques in all those applications, where homogeneous objects to be classified are much bigger than the pixel size.[8] It was the case in our study when monitoring agricultural fields of mean size of 4oo pixels. We modified the algorithm to allow arbitrary directed edges of partitions. After partitioning we clustered partitions by the ISODATA method and with a supervised learning we classified homogeneous objects, and pixels of inhomogene cells by maximum likelihood method.

To assist training procedure a program package was designed to gather information on the physical/cluster components of different thematic classes. This technique is based on similar methods that were applied to digital reference map. The procedure can optionally give information on the configuration of component clusters. This method can offload the interpretator and contribute to the reliability of training and classification reducing the costs and time requirements of iterative learning.

C. CLASSIFICATION METHODS

We used during this project the maximum likelihood classification method. We implemented this algorithm with some options. The classification scheme is that given P_i, p_i, T_i $i=1,2,\ldots,N$ we decide class c_j if

$$A(x)=P_j p_j(x) = \max_{i=1,..N} \left\{ P_i p_i(x) \right\}$$

$$\text{and } P_j p_j(x) \geqslant T_j$$

where N is the number of classes, c_j denotes jth class, P_i and $p_i(x)$ are the a priori probability of class c_i and conditional probability density function of pixel intensities belonging to c_i respectively. T_i is the threshold that limits the $A(x)$ value to be too small in case of which the pixel does not "resemble" to the c_i class enough. /If $A(x)<T_i$: x will be rejected/. With this a priori weight and different thresholds one can adjust an adequate classification rate. In the practical solution however, normal distributions ($p_i(x)$) are assumed and besides, a lookup table is used to assign each pixel. To achieve further increase in speed the symmetry of covariance matrix was exploited.

To further respond to users' interest one can modify the maximum likelihood decision rule /MLDR/ with help of loss function $L(i,j)$[9]. $L(i,j)$ expresses the loss coming from a decision when a pixel actually belonging to c_j is classified to c_i. The decision rule that minimize the expected /or average/ loss to the whole image is called Bayes optimal /BODR/. User can introduce antisymmetric decisions which treat transitions from c_j to c_i different from c_i to c_j, and can control the error of omissions and commissions independent and by classes. The result of the classification can be characterized by the loss instead of number or ratio of misclassification belonging to each class.

D. COMPUTER AIDED RESULT TESTING

Once a reference thematic map is in the computer we can compare classification results by the computer. This is a convenient way how one can get reliable information of goodness of classification. In case of multitemporal analysis of agricultural fields where there are rather small changes in positions of boarders only the thematic codes should be updated.

Generally we are interested not only in the amount of confusions but the direction of transitions as well. There are often differences in loss coming from misclassifications. This loss can also be a function of user's interest /market and other conditions etc/. We can express this interest by numerical terms simply entering a loss function, quite similar to that used in BODR method. The difference is that while the latter can affect the decision rule itself the former only helps to estimate the appropriateness of classification result.

V. RESULTS AND DISCUSSION

After the preprocessing phase we clustered data of selected subimages S2-S7 corresponding to different dates /t_A, t_B, t_C, t_D, t_M/. The results reflected well the temporal changes of vegetation and verified most the inhomogeneities that could be seen on aerial photoes. Illustration of these within-field inhomogeneities is shown on Figure. 1.a. The results were similar with other subimages and dates. One of the two exceptions was the clustermap of multitemporal data. That was more homogeneous that can be followed from that the temporary inhomogeneities might balance the effect of each other. The previously partitioned subimage led to similar result.

Because of the inhomogeneities it was very hard to define thematic classes. It was not possible to locate homogene areas that would represent different growing stages /subclasses/. Sometimes when relatively uniform fields were found the spectral properties coincided with that of lots of inhomogene spots scatterred in the fields.

Before extrapolating training data to classify a bigger area we tested the re-

Figure 1.a.Clustermap /S2, t_B/.

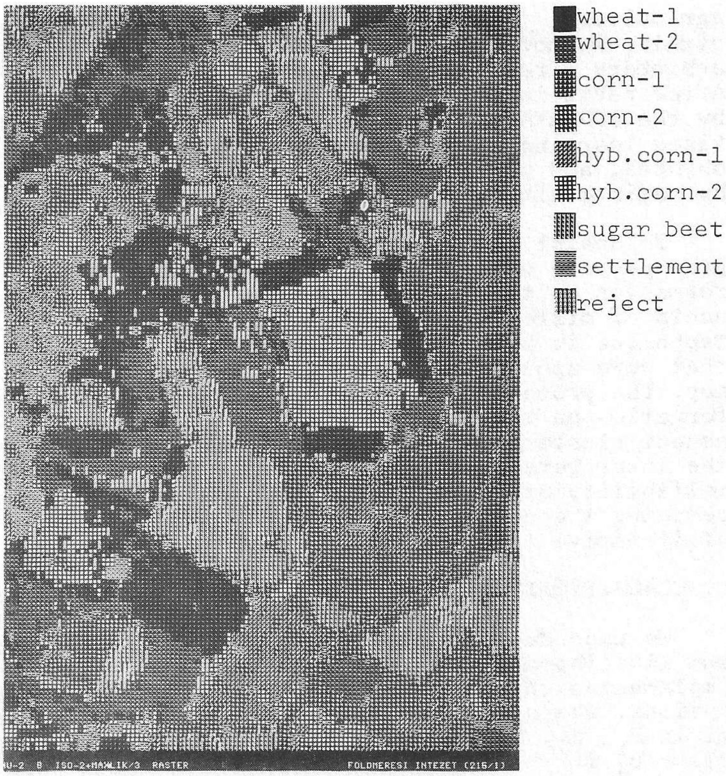

Figure 1.b. Classification map.

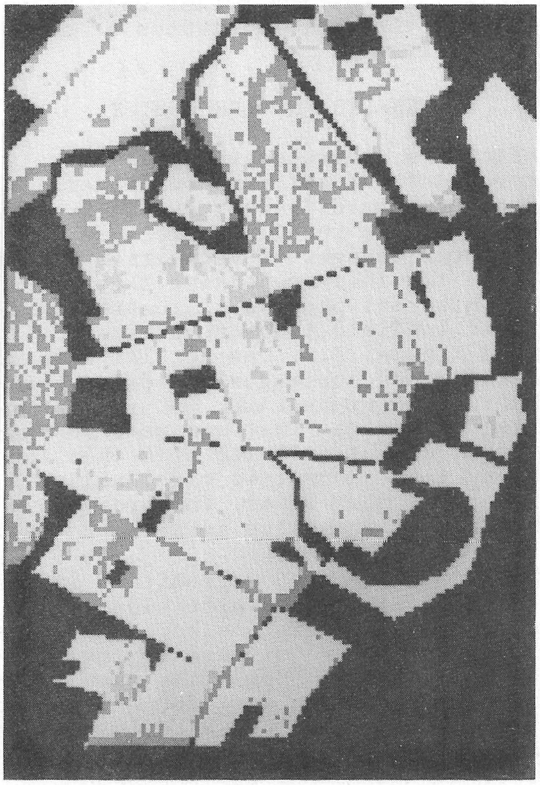

Figure 1.c. Difference image.
/Black: excluded area; white: correct class/

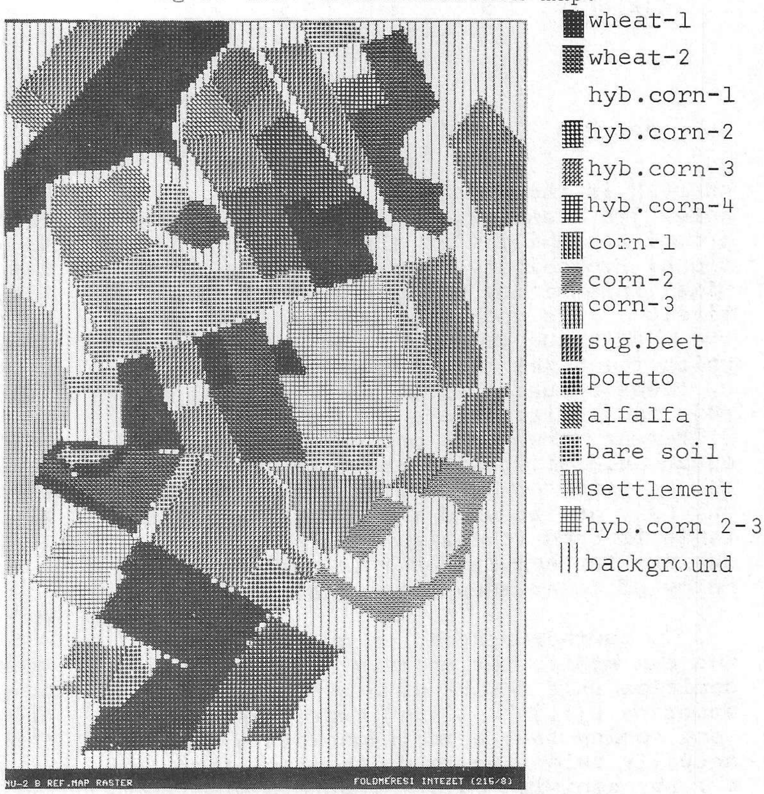

Figure 1.d.Digital reference thematic map.

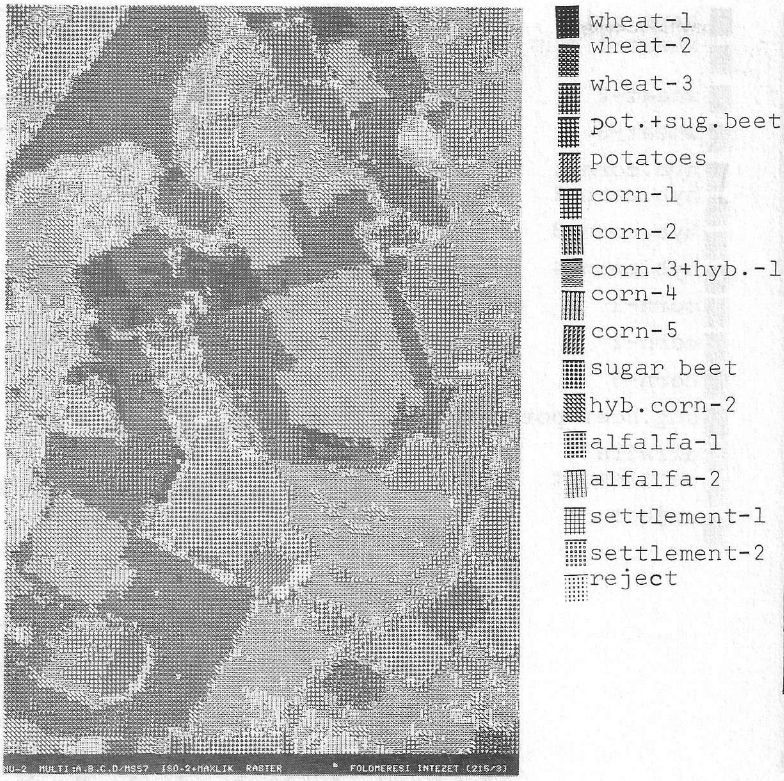

Figure 2. Classification map of multitemporal image.

		Classified as / # pix./											
		1.	2.	3.	4.	5.	6.	7.	8.	9.	Σpix	Σerr	% correct
C	1.	7o6	28	o	o	o	o	o	1o	6	75o	44	94
L	2.	1o	389	o	o	o	o	o	4	22	425	36	92
A	3.	o	o	184	4	o	3	o	o	3	194	1o	95
S	4.	o	o	o	371	46	2	o	o	o	419	48	88
S	5.	o	o	o	29	37o	21	o	6o	o	48o	11o	77
	6.	9	o	o	o	o	8o2	o	46	o	861	59	93
	7.	o	o	27	o	o	o	9o7	o	55	989	82	92
	8.	11	o	1	45	117	45	o	28o	7	5o6	226	55

Legend: 1. wheat-1; 2. wheat-2; 3. corn-1; 4. corn-2; 5. hybrid corn-1; 6. hybrid corn-2; 7. sugar beet; 8. settlement; 9. reject

Table 1. Confusion matrix. Classification result of S2 subimage from t_B.

	Classified as / # pix./																
	1.	2.	3.	4.	5.	6.	7.	8.	9.	1o.	11.	12.	13.	14.	Σpix	Σerr	% correct
C 1.	11o	1o	o	o	o	o	o	o	o	o	o	o	o	o	12o	1o	92
L 2.	o	46o	25	o	o	o	o	o	o	o	o	o	o	o	485	25	94
A 3.	o	o	524	o	o	o	o	o	o	54	o	o	3	3	584	6o	89
S 4.	o	o	o	269	o	o	o	o	o	o	o	o	o	3	272	3	98
S 5.	o	o	o	o	144	o	o	o	o	o	o	o	o	25	173	25	83
6.	o	o	o	o	o	33o	4	8	o	o	o	o	o	o	346	12	95
7.	o	o	o	o	o	o	74	o	o	o	o	o	o	4	78	4	94
8.	o	o	o	o	o	o	o	1o75	o	o	o	o	17	o	11o5	17	97
9.	o	o	o	o	o	o	o	o	813	o	o	o	o	1o	823	1o	98
1o.	o	o	o	o	o	o	o	o	o	74o	o	o	o	6	746	6	99
11.	o	o	o	o	o	o	o	o	o	o	22	o	o	39	61	39	36
12.	o	o	o	o	o	o	o	26	o	4o	o	11o	137	o	313	2o3	35
13.	o	o	o	o	o	o	o	85	o	118	o	3oo	1oo	o	6o3	5o3	16

Legend: 1.wheat /ploughed in June/; 2.wheat /ploughed in Sept./; 3. wheat /before plough/; 4. potatoes and sugar beet stubble; 5. potatoes; 6. corn-1; 7. corn-2; 8. corn-3+ hyb. corn-1; 9. sugar beet; 1o. hyb. corn-2; 11. alfalfa-1; 12. alfalfa-2; 13. settlement; 14. reject

Table 2. Confusion matrix for classification result of subimage S2, multitemporal /t_M/

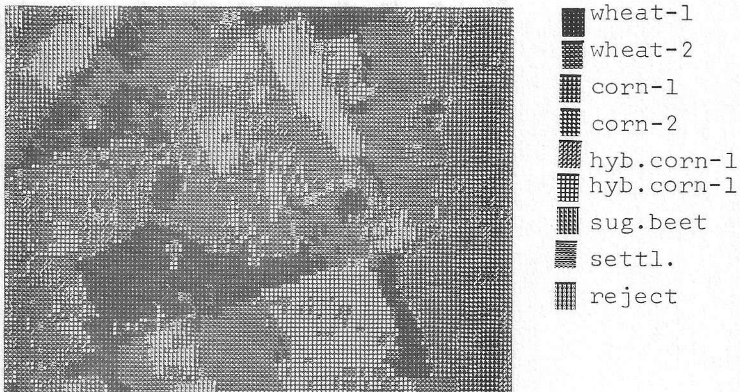

Figure 3. Result map of Bayes classification.

Reference category	# pix	% correct
1. bare soil	37o	91
2. wheat-1	1794	97
3. wheat-2	738	98
4. wheat-3	799	91
5. hyb. corn-1	261	98
6. hyb. corn-2	475	83
7. hyb. corn-3	227	88
8. hyb. corn-4	284	93
9. corn-1	419	97
1o. corn-2	222	85
11. corn-3	2o1	98
12. sugar beet+potato	545	94
13. alfalfa	45	92
14. settlement	6o3	26

Table 3. Classification result for partitioned image /S2 subimage, t_B/

	1.	2.	3.	4.	5.	6.	7.	8.
1.	0	1	15	15	15	15	8	1o
2.	2	0	15	15	15	15	8	1o
3.	6	7	0	1	2	2	8	2o
4.	6	7	1	0	1	1	8	2o
5.	6	7	3	2	0	1	8	2o
6.	6	7	3	2	1	0	8	12
7.	7	8	15	15	15	6	0	8
8.	3o	3o	2o	2o	2o	7	1o	0

Legend:

1.wheat-1,
2.wheat-2,
3.corn-1,
4.corn-2,
5.hybrid corn-2,
6.hybrid corn-3,
7.sugar beet,
8.settlement

Table 4. Loss matrix for Bayes decision

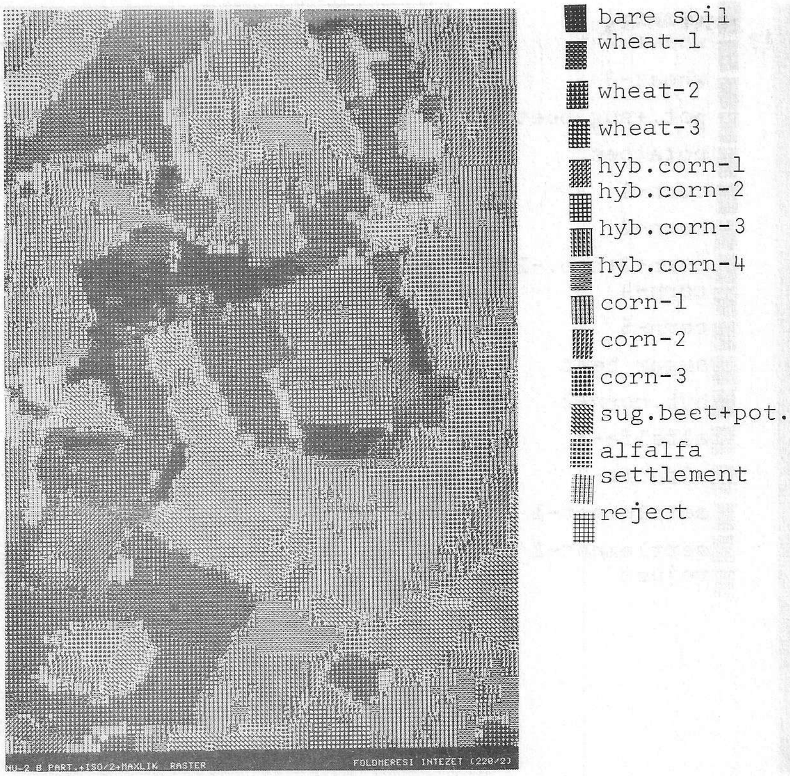

Figure 4. Classification of partitioned image /S2, t_B/

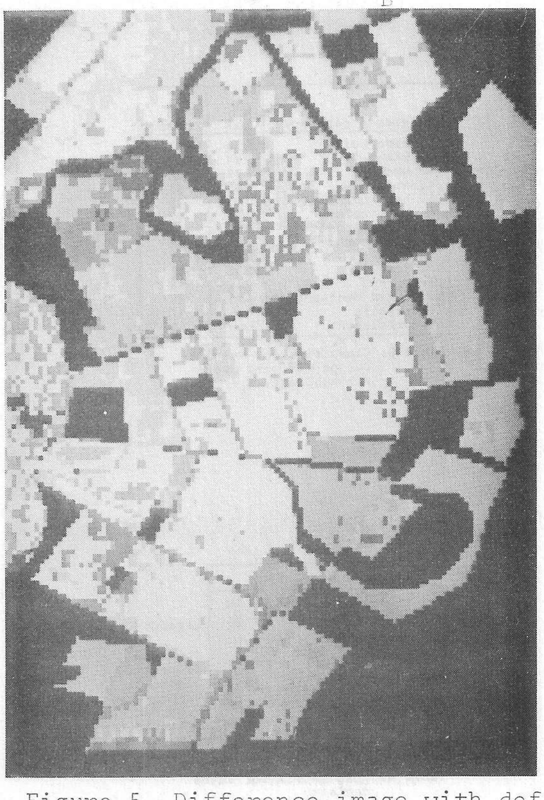

Figure 5. Difference image with defined loss /Black: excluded area, white: correct class/

Transitions of classes	8 → 1,2	7,8 → 3,4,5	1,2 → 3,4,5,6	3,4,5,6 → 8
Max.likl. classif.	o,1%	5,5%	o,46%	41,1%
Bayes classif.	Ø%	o,5%	o,15%	22,3%

Table 5. The effect of loss function in BODR

category	1.	2.	3.	4.
#pixel	5679	4995	1891	713
#correct classif.	4516	4145	1432	3o9
% correct classif.	79.5	83.o	75.7	43.3

Legend: 1.wheat; 2. corn;
3.sugar beet; 4. settlement

Table 6. Classification result of subimage S2, t_B. Computed from the difference classification map and reference map.

A \ B	1.	2.	3.	4.	5.	6.	7.	8.	9.
1.	1	3	18	18	15	15	2o	32	1o
2.	5	1	17	17	14	14	15	31	1o
3.	25	23	5	4	2	2	12	31	1o
4.	23	21	5	4	1	2	11	31	1o
5.	19	18	4	3	2	1	11	31	1o
6.	15	15	4	3	2	2	11	31	1o
7.	16	15	4	5	3	3	12	31	1o
8.	12	12	4	5	3	3	12	31	1o
9.	2o	18	5	4	5	5	12	31	1o
1o.	4o	4o	1o	12	8	8	1	31	1o
11.	8	8	2o	2o	2o	2o	5o	2	2
12.	6o	6o	14	1o	12	12	7o	1	2
13.	2o	2o	5	3	1	1	11	31	1o

Legend:
Reference image /A/: 1. wheat-1; 2. wheat-2; 3. hyb. corn-1; 4. hyb.corn-2; 5. hyb. corn-3; 6.hyb. corn-4; 7. corn-1; 8. corn-2; 9. corn-3; 1o. sugar beet; 11. bare soil; 12. settlement; 13. hyb.-2-3-4
Classified image /B/: 1. wheat-1; 2. wheat-2; 3. corn-1; 4. corn-2; 5. hyb. corn-1; 6.hyb. corn-2; 7. sugar beet; 8. settlement; 9. unclassified

Table 7. Loss matrix for substraction classification /S2 subimage, t_B/ and reference map.

A \ B	# [%] 1	2	3	4	5	6	7	8	9	pix	err pix	%err	loss	%loss
1.	43	38	1	1	1	5	o	5	1	2393	515	15.9	15492	22.o
2.	3	75	o	1	o	1	o	1	15	1362	284	8.8	4723	6.7
3.	o	o	1	22	63	7	o	4	o	527	25	o.8	2o26	2.9
4.	o	o	2	7	32	23	o	32	o	557	189	5.8	6421	8.9
5.	o	o	1	17	9	54	o	16	o	131	22	o.7	855	1.2
6.	31	3	2	1	o	57	1	2	o	83	32	1.o	615	o.9
7.	o	o	7o	23	2	o.	o	o	1	1146	33	1.o	5252	7.4
8.	o	o	36	4o	17	1	o	3	o	474	16	o.5	2433	3.5
9.	o	o	o	66	21	5	o	4	o	292	17	o.5	1659	2.4
1o.	o	o	9	3	o	o	77	1	5	1682	38o	11.7	5934	8.4
11.	73	o	o	o	o	6	o	2	14	1384	1144	35.2	1118o	15.9
12.	4	4	1	8	22	11	o	43	3	713	379	11.7	8137	11.6
13.	12	o	o	1	1	79	o	4	1	1187	211	6.5	5656	8.o
										13278	3247		7o383	

Legend:
Reference image /A/: 1.wheat-1; 2. wheat-2; 3. hyb.corn-1; 4.hyb.corn-2; 5.hyb.corn-3; 6. hyb.corn-4; 7.corn-1; 8.corn-2; 9. corn-3; 1o.sugar beet; 11. bare soil; 12. settlement; 13.hyb.-corn-2-3-4;
Classified image/B/: 1. wheat-1; 2. wheat-2; 3.corn-1; 4. corn-2; 5. hyb. corn-1; 6.hyb. corn-2; 7. sugar beet; 8. settlement; 9. unclassified.

Table 8. Confusion matrix with losses between classification map and reference map.

sults in several way. On Figure 1.b. the resulted thematic map of maximum likelihood classification can be seen. As the digital reference thematic map did not coded the inhomogeneities and expressed only simple land use categories, with help of "inclusive" loss matrix we allowed transitions within categories. Figure.1.d. shows the inclusive difference image and Table 6. corresponds to that. Table.1. was made taking inhomogeneities into account.

The general difficulty in accurately classifying sparse villages can be observed from both Table 1. and Figure 1.d. One of the reasons is the fact that these types of villages have lots of bigger green spots /gardens, groups of trees etc/ and the contribution of spectrally different artificial materials /roads, roofs/ is rather small and spatially nonuniformly distributed. In fact, the classification of previously partitioned image /Figure 4, Table 3./ shows this more clearly. As in June the hybrid corn is undeveloped the integrated Landsat pixel itself unsatisfactory to differentiate these user categories. The integration effect of partitioning which was useful to decrease the effect of field-inhomogeneities, is responsible for the increasing error in classifying settlement.

Examining the classification results of segmented subimage a striking increase in percent of correct classification can be observed together with the ability of distinction more classes than it was possible from per point procedure. /Figure 4. Figure 1.b., Table 3.-Table 1./. This definite increase in the number of detectable classes with an average 5 percent improvement in correct classification offer a possible way to compensate effect of field inhomogeneities. This can be advantageous mainly in making different land use maps. In case of recognition settlements one possible way of improving results might be the use of texture information in classification.

Similar improvement can be seen on results of the classification of multitemporal data /Figure 2, Table 2./. As in multitemporal data a certain progress in growth of vegetation is accumulated, to the correspondence with categories of a definite date we have to use additional identifiers to vegetation classes: the actions and dates of cultivation /Table 2./. Beyond the smoothing effect of this data discussed above as an interesting effect the capture of alfalfa can be noticed. This is because of the spectral similarities and the poor training data of alfalfa.

On rather inhomogene areas the use of segmented images in classification procedure can give misleading results. When we are forced to use per-point classification methods, on the basis of experiences of the training and knowledge on the area we can adjust the classification using the Bayes optimal decision rule. After we noticed commission-error in the different classes in maximum likelihood classification /originating mainly from settlement pixels/ we defined a special loss function to cut this type of error /Table 4./. The numbers in the matrix have only relative meaning. As for example the were 117 commission-error in class 5 /Table 1./ we set $L/8,5/=20$ to prevent or make more difficult for the actually settlement pixels to get into hybrid corn-1 class. Similar were done by pairs corn -wheats, corn-sugar beet, corn, wheat-settlement etc. The improvement in result can be seen in Table 5. Beside the compensation of bad separability between spectrally similar or dispersed classes there is another interpetation of usage of this technique. If for example one is interested in underestimation of expected yield of wheat he should define the loss matrix similarly as it is done in Table 4.

Given a reliable classifier, sometimes the error percents and the confusion matrix fails to express the financial or other interest of users. As an example in Table 7. a loss matrix is given with help of which we wish to express our interest when assessing classification result of S2, t_B subimage. Values here represent estimated relative loss coming from classification. The difference with the digital reference thematic map is computed and the result is shown in Table 8. /Note that in the difference weighing loss matrix in Table 7. there are nonzeroes at positiones correspond to correct classification. It was used like that to avoid zero in ratio comparison/ In Table 8. percent errors should read as contribution ratio within the total error. The difference with percent losses are striking.

VI. CONCLUSIONS

It is substantial to choose the adequate technique in processing remotely sensed data. The optional use of multitemporal, segmentation, Bayes decision classification techniques depend on the problem and conditions of area. The advantage of multitemporal and per-field techniques are obvious and the result tester difference-method seems feasible. The use of more appropriately detailed digital reference thematic map might contribute to the reliability of classifications a lot.

REFERENCES

1. G. Büttner, É. Csató, F. Csillag and A. Szilágyi, "Multispectral Observations of Agricultural Fields in the Kisköre Test-Area" Proceedings of IGARSS'82. München, May 1982.

2. O. Dalia, "Geometrical Transformation of Digital Image" in Hungarian, Geodézia és Kartográfia 1983/1.

3. T.K. Cary, J.C.Lindenlaub, "A Case Study Using LARSYS for Analysis of Landsat Data", LARS Information Note No. 05075.

4. P.H. Swain, "Pattern Recognition: A basis for Remote Sensing Data Analysis", LARS Information Note No. 11572.

5. A.G. Wacker, D.A. Landgrebe, "Minimum Distance Classification in Remote Sensing", 1st Canadian Symposium on Remote Sensing, 1972., pp. 577-599.

6. R.O. Duda, P.E. Hart, "Pattern Classification and Scene Analysis", Wiley, 1973.

7. P. Letts, "Unsupervised Classification in theARIES Image Analysis System", 5th Canadian Symposium on Remote Sensing, Victoria, Aug. 1978.

8. R.L. Kettig, D.A. Landgrebe, "Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects", IEEE Transactions on Geoscience Electronics, vol GE-14 no. 1, pp. 19-26, 1976.

9. W.S. Meisel, "Computer-Oriented Approaches to Pattern Recognition", Academic Press, 1972.

10. G.T. Batista, M.M. Hixson, M.E. Bauer, "Crop and Soybean Landsat MSS Classification Performance as a Function of Scene Characteristics", Proc. of MPRSD'82, pp. 178-187.

ACKNOWLEDGEMENT

The authors would like to express special thanks to their colleagues who kindly helped in typing the manuscript and preparing illustrations.

This work was sponsored by the National Office of Lands and Mapping with the Ministry of Food and Agriculture.

Gabor Csornai obtained M.S. in Mathematics and Physics at the University Lorand Eotvos,Budapest, Hungary. As a research scientist he worked in the field of digital picture processing. From 1978 to 198o worked with the L. Eotvos University as an assistant lecturer. Since 1977 he has been involved in projects for application of remote sensing and lectured "pattern recognition" at the L. Eotvos University. In 198o he joined to the Remote Sensing Department of Institute for Geodesy and Cartography Budapest. Since then he has been involved in projects for "Earth resources". He was one of the leaders of project to elaborate the first minicomputer processing system for R.S. data in Hungary. He is the leader of a project to study and develop methods feasible for agricultural applications of remote sensing. His area of interest is picture processing and pattern recognition.

Oliver Dalia graduated from L.Eotvos University, Budapest in 1981 and obtained M.S. in computer science. Since 1981 he has been working as software engineer at Remote Sensing Dept. of Institute for Geodesy and Cartography-Budapest. He is involved in a project to study and develop methods of agricultural applications of remote sensing. His main area of interest is digital picture processing and pattern recognition. He attends a special postgraduate course for remote sensing engineering.

Ágnes Kozics-Gothár graduated from L. Eotvos University, Budapest in 1981 and obtained M.S. in computer science. Since 1981 she has been working as software engineer at Remote Sensing Dept. of Institute for Geodesy and Cartography-Budapest. She is involved in a project to study and develop methods of agricultural applications of remote sensing. Her main area of interest is digital picture processing and pattern recognition. She attends a special postgraduate course for remote sensing engineering.

Judit Vámosi graduated from the Technical University Budapest as an engineer of geodesy in 1978.
She joined the Institute for Geodesy and Cartography in 1979. First she worked in projects of astro-geodesy. From 198o she has been working at the Remote Sensing Dept. She is involved in a project to study and develop methods, feasible for agricultural application of remote sensing. Her area of interest is interpretation of remotely sensed images.