Inclusion of Prior Probabilities Derived from a Nonparametric Process into the Maximum-Likelihood Classifier

Fabio Maselli, Claudio Conese, Ljiljana Petkov, and *Raffaello Resti*
I.A.T.A. (Istituto di Analisi ambientale e Telerilevamento applicati all'Agricoltura)-C.N.R., P.le delle Cascine 18, 50144 Firenze, Italy

ABSTRACT: The classical land-cover classification methods based on remotely sensed data have often led to unsatisfactory results, partly due to their intrinsic limitations. In effect, parametric procedures such as the maximum-likelihood classifier are statistically stable and robust but lack in flexibility and in the capability of making correct area estimates. On the other hand, nonparametric classifiers are generally too sensitive to distribution anomalies and are critically dependent on training sample sizes.

A solution to these problems is represented by the insertion of prior probabilities derived from a nonparametric process in a conventional parametric classifier. In the present paper an example of such a method is put forward in order to merge the advantages of parametric and nonparametric strategies without the relevant shortcomings. The statistical basis of the proposed procedure is presented, and its capabilities are examined by means of a case study carried out in a spectrally complex environment of Tuscany (central Italy) using Landsat TM data. The case study has been planned so as to highlight the superior performance of the new method in different situations. The results, evaluated by common statistics, are undoubtedly satisfactory under all the points of view considered.

INTRODUCTION

SINCE THE LAUNCH OF THE FIRST SATELLITES for Earth resources exploration, digital methods of classification of multispectral remotely sensed data have assumed an increasing importance as an automatic means for land-cover mapping. Hence, a great number of investigations have dealt with the application of diverse statistical procedures for the discrimination between the cover types of a territory on the basis of their spectral signatures (Hixson *et al.*, 1980; Yool *et al.*, 1986; Booth and Oldfield, 1989). Generally, such procedures can be categorized into supervised or unsupervised depending on the presence of previous knowledge of the cover types examined and into parametric and nonparametric on the basis of the assumptions about the shape of the data distributions in the N-dimensional feature space (Sabins, 1977). Actually, among the supervised strategies, both parametric and nonparametric procedures show several intrinsic limitations which have often prevented the full exploitation of remotely sensed data for applicative purposes.

Parametric methods rely on the assumption that each group of data can be enclosed by a boundary with a defined shape; generally, multinormality in the N-dimensional space is assumed. One of the most widely known and used supervised parametric classifier is the maximum-likelihood classifier, which guarantees optimum performance when the basic assumption of multinormality is approximately valid. Among the reasons for its success is the requirement for a quite limited number of points for its training, and its relative robustness towards distribution anomalies. So it has been considered to be the most advanced classification strategy for a long period (Estes *et al.*, 1983). On the other hand, the maximum-likelihood classifier, like all the other parametric procedures, shows marked limitations when the spectral distributions of the cover categories are very far from normal, which is a very usual case in complex and heterogeneous environments. Furthermore, all parametric classifiers suffer from deficiency in area estimates, which can be extremely noticeable when the cover types are very different in extent (Maselli *et al.*, 1990).

To overcome these problems, some researchers have recently proposed the use of nonparametric methods mainly for the classification of natural surfaces (Skidmore and Turner, 1988). These methods, which make no assumption about the shape of the spectral distributions of the data, except that they can be grouped by a discriminant function, are expected to present many advantages in spectrally irregular situations. From a theoretical point of view, they can be seen as an attempt to overcome the well known problem of the low correspondance between cover categories and defined spectral classes. In practice, they have been demonstrated to perform far better than the conventional parametric procedures in many applications, and they also allow improvements in area estimates by means of simple modifications, as those described subsequently. The counterparts of these advantages are however remarkable, mainly because of the extreme sensitivity of nonparametric classifiers to the presence of biased training sets. In fact, the lack of assumptions regarding the shape of the data distributions permits the reliance on erroneous distributions not statistically representative of the entire population. Obviously, this is especially true when the training samples are constituted of a small number of points, so that in these common cases these procedures become impractical (Dillon and Goldstein, 1984).

In this context, the need is felt for a procedure which merges the advantages of the two basic strategies. An example of such a procedure is put forward here, based on the theory of the insertion of prior probabilities into maximum-likelihood processes described by Swain and Davis (1978) and Strahler (1980), and on the work of Skidmore and Turner (1988) about a particular nonparametric classification method. As will be shown, the new procedure joins the robustness and stability of the conventional maximum-likelihood method to the flexibility and suitability for correct area estimates of the nonparametric classifier.

In the present paper, a section is dedicated to the description of the main features of the two basic procedures mentioned and to the presentation of the new classification method, together with its theoretical principles. Next, a case study is exposed consisting of an application of the three classification strategies for a land-use inventory of a complex rural area in Tuscany by means of Landsat Thematic Mapper (TM) multitemporal scenes.

PHOTOGRAMMETRIC ENGINEERING & REMOTE SENSING,
Vol. 58, No. 2, February 1992, pp. 201–207.

0099-1112/92/5802–201$03.00/0
©1992 American Society for Photogrammetry and Remote Sensing

The case study has been planned in order to highlight the different performances of the procedures under examination depending on training sample size, which was expected to be a critical factor, especially when using nonparametric methods. The results have been evaluated by comparison with wide ground references employing appropriate statistical measures. Finally, a discussion is reported including the conclusions about the case study and a critical analysis of the possibilities of the new classifier.

CLASSIFICATION PROCEDURES

CONVENTIONAL MAXIMUM-LIKELIHOOD CLASSIFIER

The maximum-likelihood classifier is considered one of the most accurate and efficient discrimination procedures; under the assumption of multivariate normal distributions of the groups examined, a point classified by this method has the maximum likelihood of correct assignement (Curran, 1985). In the case of remotely sensed data, the discriminant function to be minimized for each pixel according to the maximum-likelihood theory without considering any prior probability is given by the following formula (Strahler, 1980):

$$F = (\mathbf{X}\text{-}\mathbf{M})'\ \mathbf{C}^{-1}\ (\mathbf{X}\text{-}\mathbf{M}) + \mathrm{Ln}|\mathbf{C}| \tag{1}$$

where

$\mathbf{X}$ = pixel vector,

$\mathbf{M}$ = mean vector of the class under examination, and

$\mathbf{C}$ = variance-covariance matrix of the class under examination.

By means of the standardization on the inverse of the variance-covariance matrix of each class, the process takes into account not only the marginal properties of the data sets, but also their internal relationships. This is one of the reasons for the great robustness of the process and for its relative insensitivity to distribution anomalies. Anyway, if the spectral distributions of the categories are very far from normal, the procedure shows bad performances, and, as no information about the actual dimension of the groups is inserted, area estimates tend to be rather inaccurate, especially if the cover surfaces are very different in size (Maselli *et al.*, 1990).

NONPARAMETRIC CLASSIFIER OF SKIDMORE AND TURNER REVISITED

This classifier, proposed by Skidmore and Turner in 1988, relies on the extraction of probabilities from the grey-value frequency histograms of the classes considered. Mathematically, these probabilities are computed as

$$P = Fr\ /\ Frt \tag{2}$$

where

Fr = count of pixels of the class under examination at pixel vector, and

Frt = sum of counts of all the classes at pixel vector.

As demonstrated by the authors, this classifier shows high performance in most actual situations when the spectral distributions of the cover categories are far from normal, and it also allows the direct estimation of the probability of correct assignment to a class (Skidmore, 1989). On the other hand, this classifier is expected to be affected by the negative aspects previously described common to all nonparametric methods.

In the procedure used in the present work some characteristics have been introduced which were not present in the original method (Maselli et al., 1991). First, in order to fully exploit its capabilities, the classifier has been used on linearly independent variables derived from a principal component analysis. Second, a mean filtering with a range of three grey values has been applied to the frequency histograms of each class, so as to decrease the variability in the spectral distributions of the training sets. Finally, a different weight, proportional to the size of the relevant training sample, is given to each class during the classification process in order to attain better area estimates.

MAXIMUM-LIKELIHOOD CLASSIFIER USING PRIOR PROBABILITIES DERIVED FROM THE NONPARAMETRIC PROCESS

As proved by many investigations, the assumption of equal prior probabilities for all categories during the classification of remotely sensed data is often statistically unsatisfactory. The procedure proposed here is fundamentally based on the theory of the insertion of prior probabilities in maximum-likelihood processes and on the principles of the nonparametric classifier proposed by Skidmore and Turner (1988), revisited as shown above. According to the first, if an element under examination has a prior probability P of belonging to a class, this probability can be inserted into a maximum-likelihood process by modifying the discriminant function in the following way:

$$F = (\mathbf{X}\text{-}\mathbf{M})'\ \mathbf{C}^{-1}\ (\mathbf{X}\text{-}\mathbf{M}) + \mathrm{Ln}|\mathbf{C}| - 2\ \mathrm{Ln}\ \mathrm{P}. \tag{3}$$

Prior probabilities can be estimated by various means, such as previous and independent information or a random sample of the ground data. The work of Skidmore and Turner gives the possibility of finding out the prior probability P from the sample frequency histograms. In effect, as the frequency histograms are direct expressions of objective properties of the cover categories, they can be correctly assumed as describing intrinsic attributes of these and therefore can be used to derive prior probabilities. Hence, this probability can be inserted into the conventional parametric classifier in order to increase the information available for the discrimination of the cover categories. From an application viewpoint, such a union should yield good results by joining the advantages of the two systems without the relevant limitations. In particular, the new method should show the robustness and stability of the parametric classifier even when trained on small samples, because the definition of statistically stable parameters (means, variances and covariances) should prevent the negative effects of the selection of biased training samples not representative of the entire populations. On the other hand, the presence of nonparametric measures should allow a noticeable flexibility of the procedure and should lead to remarkable improvements in area estimates.

CASE STUDY

Bearing in mind the different features of the three classifiers considered, the case study has been planned so as to evaluate their capabilities in a particularly complex environment. A country zone near Florence about which a deep knowledge was available has been deemed suitable for this aim, because of its extremely heterogeneous and irregular cover surfaces. Moreover, as the size of the training samples is expected to affect differently the behavior of the three procedures, the research has been also directed towards the investigation of the effects of training sample size on the classification results.

STUDY AREA AND GROUND REFERENCE COLLECTION

The study area is located southeast of Florence at approximately 43° 41′ north latitude and 11° 33′ east longitude (Figure 1). The altitude of the zone ranges from about 100 m in the area adjacent to the Arno river to approximately 1400 m, with a climate which follows the altitudinal trend from mesomediterranean to submediterranean (UNESCO-FAO,1963). Vegetation is distribuited along the altitudinal gradient in three bands. The first band occupies the plain zone near the river and is covered by small urban centers and cultivations of cereals (mainly wheat). Where the altitude increases over 200 m, a mixture of natural and agricultural cover types is present; the former are mainly deciduous woods consisting of several oak and chestnut species with different densities; the latter are represented almost exclusively by olive groves, which can show different appearances depending on the agricultural practices in use. Finally, the highest zones are completely covered by deciduous and coniferous woods; also, in this case, the surfaces are generally mixed, and often even the identification of the dominant species is problematic.

From this succinct description, the difficulty in the spectral characterization of this kind of environment is obvious. Furthermore, the method of ground reference collection has not been the most efficient for this characterization, because it was planned in order to achieve a usual land-use map. The reference cover categories have been identified chiefly on the basis of direct ground surveys, which are not specifically suited to the definition of spectrally homogeneous surfaces. Actually, this is a rather common case in many applications of land-use inventories and can be thought of as one of the main sources of the irregularity in spectral distributions of the cover categories. Such an irregularity is often a cause of suboptimal performance of automatic classifications, but, in the present case,it represents an interesting feature for testing the actual capabilities of the different discrimination procedures.

Materials and Methods

The processing of remotely sensed and ground data was carried out on a Digital Equipment Corporation VAX 11/750 using programs planned and created in FORTRAN 77 in the computer center of I.A.T.A.-C.N.R. For the statistical analyses, the GENSTAT 5 statistical package was employed.

*Satellite Data.*Two Thematic Mapper scenes of the study area were utilized for the research, extracted from frame 192, track 30, quarter 2; the two scenes were chosen, among those available in suitable periods of a growing season, in order to maximize the multitemporal information deriving from the changing phenology of vegetation (Conese and Maselli, 1991). The first scene was acquired on 26 May 1988 when vegetation was at the peak of its activity in this area, while the second scene was taken on 14 August 1988 when, due to the mediterranean arid season, vegetation showed different levels of water stress depending on its more or less pronounced xerophilous nature.

Fig. 1. Geographical location of the study area.

Prelininary Data Processing. The reference areas were acquired by means of a digitizer; all the available cover categories were digitized separately, excluding only areas about which sufficient knowledge was not available. Due to the extreme fragmentation of the cover types, the process of digitization was highly time consuming. The two TM scenes were georeferenced by means of ground control points using a linear bivariate regression method. Next, in order to decrease the complexity of the subsequent processing and to render the remotely sensed images statistically uncorrelated, a data compression by means of principal component analysis was applied independently to the two study scenes. Only the first three components of each scene were stored, as they retain most of the information provided by the sensor (Horler and Ahern, 1986), and these were used for the rest of the research.

Because the total number of cover categories was too high for a good spectral identification of them, a work of class redefinition was carried out on the basis of previous knowledge of the cover surfaces and of their spectral similarity. For the estimation of the second parameter, the spectral signatures of all the surfaces were determined and were used to compute some classical indices of spectral separability such as Transformed Divergence and Bhattacharyya Distance (Thomas *et al.*, 1987). After the evaluation of the relevant results, five classes were deemed sufficent to represent the most important cover types of the zone: coniferous forest, deciduous wood, olive groves, cultivations of cereals and urban areas (Table 1); therefore, all the digitized surfaces were grouped into these five classes for the following processing (Plate 1).

Training, Classification, and Evaluation of Results. To properly evaluate the capabilities of the three classifiers depending on the size of the training samples, the first phase consisted in the identification of suitable training pixels. A stratified random sampling scheme was adopted, with the total number of pixels equal to 250, 500, 1000, 2000, and 4000. The pixels were independently sampled in the cover surfaces acquired because this single pixel training responds to the requirement of maximum statistical representativeness for a given sample size (Curran and Williamson, 1986; Gong and Howarth, 1990).

Next, using the pixels selected, the parametric spectral signatures required for the maximum-likelihood classifier and the frequency histograms necessary for the nonparametric process were determined so as to train the three processes. The classifications were carried out on the multitemporal TM scene by means of the three classifiers described. In the case of the parametric and parametric-nonparametric processes, the pixels were attributed to a class if their grey values were within the range mean ± 3 standard deviations of the relevant spectral signature in all the six principal components; for the nonparametric process, such attribution was performed when the smoothed training sample frequency corresponding to the pixel vector was not equal to zero. No cosmetic filtering was applied to the classified images because it can confound the interpretation of results.

Table 1. Cover Categories Considered in the Research and Relevant Numbers of Pixels Digitized from Ground References

Class	No. of pixels
1 Coniferous forest	9717 = 12.2%
2 Deciduos wood	48336 = 60.8%
3 Cultivation of cereals	3439 = 4.3%
4 Olive grove	15373 = 19.3%
5 Urban area	2630 = 3.3%

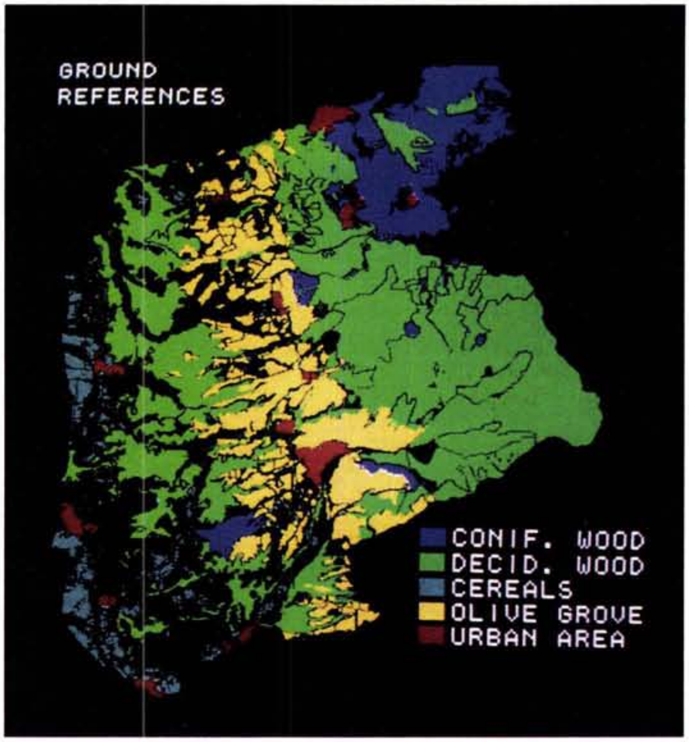

PLATE 1. Distribution of the five color classes used as ground references.

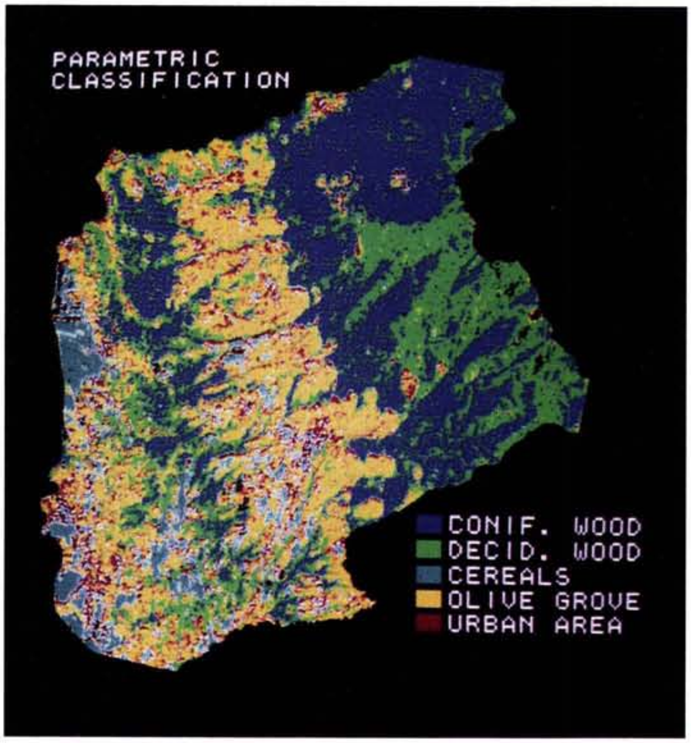

PLATE 2. Distribution of the five cover classes derived from the conventional maximum-likelihood classifier, trained on 1000 pixels.

The evalution of results was performed by comparison with all the original ground references. In this way the same pixels used for training are employed also as references, but, because they represent only a small percentage of the total (up to about 5 percent), the statistical value of the final comparison is not significantly reduced. Two parameters have been considered, the Kappa coefficient of agreement and the percentage of classified pixels. The Kappa statistic, first described by Cohen (1960) and introduced into the remote sensing community by Congalton *et al.* (1983), takes into consideration all the elements in an error matrix, and it was recommended by Rosenfield and Fitzpatrick-Lins (1986) as particularly suitable for remote sensing. The percentage of classified pixels has been utilized bearing in mind the limited capabilities of nonparametric methods for the identification of infrequent pixels.

In order to give an idea of the general patterns of misclassification sources, three examples of classified images and relevant error matrices and Kappa coefficients resulting from the procedures trained on 1000 pixels are reported in Plates 2 to 4 and Tables 2 to 4. Because a certain variability was noted in the results of the classifiers, especially when trained on small samples, the entire process of identification of the training points, classifications of the scenes, and evaluation of the results was repeated ten times. Therefore, the values summarized in Figures 2 and 3 represent the averages of these ten replications, and this has given the possibility of evaluating the significance of the differences found. A two-way analysis of variance was applied to both the variables examined (Kappa accuracy and percentage of classified pixels), following the experimental design schematized in Tables 5 and 6. The main effects of the two factors (kind of classifier and number of training pixels) were analyzed together with their interactions and including comparisons within each possible combination of the first factor, which of course is the most interesting one. Next, in the presence of significant interaction, the analysis was also applied to each single level of the two factors.

TABLE 2. ERROR MATRIX OF THE CONVENTIONAL MAXIMUM-LIKELIHOOD CLASSIFIER TRAINED ON 1000 PIXELS.

Class	1	2	3	4	5	Row Marg. Summ.
1	7492	18668	0	727	45	26932 = 34.8%
2	1270	22999	0	260	334	26863 = 34.7%
3	10	414	2558	834	390	4206 = 5.4%
4	144	3241	129	9028	570	13112 = 17.0%
5	189	2109	487	2401	1040	6226 = 8.1%
Column M.S.	9105 = 11.8%	47431 = 61.3%	3174 = 4.1%	15250 = 19.7%	2379 = 3.1%	77339 100.0%
Kappa = 0.3749		Var(Kappa) = 0.000007469				

TABLE 3. ERROR MATRIX OF THE NONPARAMETRIC CLASSIFIER TRAINED ON 1000 PIXELS.

Class	1	2	3	4	5	Row Marg. Summ.
1	6408	2413	1	101	10	8933 = 12.1%
2	2382	40517	67	3936	207	47633 = 64.5%
3	3	67	501	261	146	978 = 1.3%
4	171	3936	702	9589	974	15372 = 20.8%
5	11	207	116	462	169	965 = 1.3%
Column M.S.	8975 = 12.2%	47140 = 63.8%	1469 = 2.0%	14346 = 19.4%	1951 = 2.6%	73881 100.0%
Kappa = 0.5759		Var(Kappa) = 0.000008023				

RESULTS

From a preliminary visual examination of the classifications obtained, some interesting information can be derived about

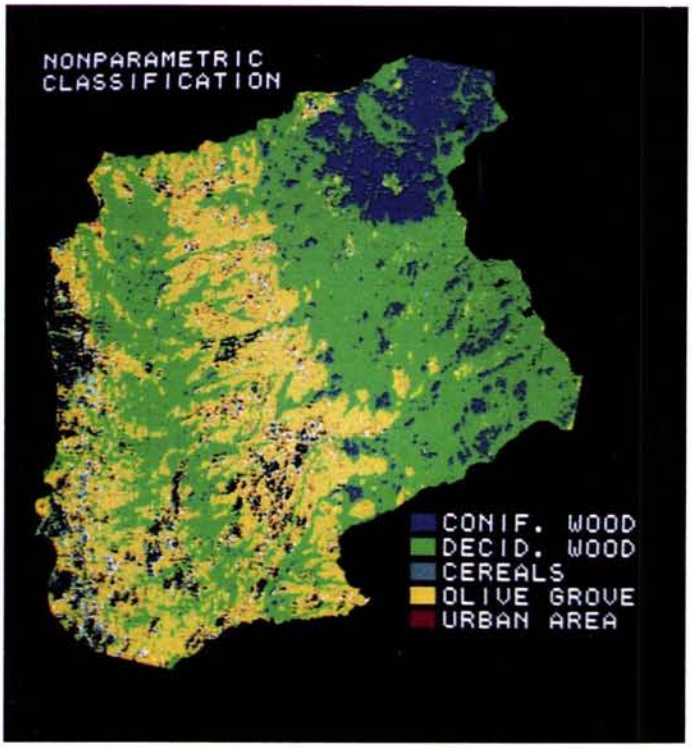

PLATE 3. Distribution of the five cover classes derived from the nonparametric classifier of Skidmore and Turner (1988) modified, trained on 1000 pixels.

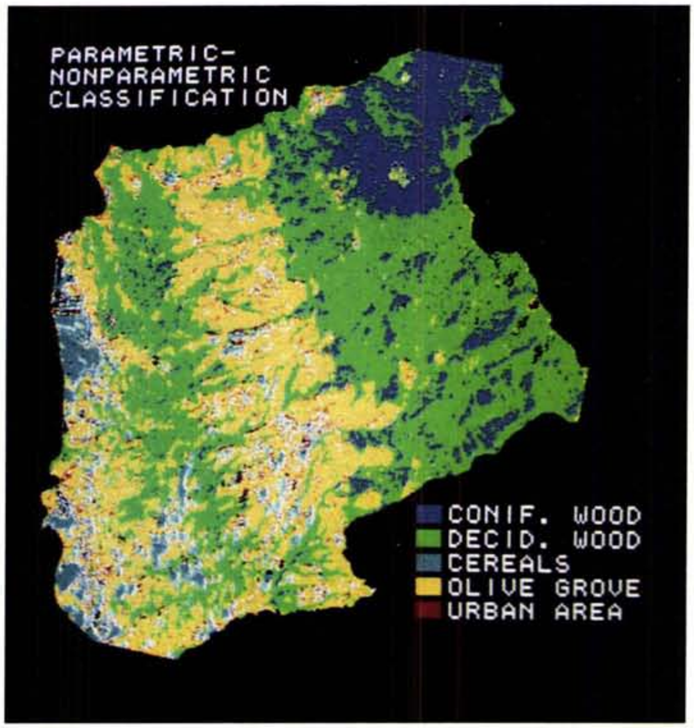

PLATE 4. Distribution of the five cover classes derived from the new maximum-likelihood classifier using nonparametric prior probabilities, trained on 1000 pixels.

TABLE 4. ERROR MATRIX OF THE NEW PARAMETRIC CLASSIFIER USING NONPARAMETRIC PRIOR PROBABILITIES TRAINED ON 1000 PIXELS.

Class	1	2	3	4	5	Row Marg. Summ.
1	6738	3811	0	162	9	10720 = 14.0%
2	2104	38511	1	3220	473	44339 = 57.7%
3	10	307	2291	655	360	3623 = 4.7%
4	171	3907	540	10153	1023	15794 = 20.6%
5	56	598	303	928	471	2356 = 3.1%
Column M.S.	9079 = 11.8%	47164 = 61.4%	3135 = 4.1%	15118 = 19.7%	2336 = 3.0%	76832 100.0%
Kappa = 0.5860	Var(Kappa) = 0.000006892					

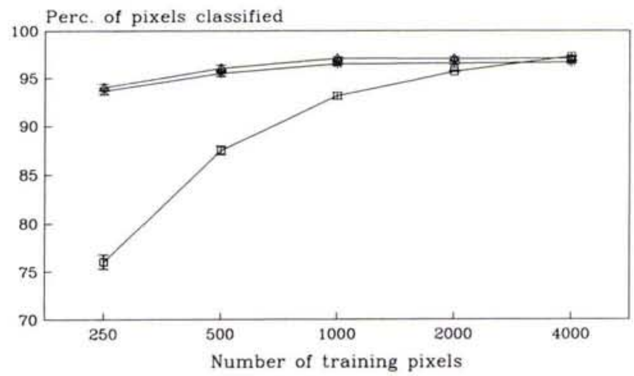

FIG. 2. Variations in the percentage of pixels classified by the three processes depending on the size of the training samples; averages of ten replications and confidence intervals at $P = 0.99$ (asterisk = conventional maximum-likelihood classifier; square = nonparametric classifier of Skidmore and Turner (1988) modified; triangle = new maximum-likelihood classifier using nonparametric prior probabilities).

the behavior of the three procedures. As indicated in Plates 2 to 4, the usual maximum-likelihood classification shows a general tendency towards bad area estimates; in particular, wide shadowed areas of deciduous wood are attributed to coniferous forest, and the extent of the urban category is highly overestimated too. The nonparametric classifier leaves wide areas unclassified, especially when trained on small samples, so that many pixels cannot be attributed to any cover category, which is clearly a remarkable limitation from a user's perspective. Both these problems are particularly alleviated by the use of the new parametric process relying on nonparametric prior probabilities.

An examination of Tables 2 to 4 tends to confirm these patterns in quantitative terms. As fairly visible, the conventional maximum-likelihood classification highly overestimates the extent of class 1 and 5 with respect to class 2 and 4; as a consequence, Kappa accuracy is so low as to invalidate even the utility of the automatic process. Under this point of view, the nonparametric classifier leads to marked improvements in classification performances, with a far higher Kappa coefficient of agreement, but it leaves large areas not assigned to any category, so that the total number of classified pixels is lowered by about 5 percent. Instead, the new process produces a classification accuracy even higher than that of the nonparametric classifier without substantialy altering the number of pixels classified. In particular, the correspondence between the actual and automatically computed extent of the categories, which is a very useful parameter from a user's perspective, reaches an optimum level by the utilization of the new, mixed procedure; this can be partly attributed to the inclusion of nonparametric weights depending on the size of each class into the parametric defini-

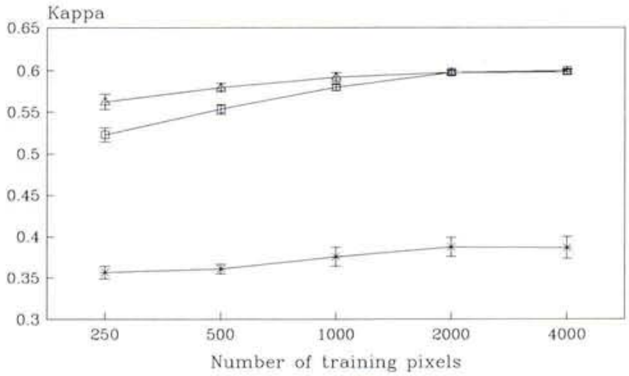

FIG. 3. Variations in the Kappa accuracy of the three classifiers depending on the size of the training samples; averages of ten replications and confidence intervals at $P = 0.99$ (asterisk = conventional maximum-likelihood classifier; square = nonparametric classifier of Skidmore and Turner (1988) modified; triangle = new maximum-likelihood classifier using nonparametric prior probabilities).

TABLE 5. TWO-WAY ANALYSIS OF VARIANCE PERFORMED ON THE PERCENTAGE OF CLASSIFIED PIXELS: PROBABILITIES FOR VARIANCE RATIOS (F) OF THE COMPARISONS EXAMINED. FACTOR 1(C1) = CLASSIFIER (THREE LEVELS: PARAMETRIC, NONPARAMETRIC, PARAMETRIC USING NONPARAMETRIC PRIOR PROBABILITIES). FACTOR 2 (TP) = NUMBER OF TRAINING PIXELS (FIVE LEVELS: 250, 500, 1000, 2000, 4000).

Analysis on global design:

Design	Source of variation TP	Cl	TP.Cl
Cl(1,2,3) × TP(1...5)	<.01	<.01	<.01
Cl(1,2) × TP(1...5)	<.01	<.01	<.01
Cl(1,3) × TP(1...5)	<.01	<.01	.36
Cl(2.3) × TP(1...5)	<.01	<.01	<.01

Analysis on each level of the 2 factors (performed only in presence of significant interaction):

Design	Level of TP 1	2	3	4	5
Cl(1,2,3)	<.01	<.01	<.01	<.01	<.01
Cl(1,2)	<.01	<.01	<.01	<.01	<.01
Cl(2,3)	<.01	<.01	<.01	.79	.39

Design	Level of Cl 1	2	3
TP(1...5)	<.01	<.01	<.01

tion of the relevant shapes in the multi- dimensional feature space. The significance of the differences in Kappa accuracy found between the three error matrices has also been evaluated by means of the Zeta test (Cohen, 1960). Because the reference pixels are extremely numerous, all the Kappa variances are very small and the resulting Zeta values are highly significant (Zeta 1-2 = 51.54, Zeta 1-3 = 55.55, Zeta 2-3 = 2.59); this clearly indicates that actual diversities are present in the performances of the three classifiers.

The variations in total number of pixels classified and Kappa accuracy depending on the size of the training samples are fairly visible in Figures 2 and 3. The maximum-likelihood process tends to attribute almost all the pixels to some cover category in all cases but its performance is always low in terms of Kappa accuracy. This confirms the difficulties of the process in obtaining good results in zones with complex spectral features, mainly due to its low flexibility and intrinsic deficiency in area estimates. The nonparametric process seems to overcome almost completely these problems, but it shows an extreme sensitivity

TABLE 6. TWO-WAY ANALYSIS OF VARIANCE PERFORMED ON THE KAPPA ACCURACY: PROBABILITIES FOR VARIANCE RATIOS (F) OF THE COMPARISONS EXAMINED. FACTOR 1(C1) = CLASSIFIER (THREE LEVELS: PARAMETRIC, NONPARAMETRIC, PARAMETRIC USING NONPARAMETRIC PRIOR PROBABILITIES). FACTOR 2 (TP) = NUMBER OF TRAINING PIXELS (FIVE LEVELS: 250, 500, 1000, 2000, 4000).

Analysis on global design:

Design	Source of variation TP	Cl	TP.Cl
Cl(1,2,3) × TP(1...5)	<.01	<.01	<.01
Cl(1,2) × TP(1...5)	<.01	<.01	<.01
Cl(1,3) × TP(1...5)	<.01	<.01	.94
Cl(2,3) × TP(1...5)	<.01	<.01	<.01

Analysis on each level of the 2 factors (performed only in presence of significant interaction):

Design	Level of TP 1	2	3	4	5
Cl(1,2,3)	<.01	<.01	<.01	<.01	<.01
Cl(1,2)	<.01	<.01	<.01	<.01	<.01
Cl(2,3)	<.01	<.01	<.01	<.01	<.01

Design	Level of Cl 1	2	3
TP(1...5)	<.01	<.01	<.01

to the size of the training samples, so that only the classifications obtained by the process trained on many reference pixels (N>1000) can be considered acceptable in terms of Kappa accuracy and, above all, of percentage of classified pixels. Far better results are achieved by the use of the parametric classifier using nonparametric prior probabilities; it shows high performance in terms of both the parameters considered, even when trained on relatively low numbers of training pixels, and the classification accuracies measured by the Kappa statistic are generally higher than those of the other classifiers. Even if, as expected, the asymptotic tendency with the increase in the training sample size is favorable to the nonparametric process, this is appreciable only over a high number of pixels.

As seen in Tables 5 and 6, the two-way analysis of variance performed on the two variates yielded almost all highly significant differences, partly due to the quite low sample dispersions. In the global design, the two main factors and the relevant interactions are highly significant for both the variates. Such a pattern persists in the comparisons between each pair of classifiers, apart from interaction in the case of the conventional parametric and the new classifier; this indicates that only in that case there are no evident effects of training sample size on the different behaviors of the three procedures. In any case, the analyses in each single level of both factors performed in the presence of significant interaction showed that only the comparison between the results of the nonparametric and the new process gives nonsignificant differences in terms of percentage of classified pixels for high numbers of training pixels, while all the other differences are highly significant. Globally, the analyses of variance indicate that both the kind of classifier and the training sample size are highly significant factors for the results of the classifications. This gives a general meaning to the trends described and renders the conclusions achieved more widely extendable.

SUMMARY AND DISCUSSION

The necessity for efficient and cost-effective methods of land-use inventories has recently led to investigating the possibilities of remote sensing techniques as a means for collecting precise and objective information synoptically over large areas. In particular, the advent of high resolution sensors such as the Landsat TM and SPOT HRV has increased users' expectations, especially in European countries which present peculiar problems connected with the extreme fragmentation and irregularity of the cover surfaces. Unfortunately, many applications of the standard methods of remotely sensed data processing for land-cover classifications have not led to satisfactory results, so that the temptation has sometimes arisen that these techniques can have only limited utility in most real situations (Hall-Konyves, 1990).

In effect, the classical parametric classification procedures have general difficulties in discriminating between surfaces with complex and irregular spectral features; in these cases area estimates suffer from noticeable problems and, moreover, the whole procedure appears inflexible. The use of nonparametric methods recently proposed by some researches can only partially solve these problems because of their need for too large training samples in order to work properly.

The current paper proposes a new procedure which can merge the advantages of parametric and nonparametric classifiers; its statistical bases have been presented and discussed, relying on previous investigations. Next, a case study has been examined regarding the use of TM data on a particulary complex environment of Tuscany in order to test the performance of the new procedure in a real situation and to compare it with those of the conventional methods. The results confirm the validity and efficiency of the procedure, which performs significantly better than the usual classifiers in terms of global accuracy and of extent of areas identified, especially when trained on small samples. Because the modification proposed is extremely simple and easy to implement, the method can be considered ready also for operational applications. Meanwhile, further research is being directed towards the evaluation of discrimination error probabilities from the new process and its possible inclusion into a land information system.

ACKNOWLEDGMENTS

The authors want to thank the *PE&RS* referees, and particularly Dr. George H. Rosenfield, for their useful comments and suggestions on the first draft of the present paper.

REFERENCES

Booth, D. J., and R. B. Oldfield, 1989. A comparison of classification algorithms in terms of speed and accuracy after the application of a post-classification modal filter, *Int. J. of Remote Sensing*, 10(7):1271–1276.

Cohen, J., 1960. A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, 20(1):37–46.

Conese, C., and F. Maselli, 1991. Use of Multitemporal Information to Improve Classification Performance of TM Scenes in Complex Terrain. *ISPRS Journal of Photogrammetry and Remote Sensing*, in press.

Congalton, R. G., R. A. Mead, R.G. Oderwald, and J. Heinen, 1983. Assessing Landsat Classification Accuracy Using Discrete Multivariate Analysis Statistical Techniques. *Photogrammetric Engineering & Remote Sensing*, 49(12):1671–1678.

Curran, P. J., 1985. *Principles of Remote Sensing*. Longman, London, England, 216 p.

Curran, P. J., and H. D. Williamson, 1986. Sample Size for Ground and Remotely Sensed Data. *Remote Sensing of Environment*, 20(1):31–41.

Dillon, W. R., and M. Goldstein, 1984. *Multivariate Analysis; Methods and Applications*. John Wiley & Sons, New York, N.Y., 384 p.

Estes, J. E., E. J. Hajic, and L. R. Tinney, 1983. Fundamentals of image analysis: analysis of visible and thermal infrared data, *Manual of Remote Sensing, 2nd ed.* (R.N. Colwell, Ed.), American Society of Photogrammetry, Falls Church, Virginia, pp. 987–1124.

Gong, P., and J. Howarth, 1990. An Assessment of Some Factors Influencing Multispectral Land-Cover Classification. *Photogrammetric Engineering & Remote Sensing*, 56(5):597–603.

Hall-Konyves, K., 1990. Crop monitoring in Sweden. *Int. J. Remote Sensing*, 11(3):461–484.

Hixson, M., D. Scholz, and N. Funs, 1980. Evaluation of Several Schemes for Classification of Remotely Sensed Data. *Photogrammetric Engineering & Remote Sensing*, 46(12):1547–1553.

Horler, D. N. H., and F. J. Ahern, 1986. Forestry information content of Thematic Mapper data. *Int. J. Remote Sensing*, 8: 1785–1796.

Maselli, F., C. Conese, G. Zipoli, and M. A. Pittau, 1990. Use of Error Probabilities to Improve Area Estimates Based on Maximum Likelihood Classifications. *Rem. Sensing of Environment*, 31:155–160.

Maselli, F., C. Conese, G. Maracchi, and L. Bottai, 1991. Statistical Methods to Improve the Performance of Nonparametric Classification Procedures. To be presented at IGARSS'91, 3–7 June 1991, Espoo, Finland.

Rosenfield, G. H., and K. Fitzpatrick-Lins, 1986. A Coefficient of Agreement as a Measure of Thematic Classification Accuracy. *Photogrammetric Engineering & Remote Sensing*, 52(2):223–227.

Sabins, F. F., 1977. *Remote Sensing Principles and Interpretation*. W. H. Freeman and Company, San Francisco, California, pp. 233–275.

Skidmore, A. K., 1989. An Expert System Classifies Eucalypt Forest Types Using Thematic Mapper Data and a Digital Terrain Model. *Photogrammetric Engineering & Remote Sensing*, 55(10):1449–1464.

Skidmore, A. K., and B. J. Turner, 1988. Forest Mapping Accuracies Are Improved Using a Supervised Nonparametric Classifier with SPOT Data. *Photogrammetric Engineering & Remote Sensing*, 54(10):1415–1421.

Strahler, A. H., 1980. The Use of Prior Probabilities in Maximum Likelihood Classification of Remotely Sensed Data. *Remote Sensing of Environment*, 10:135–163.

Swain, P.H., and S.M. Davis, 1978. *Remote Sensing: The Quantitative Approach*. McGraw Hill, New York, 156 p.

Thomas, I. L., N. P. Ching, V. M. Benning, and J. A. D'Aguanno, 1987. A review of multi-channel indices of class separability. Int. J. Remote Sensing, 8(3):331–350.

UNESCO-FAO, 1963. Bioclimatic map of the Mediterranean zone. Ecological Study of the Mediterranean Zone. *Arid Zone Research*, pp. 13–17.

Yool, S. R., Y. L. Star, J. E. Estes, D. B. Botkin, D. W. Eckhardt, and F. W. Davis, 1986. Performance analysis of image processing alghorithms for classification of natural vegetation in the mountains of Southern California. *Int. J. Remote Sensing*, 7(5):683–702.

(Received 13 August 1990; revised and accepted 29 May 1991)

CALL FOR PAPERS: REMOTE SENSING OF ARCTIC ENVIRONMENTS

Tromso, Norway ♦ 4-6 May 1992

Organized by The Roald Amundsen Centre for Arctic Research, Foundation of Applied Research at the University of Tromso, Tromso Satellites Station/Norwegian Space Centre; and Akvaplan-niva AS, Marine Consultants, Tromso, this symposium will focus on remote sensing applications of both arctic and antarctic environments. Topics include: • monitoring & studying of marine & terrestrial resources & environments • geology, glaciology, & oceanography • atmospheric & climatic studies • natural resource management & pollution monitoring • related historical & economic developments •

Abstracts of 300 words are due by 1 January 1992, & must include the title, author's name(s) & address, affiliation, & presentation. Contact: The Roald Amundsen Centre for Arctic Research, University of Tromso, N-9000 Tromso, Norway. Tel +47 83 45 240; fax +47 83 80 705.