Using Cluster Analysis to Improve the Selection of Training Statistics in Classifying Remotely Sensed Data

*Emilio Chuvieco** and *Russell G. Congalton*
Department of Forestry and Resource Management, University of California, Berkeley, CA 94720

ABSTRACT: A methodology for using cluster analysis to merge unsupervised classes and supervised training fields together for use in the classification process is described. The technique combines the advantages of the two classification approaches while minimizing the disadvantages. Discriminant analysis is used to test the quality of the merging process while discrete multivariate analysis techniques are used to assess the accuracy. The results indicate that higher accuracies can be achieved using this proposed approach than from supervised or unsupervised classification alone.

INTRODUCTION

A REVIEW of the remote sensing literature distinguishes three successive steps in the digital classification process. In the first phase or training phase, the seed statistics used to identify the informational categories are generated. The second phase involves the assignment of the non-sampled pixels (those not used in the training phase) to one of these informational categories. The third phase outputs and assesses the results. Traditionally, the assignment phase has occupied the main attention of land-cover specialists. Different strategies have been developed to improve the performance of the classifier by introducing new algorithms (Wharton and Turner, 1981; Swain *et al.*, 1981; Tom and Miller, 1984) or by incorporating ancillary information (Richards *et al.*, 1982; Strahler, 1984; Franklin *et al.*, 1986).

However, not much attention has been devoted to the selection of training statistics. An important assumption made here is that the training statistics adequately represent the spectral characterisitics of the image to be classified. This assumption is frequently not true because both the supervised and unsupervised methods of extracting the training statistics are incomplete (Justice and Townshend, 1982; Hoffer and Swain, 1980; Campbell, 1987). For this reason, several authors have emphasized the importance of the training stage for achieving reliable classification results (Hixon *et al.*, 1980; Story and Campbell, 1986). A bad definition of the category, in terms of its spectral signature (training statistics), can result in severe errors in the assignment process.

This paper explores the influence of different schemes for selecting training statistics on the classification results. Cluster analysis is presented as a technique to improve the selection process, while discriminant analysis allows one to test the quality of the grouping process. Discrete multivariate categorical analysis techniques are employed to assess the accuracy of the different training schemes.

TEST AREA

This project was initiated under a broader study of forest fire mapping and prevention using Thematic Mapper (TM) data. The area selected is on the Mediterranean coast of Spain (Figure 1). This area is especially affected by forest fires due to its mediterranean climate, with cool winters and warm summers. The annual rainfall ranges from 400 to 800 mm, mainly concentrated during Fall and Spring, with a very dry summer. The annual water budget yields a deficit of 250 mm.

The topography of the area is complex with a continuous succession of different slopes, which are especially steep in the interior "sierras." Only in the vicinity of the shoreline has a litoral plain developed. This area is used for agricultural production, mainly citrus trees and orchards. There are also some agricultural zones in the interior uplands which consists of broad extensions of almond trees and vineyards.

Forest lands cover the higher areas (above 600 m). The major species are aleppo pine (Pinus halepensis) and maritime pine (Pinus pinaster). Scrub species cover many transitional areas. These species are typical of the mediterranean ecology and include Genista scorpius, Rosmarinus officinalis, and Quercus coccifera.

The agriculture, as well as the natural land cover, shows extreme fragmentation in the area analyzed (see Figure 2). The cultural practices in this zone result in a very complex parcel structure. Many of the agricultural properties, especially the irrigated crops, are less than 1 ha in size. This complexity confuses the classification task by introducing many pixels with mixed signatures as a result of the boundary effect. This problem also occurs in the forest, although in this case it is caused by a mixture between forest of various stand heights and scrub with different densities. This lack of homogeneity is crucial to understand some of the misclassifications obtained later. In addition, because of this complexity, this area is ideal for testing the methodology proposed here.

The data used in this project included a TM scene acquired on 26 June, 1984. Aerial photography taken one year later was employed for the identification of training fields as well as for assessing the results. This photography was the closest aerial survey to the date of the image acquisition. In addition, there were no significant changes in the agricultural crops and natural vegetation of the area between these days.

METHOD

Traditionally, classification strategies have been grouped into two broad categories – supervised and unsupervised – according to the procedure employed to obtain the training statistics. The supervised approach involves the selection of areas on the image which statistically characterize the informational categories of interest. The unsupervised approach attempts to identify spectrally homogenous groups within the image. Both procedures have advantages and disadvantages. The supervised approach is subjective in that the analyst tries to classify

*Now at the Department of Geography, University of Alcala de Henares, Calle de los Colegios, 1 Madrid, Spain.

PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING,
Vol. 54, No. 9, September 1988, pp. 1275–1281.

0099-1112/88/5409–1275$02.25/0

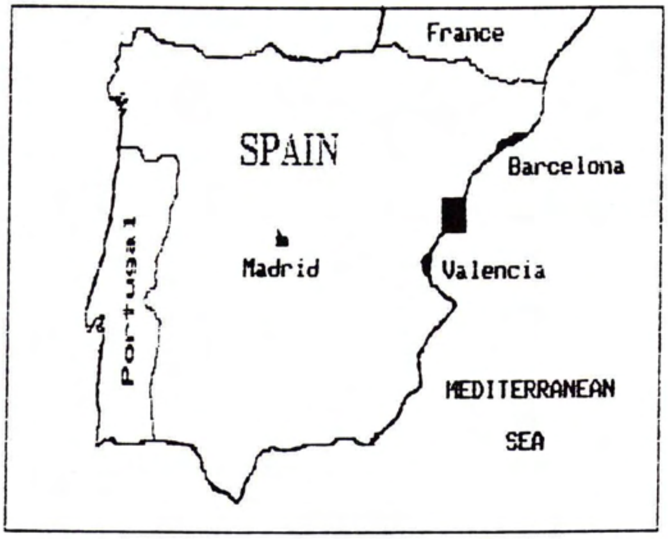

FIG. 1. Location of study area outlined in black.

informational categories which are often composed of several spectral classes. On the other hand, the unsupervised approach usually results in spectral groupings that may have an unclear meaning from the user's point of view.

The objective in this paper was to combine the training statistics generated from both classification approaches by using two multivariate statistical techniques: cluster and discriminant analysis. In other words, cluster analysis was used to group together training statistics generated from both classification approaches. The strength of these groupings was then tested using discriminant analysis. An improvement in the classification results is expected because of the improved grouping of training statistics.

Cluster analysis has been employed in the training phase of a number of previous studies. Several researchers have used it to reduce the number spectral groupings generated by the unsupervised classification approach (Cosentino, 1981; Wheeler and Rudd, 1986; Franklin *et al.*, 1986). It is very important to note that the unsupervised approach is commonly referred to as clustering and results in statistics that are for spectral clusters. In this paper, we will always refer to the unsupervised approach as the unsupervised approach. We will reserve the term "clustering" to mean the grouping together of training statistics from both classification approaches to form combined or hybrid training statistics. In past studies, clustering was used to identify homogeneous groups of unsupervised-generated spectral classes. This reduction in the number of groups to classify results in a decrease in time required for the classification.

The approach proposed in this paper uses cluster analysis as a tool for improving the definition of the training statistics used in the classification process. It is not simply a reduction process for the unsupervised approach, but rather a way of combining similar groupings from both the supervised and unsupervised approaches. The results then of this clustering are threefold. It is possible to generate groupings of training statistics composed of only supervised statistics, or of only unsupervised statistics, or of a combination of the two. The groupings generated from only supervised statistics will contain informational categories alone and may have little spectral correspondence. The reason for this result is that the supervised approach identifies informational categories in its training statistics. The groupings generated from only the unsupervised statistics will relate well to the spectral characteristics of the image, but may not be of informational use. Again, the reason for this is that the results of unsupervised classification are spectral classes, not informational categories. Finally, the groupings that contain both supervised and unsupervised statistics provide a powerful match between the informational categories and the spectral classes. Therefore, it is these groupings that show the advantages of this technique in that these groupings now help interpret the meaning of the unsupervised classes as well as improve the spectral definition of the informational categories. In other words, the cluster analysis has provided an easy way to group similar statistics while at the same time labeling them.

The process proposed in this paper begins with the generation of supervised and unsupervised statistics from the TM imagery. Eight informational categories were chosen to meet the objective of mapping the area for forest fires. These informational categories include agricultural land (dry and irrigated crops), natural vegetation (pine trees, dense scrub, and scrub with bare soil), urban areas, residential areas, and water. A supervised analysis was performed using four training fields per category in order to obtain a representative sample of their spectral dispersion. The analysis therefore yielded 32 training fields (four training fields per informational category times eight informational categories). Criteria such as topographic location, density, and soils were considered in the selection of these training fields.

Two unsupervised analyses were also performed on the same TM image. One of the main problems of the unsupervised approach is the proper choice of the parameters that control the analysis. Parameters such as number of pixels to sample, distance between pixels, number of spectral classes to generate, and measure of difference between spectral classes are important in the analysis. In our analysis, the number of pixels sampled and the distance between pixels between pixels were varied in an attempt to better define the spectral groups included in the image. The first analysis used ten digital values of maximum distance between the centroids of the spectral classes and sampled one out of every five pixels. The second analysis reduced the distance between centroids to five digital values, while it sampled every 10th pixel. Two sets of unsupervised classes were obtained from the analysis; one set had 12 spectral classes and the other had 26.

After the supervised and unsupervised analysis was performed, 70 training statistics (32 supervised and 12 plus 26 unsupervised) were available for the cluster analysis. The objective of this cluster analysis, then, is to group these 70 classes into homogeneous clusters or groups for use in the assignment phase of the classification.

Among the different algorithms used in cluster analysis, the hierarchical method is one of the most precise and computationally efficient, especially when a limited number of classes is involved (Everitt, 1980). In this algorithm, the classes are merged progressively, two in each step, until all classes belong to the same cluster or group. This grouping can result either in a merging of two single classes, or in a class being merged with an already formed grouping, or in merging two groupings. The only limitation is that once the class is assigned to one group it cannot change its membership. At the end of the process, the user selects the step at which the clustering is stopped, usually when two classes very remote in the distance matrix are merged.

The criteria used to calculate the distance between classes is also very important to the final results. The most common criteria used is the Euclidian distance, which assumes orthogonal axes. This assumption is not valid for TM bands because there is a high correlation between the spectral bands. The use of another criteria of measurement is recommended in these cases (Johnston, 1978). The squared Euclidian distance was selected in this analysis.

FIG. 2. Aerial photograph showing the diverse and fragmented vegetation of the study area.

Finally, the measurement points between clusters can be computed with different criteria as well. The most common ones are the single and complete linkage methods (Everitt, 1980). The former considers the nearest element between clusters in order to calculate the distance, while the latter uses the farthest element. The complete linkage method was employed here, because it is more suitable for grouping when there is a small range of variation between cases.

Once the cluster analysis of the training statistics was completed, discriminant analysis was used to evaluate the strength of the grouping. Discriminant analysis is a multivariate technique that attempts to find a new set of functions which maximize the ratio of the variance between and within groups. The analysis involves a linear transformation of the original variables in such a way that the new functions maximize the separation between the already formed groups. These new variables are orthogonal and successively accumulate the maximum amount of variance. After these functions have been found, it is possible to regroup each one of the original training classes to test its membership in the correct grouping. Discriminant analysis therefore provides a way of statistically testing the identity of the grouping (Johnston, 1978; Hand, 1981).

After running a discriminant analysis on the groups formed by the clustering of the training statistics, each one of the final groups was defined by the average value of its members. Then these average statistics were input into the classification algorithm to be used in the assignment phase of the classification process.

Upon completion of the assignment phase, it was necessary to compare the results of this clustering of training statistics from both classification approaches with the results of the traditional supervised and unsupervised approaches. In recent years, discrete multivariate statistical techniques have been introduced to refine the process of accuracy assessment (Congalton *et al.*, 1983). These techniques, the normalization of an error matrix and the KHAT statistic, along with the traditional overall accuracy were used in this research.

The starting point in any assessment procedure is obtaining the reference data set required to generate the error matrices. Using the aerial photography, 1000 random points were located by x and y coordinate. For each point, the actual informational category was recorded. A FORTRAN program was written to sort this set of points (according to lines and columns on the image) and to extract the category assigned to each point on the classified image. The reference data (category as derived from the aerial photograph) was then compared to the classified image to generate an error matrix.

Three measures of accuracy were analyzed: overall performance accuracy, KHAT, and normalized performance accuracy. Overall performance accuracy is the traditional accuracy value or percent correct. The KHAT value is a measure of similarity that can be used to test if the different classifications are significantly different from each other. The KHAT value is an accuracy measure that includes more information than the overall performance accuracy measure. The KHAT value indirectly incorporates the error (off-diagonal elements) in the error matrix. The normalized performance accuracy is a more inclusive measure of accuracy than either KHAT or overall performance. It directly includes the information in the off-diagonal elements of the error matrix (Congalton *et al.*, 1983). All three measures of accuracy were applied to the classifications generated in this study.

RESULTS

CLASSIFICATION

The mean values of the 70 training classes derived from the supervised and unsupervised classification approaches were combined using cluster analysis. After the clustering was completed, the 70 training classes were reduced to 12 groups which were selected because of a high increment in the distance coefficient at that point. These groups were then used in the assignment phase of the classification. The mean values of the final groups appear in the Table 1.

A careful study of Table 1 reveals several interesting observations. The combination of supervised and unsupervised classes has a double advantage. On the one hand, it helps to give meaning to (i.e., label) the unsupervised classes by associating them with known supervised (or informational) categories. On the other hand, it reduces the subjectivity of the supervised selection because it discovers any grouping that has no defined spectral association, that is, it identifies groups with only supervised classes as members. In other words, these groups are artificial (i.e., informational but not spectral) and may not be derived directly from the spectral information contained within the image. For instance, the urban and residential categories (Groups 6,7, and 8) do not have any unsupervised classes associated with them, which means that they do not have any clear spectral correspondence. In the case of the urban areas, this fact can be due to their small extension in this scene. However, with respect to residential areas, the fact is more related to the high dispersion associated with this category, formed by the different objects (buildings, trees, lawns, roads, etc.) which makes it especially difficult for mapping (Jensen and Toll, 1982; Toll, 1984).

Another problem that arises because of this clustering is the combining of classes with, at least theoretically, clear independent meaning. The case of mixing the irrigated crops with scrub (in steep areas) in Group 12 is a good example of this problem. A closer look at these associations, however, reveals some possible explanations. Crops, as well as scrub, have an important influence on the soil and therefore on the spectral signature of the category. The former are irrigated, but usually in the late afternoon, so they show a dry background at the time of acquisition of the imagery. More importantly, the time of the year is not the best time for discrimination between them, because the scrub still maintains some vigor from the spring rains while the crops have not yet reached maturity.

The discriminant analysis applied to this grouping to test the quality of the membership showed that improvement in the definition of some groupings was still possible. It was also evident that some of these groupings resulted from strong association of their members in only a few bands. In other words, certain TM spectral bands seemed more important than others in clustering the 70 training classes into the twelve groups listed in Table 1. The discriminant function coefficients also confirmed this idea. These coefficients provide the correlation between the original bands and the discriminant functions. Considering that these functions maximize the separation between groups, it should be concluded that the higher the correlation with the first discriminant functions, the higher the importance of the original band in the final grouping. In this case, Bands 7, 5, 1, and 2 showed higher correlations with the first three functions, which contained 90 percent of the original variance.

The first time the cluster analysis was performed on the 70 training classes, no standardization was performed. However, as shown above and despite the fact that each TM band has the same range of spectral values (i.e., 0 to 255), each band does have a different distribution. Therefore, it is expected that the bands with bigger dispersions have stronger influence in the computation of the distance measurement used in the cluster analysis. In this case, Band 5 and Band 7 had the higher standard deviation (41.42 DN and 24.19 DN, respectively).

In order to avoid the influence of the band distribution on the clustering, a second cluster analysis was performed in which the 70 training classes were standardized before any further analysis was applied. The training statistics were standardized by the traditional method, substracting from each value the mean and dividing it by the standard deviation. This standardization has the effect of making each spectral band of equal importance. The results of this second cluster analysis are presented in Table 2. In this analysis, 18 groups were selected from the 70 standardized training classes. Again, a higher increment in the distance coefficient was the criteria used to determine the number of final groups.

The results of this analysis are more understandable and easier to explain. The confusion between irrigated crops and scrub is still present, but it has been simplified. Now there is a group (number 15) that identifies irrigated crops and is not confused with scrub. The urban classes formed several single groups, while the water has split into two groups according to its depth. The new clustering also isolates categories with only unsupervised classes. Again, this fact is interesting because it demonstrates that there is actually some unique information in the image data that has not been identified in any of the informational categories of interest.

TABLE 1. GROUPS FORMED FROM THE CLUSTER ANALYSIS OF THE 70 TRAINING STATISTICS (ORIGINAL BANDS).

Group	B1	B2	B3	(mean values) B4	B5	B6	B7
1. DRY1, MAT1, CLUST12	116	60	77	98	151	136	77
2. DRY2, DRY3, URB1, MAT3, CLUST5 CLUST10, CLUS9, CLUS20, CLUS21	107	53	69	88	143	140	75
3. DRY4, CLUS3, CLUS18, CLUS22, CLUS25	101	44	48	74	103	133	48
4. PINE1, PINE2, PINE3, CLUST8, CLUS8	88	36	34	60	56	126	22
5. PINE4, CLUST6, CLUST7, CLUS11, CLUS2, CLUS5, CLUS7, CLUS13, CLUS17 CLUS24	94	40	40	70	79	130	34
6. URB2	148	75	95	88	171	133	114
7. URB3, URB4	136	65	85	83	153	136	92
8. RES1, RES3	122	53	71	79	113	134	63
9. RES2, MAT2, MAT4, CLUST1, CLUS6, CLUS12	110	52	62	86	126	137	63
10. RES4, SCR1, SCR4, CLUST4, CLUST9, CLUS10, CLUS16, CLUS19, CLUS23, CLUS26	106	47	56	82	114	133	63
11. WAT1, WAT2, WAT3, WAT4, CLUST3, CLUS1, CLUS14	92	29	21	12	7	116	4
12. NAR1, NAR2, NAR3, NAR4, SCR2, SCR3 CLUST2, CLUS11, CLUS15	98	43	46	86	96	132	41

(DRY = Dry crops; MAT = Scrub with bare soil; PINE = Pines; URB = Urban areas; RES = Residential areas; WAT = Water; NAR = Irrigated crops; CLUST = Unsupervised analysis, 12 classes; CLUS = Unsupervised analysis, 26 classes).

TABLE 2. GROUPS FORMED FROM THE CLUSTER ANALYSIS OF THE 70 TRAINING STATISTICS (STANDARDIZED BANDS).

Group	B1	B2	B3	(mean values) B4	B5	B6	B7
1. DRY1, MAT1, MAT3, CLUST12	117	60	73	96	147	136	74
2. DRY2, CLUS4, CLUS6, CLUS21	101	49	63	85	135	139	69
3. DRY3, CLUST5, CLUST10, CLUS9 CLUS20	106	52	71	89	147	139	77
4. DRY4, RES4, SCR1, SCR4, CLUST2 CLUST4, CLUST9, CLUS10, CLUS15 CLUS16, CLUS18, CLUS19, CLUS22 CLUS23	103	47	53	80	110	133	51
5. PINE1, PINE2, PINE3, CLUST8, CLUS8	87	35	33	60	54	125	21
6. PINE4, CLUST6, CLUST7, CLUS2, CLUS5, CLUS7, CLUS17, CLUS24	94	39	40	69	79	130	33
7. URB1	116	58	78	74	136	140	86
8. URB2	148	75	95	88	171	133	114
9. URB3, URB4	136	65	85	83	153	136	92
10. RES1	127	52	69	75	112	132	62
11. RES2, MAT4	116	53	63	87	118	130	60
12. RES3, MAT2	114	55	71	87	120	136	60
13. WAT1, WAT4, CLUST3, CLUS1	90	28	20	11	7	116	4
14. WAT2, WAT3, CLUS14	101	36	24	13	9	116	5
15. NAR1, CLUST11, CLUS11	97	42	50	84	89	131	38
16. NAR2, NAR3, NAR4, SCR2, SCR3	95	42	44	89	95	133	39
17. CLUST1, CLUS12, CLUS26	107	51	62	84	123	136	60
18. CLUS3, CLUS13, CLUS25	100	44	47	69	95	132	43

(The abbreviations have the same meaning as in Table 1.)

Discriminant analysis was also performed on this grouping. The results are more satisfactory. The first three functions include 95.92 percent of the original variance. In addition, all three have a canonical correlation greater than 0.90, which means that the separation between groupings is high. In addition, the Wilks-Lambda coefficient is less than 0.008 for these functions, which indicates a small within-group variation. After determining the discriminant functions, it is possible to regroup the 70 training classes into the proper grouping. In this case, all the members of the groupings were assigned to their initial group, indicating the success of the cluster analysis.

ACCURACY ASSESSMENT

Once the cluster analysis has been performed and the resulting groups have been used in the assignment phase to classify the entire study area, then it is necessary to compare these results to the standard techniques. Therefore, the strategies to be evaluated are supervised classification, unsupervised classification, cluster-training hybrid using the original bands, and cluster-training hybrid using the standardized bands. Tables 3 to 6 present the original error matrices for these four strategies, respectively. Table 7 presents the accuracy results. Note that in all three accuracy measures the cluster-training hybrid using the

TABLE 3. ERROR MATRIX FOR SUPERVISED TRAINING (VALUES IN PIXEL COUNTS).

	REFERENCE DATA							
LANDSAT DATA	URB	RESI	WAT	PINE	SCR	MAT	DRY	NAR
URB	34	3	0	0	0	12	8	0
RESI	3	18	0	0	1	12	12	4
WAT	0	1	63	0	0	0	0	0
PINE	0	1	0	167	76	7	4	1
SCR	2	0	0	4	35	16	28	8
MAT	2	14	0	0	8	97	45	3
DRY	5	3	1	2	20	42	109	0
NAR	0	1	0	9	55	11	1	52

URB = Urban Areas, RESI = Residential, WAT = Water bodies, PINE = Pines, SCR = Scrub, MAT = Scrub and Bare soil, DRY = Dry crops, NAR = Irrigated crops.

TABLE 4. ERROR MATRIX FOR UNSUPERVISED TRAINING.

	REFERENCE DATA							
LANDSAT DATA	URB	RESI	WAT	PINE	SCR	MAT	DRY	NAR
URB	0	0	0	0	0	0	0	0
RESI	0		0	0	0	0	0	0
WAT	0	1	63	0	0	0	0	0
PINE	0	1	0	136	36	3	3	1
SCR	0	3	1	42	124	32	10	28
MAT	40	14	0	1	5	104	71	0
DRY	3	10	0	2	11	8	31	10
NAR	0	0	0	1	5	0	0	24

Note: see legend of Table 3.

TABLE 5. ERROR MATRIX FOR CLUSTER TRAINING CLASSES (ORIGINAL).

	REFERENCE DATA							
LANDSAT DATA	URB	RESI	WAT	PINE	SCR	MAT	DRY	NAR
URB	34	3	0	0	0	16	12	0
RESI	3	10	0	0	0	7	1	0
WAT	0	1	63	0	0	0	0	0
PINE	0	1	0	168	82	8	5	3
SCR	2	6	1	13	74	35	19	34
MAT	3	15	0	0	2	81	31	0
DRY	4	3	0	0	17	48	139	6
NAR	0	2	0	1	20	2	0	25

Note: see legend of Table 3.

TABLE 6. ERROR MATRIX FOR CLUSTER TRAINING (STANDARDIZED).

	REFERENCE DATA							
LANDSAT DATA	URB	RESI	WAT	PINE	SCR	MAT	DRY	NAR
URB	33	3	0	0	0	15	12	0
RESI	4	15	0	0	0	5	7	0
WAT	0	1	63	0	0	0	0	0
PINE	0	1	0	164	60	7	3	3
SCR	2	6	1	17	107	33	13	46
MAT	5	13	0	1	16	105	65	5
DRY	2	2	0	0	9	32	107	3
NAR	0	0	0	0	3	0	0	11

Note: see legend of Table 3.

TABLE 7. ACCURACY MEASURES OF THE FOUR CLASSIFICATION SCHEMES (VALUES IN PERCENT).

	Overall Performance Accuracy	KHAT	Normalized Performance Accuracy
Cluster training hybrid (standardized)	60.5	52.4	63.6
Cluster training hybrid (original)	59.4	51.3	61.1
Supervised training	57.5	49.8	60.4
Unsupervised training	48.1	49.0	48.3

standardized bands had the highest accuracy while the unsupervised classification had the lowest. The results of the test of agreement between matrices (i.e., Kappa) showed no significant differences between the strategies. However, one might argue that an overall performance accuracy of 60.5 percent for the cluster-training hybrid using standardized bands versus 48.1 percent for the unsupervised classification is too great a difference to ignore, especially when the same result is demonstrated by the normalized performance accuracies.

CONCLUSIONS

Cluster analysis can be used to merge training statistics derived from supervised and unsupervised approaches. This merging has two major benefits. First, it aids in labeling unsupervised classes by grouping them with a known supervised training field. Second, it helps identify the limitations of the classification process. In other words, it highlights artificial classes that have no spectral uniqueness and, therefore, cannot be accurately classified. The results show that combining supervised and unsupervised classes together improves the accuracy of the classification. Although the results are not significant in the test of agreement, the overall performance and normalized performance accuracies show that this improvement does exist. Therefore, this methodology could be used to derive the most information out of two traditional classification techniques.

ACKNOWLEDGMENTS

The authors would like to thank the MEC-Fulbright Grant Program for providing the funding for Dr. Chuvieco's stay at the University of California, Berkeley.

REFERENCES

Campbell, J. B., 1987. *Introduction to Remote Sensing*. The Guilford Press. New York. 551 p.

Congalton, R. G., R. G. Oderwald, and R. A. Mead, 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. *Photogrammetric Engineering and Remote Sensing*, Vol. 49(12), pp. 1671–1678.

Cosentino, M. J., C. E. Woodcock, and J. Franklin, 1981. Scene analysis for wildland fire-fuel characteristics in a mediterranean climate. *Proceedings 15th International Symposium on Remote Sensing of Environment*. Ann Arbor, pp. 635–646.

Everitt, B. S., 1980. *Cluster Analysis*. Heineman Educational Books. London.

Franklin, J., T. L. Logan, C. E. Woodcock, and A. H. Strahler, 1986. Coniferous forest classification and inventory using Landsat and digital terrain data. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. G-24(1), pp. 139–149.

Hand, D. J., 1981. *Discrimination and Classification*. John Wiley and Sons, New York.

Hixson, N. M., D. Scholz, N. Fuhs, and T. Akiyamal, 1980. Evaluation of several schemes for classification of remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, Vol. 46(12), pp. 1547–1553.

Hoffer, R. M., and P. H. Swain, 1980. Computer processing of satellite data for assessing agricultural, forest and rangeland resources. *Proceedings 14th Congress of the International Society of Photogrammetry*. Hamburg, pp. 437–446.

Jensen, J. R., 1986. *Introductory Digital Image Processing. A Remote Sensing Perspective*. Prentice-Hall. Englewood Cliffs. 379 p.

Jensen, J. R., and D. L. Toll, 1982. Detecting residential land use development at the urban fringe. *Photogrammetric Engineering and Remote Sensing*. Vol. 48(4), pp. 629–643.

Johnston, R. J., 1978. *Multivariate Statistical Analysis in Geography*. Longman. London.

Justice, C., and J. Townshend, 1982. A comparison of supervised and unsupervised classification procedures on Landsat MSS data for an area of complex surface conditions in Basilicata, southern Italy. *Remote Sensing of Environment*. Vol. 12, pp. 407–420.

Owe, M., and J. Ormsby, 1984. Improved classification of small scale urban watersheds using Thematic Mapper simulator data. *International Journal of Remote Sensing*. Vol. 5 (5), pp. 761–767.

Richards, J. A., D. A. Landgrebe, and P. H. Swain, 1982. A means of utilizing ancillary information in multispectral classification. *Remote Sensing of Environment*. Vol. 12, pp. 463–477.

Story, M. H., and J. B. Campbell, 1986. The effect of training data variability on classification accuracy. *ASPRS 52nd. Annual Meeting. Technical Papers*. Washington, D.C., Vol. 4, pp. 370–379.

Strahler, A. H., 1984. Timber inventory using Landsat. *8th Canadian Symposium on Remote Sensing*. Quebec, pp. 665–674.

Swain, P. H., S. B. Valderman, and J. C. Tilton, 1981. Contextual classification of multispectral image data. *Pattern Recognition*. Vol. 13, pp. 429–441.

Toll, D. L., 1984. An evaluation of simulated Thematic Mapper data and Landsat MSS data for discriminating suburban and regional land use and land cover. *Photogrammetric Engineering and Remote Sensing*. Vol. 50 (12), pp. 1713–1724.

Tom, C. H., and L. D. Miller, 1984. An automated land-use mapping comparison of the bayesian maximum likelihood and linear discriminant analysis algorithms. *Photogrammetric Engineering and Remote Sensing*. Vol. 50 (2), pp. 193–207.

Townshend, J. R. G. (Ed.), 1981. *Terrain Analysis and Remote Sensing*. George Allen and Unwin Ltd. London.

Wharton, S. W., and B. J. Turner, 1981. ICAP: An interactive cluster analysis procedure for analyzing remotely sensed data. *Remote Sensing of Environment*. Vol. 11, pp. 279–293.

Wheeler, D. J., and M. K. Ridd, 1985. A Geographic Information System for resource managers based on multi-level remote sensing data. *ASPRS, 51st. Annual Meeting. Technical Papers*. Washington, D.C., vol. 2, pp. 528–537.

(Received 8 October 1987; revised and accepted 25 May 1988)