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A Determination of the Optimum Time of Year for Remotely Classifying Marsh Vegetation from Landsat Multispectral Scanner Data

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INTRODUCTION

Increasing demands on finite natural resources have intensified interest in the coastal zone. In the past five to ten years, U.S. federal legislation has been implemented to ensure protection and wise management of this "last frontier." Understanding the biological and physical interrelationships of the coastal zone is critical to good management. Vegetation, a primary biological factor in the wetlands and an expression of the environment, should be monitored as an indicator of the condition and productivity of a coastal area.

Difficult access in the coastal marsh restricts vegetation inventory with conventional ground survey methods. The Office of Coastal Zone Management, under the National Oceanic and Atmospheric Administration, has encouraged the use of remote sensing, a technique both practical and comprehensive in coverage, for inventory: "...the process of inventorying and mapping the nature of a state's zone, and the designation of area of particular concern almost certainly will benefit from the application of technologies such as those employing remote sensing" (ref. 1).

Coastal marshes support the growth of many plant species. Diversity is maximum in the more inland, freshwater marshes. Closer to the coast, the presence of salt limits the number of species that can successfully compete in the brackish and saline areas. Widespread surveys indicate that wiregrass, *Spartina patens*, dominates most of the brackish marshes along the Atlantic and Gulf coasts, occurring in vast marsh meadows (ref. 2 & 3). Black rush, *Juncus roemerianus*, can tolerate a higher level of salt and more frequent tidal inundation of the saline marsh. Likewise, oyster grass, *Spartina alterniflora*, and salt grass, *Distichlis spicata*, thrive in the coastal saline environment. These species sometimes occur in mixed associations, as well as monospecific stands. Where brackish grades into saline marsh, the wiregrass/oystergrass consocies commonly occurs. Buckbrush, Baccharis halimifolia, grows along the spoil banks and marsh levees as a 1.5- to 3-m tall shrub.

A vegetation type characterizes its environment. Thus, a particular marsh species acts as an indicator for salinity, soil type, tidal frequency and level. The remote identification of indicator vegetation, then, serves as a practical method to acquire data pertinent to understanding the marsh environment.

OBJECTIVES

The objective of the investigation was to determine the optimum time of year for remotely classifying marsh vegetation from Landsat multispectral scanner (MSS) data. The species dominating the brackish and saline marshes of Louisiana represented the subject plant types.

DATA ACQUISITION

The investigation was conducted at the NASA/Earth Resources Laboratory (ERL), Slidell, Louisiana, which directs the development of remote-sensing technology applications. The ERL is engaged in testing the usefulness of Landsat MSS and other satellite data for coastal zone problem-solving. Since summer 1974, the laboratory has maintained a field record of the vegetation and surface condition at various marsh locations surrounding Lake Borgne, Louisiana, shown in figure 1, as a part of on-going experiments. The available field history set the foundation for the analysis of Landsat MSS data in this investigation.

From a remote-sensing point of view, summer clouds frequently obscure the Louisiana coastal area. Clouds form almost daily over the Gulf and move inland by mid-morning between the months of May and August, making acquisition of remote-sensing data difficult. In the original design of the investigation, an aircraft carrying an MSS sensor was scheduled to fly monthly during the growing period. However, either most of the attempts at data acquisition were unsuccessful because of cloud formation or the data were unacceptable because of the effect of an oblique sun angle and wide scan. Also, the availability of the aircraft was restricted. A complete set of aircraft MSS data for the 1976 growing period was unobtainable. Thus, the investigation had to be discontinued or redesigned.

Another investigative approach was pursued. Since field records existed for the same brackish and saline marsh sites from 1974-1976, the use of satellite data acquired over the same period of time was considered. Landsat MSS data recorded on cassettes were screened over the same period for cloud-free passes. Screening took place at the Earth Resources Observations System (EROS) facility at the National Space Technology Laboratory, Bay St. Louis, Mississippi, which maintains a Landsat cassette library and image display devices.

A cloud-free pass representing each month of the marsh vegetation growing season from February through October was desired. Landsat data were not sought for November, December, and January because growth in the marsh is minimal during those months. Data from Landsat passes over the study area were selected for the following dates:

February 9, 1977	-	Landsat	frame	2749-15360
April 9, 1976	-	"	"	2443-15460
May 15, 1976	-	"	"	2479-15450
June 2, 1976	-	"	"	2497-15443
July 10, 1974	-	"	"	1717-15540
September 18, 1976	-	"	"	2605-15413
October 26, 1974	-	"	"	1825-15504

Cloud-free data were unobtainable for the months of March and August from spring 1974 through winter 1977.

The MSS of both Landsat 1 and 2 detects reflected energy from the visible through the near infrared electromagnetic spectrum in four bands: band 4, 0.5-0.6μm; band 5, 0.6-0.7μm; band 6, 0.7-0.8μm; and band 7, 0.8-1.1μm. Each pass covers approximately 160 km X 160 km, with a frequency of no less than once every 18 days over the same point on the ground. Weather conditions influence the quality of the MSS data. The scanner resolves digital elements equivalent to a ground spot size of 56 m X 79 m.

DATA PROCESSING

All data were processed at ERL using a minicomputer system which includes a Varian 75 computer with 190 k. (16 bit words) of main core and disk storage and four tape drives. It is configured with a floating point processor and an interactive image display device.

Existing ERL software programs generated the statistics and final classifications of the Landsat data. The ERL classification technique derives from a pattern recognition process based on maximum likelihood theory (ref. 4). The computer first "trains" on known samples. Then it classifies each element of the data according to the best statistical fit with one of the training classes. This procedure necessitates ground truth to identify the geographic locations of vegetation that can be used as training samples.

The eleven marsh locations for which field observations were recorded over the 2-1/2 year period became the training sample set for this investigation. The eleven samples basically represented five species: <u>Baccharis halimifolia</u>, <u>Spartina patens</u>, <u>Juncus roemerianus</u>, <u>Spartina alterniflora</u>, <u>and Disticlis</u>

spicata. This same set applied to the independent analysis of each of the seven Landsat passes.

However, the final intent was to compare the MSS classifications from all seven passes, having used the same training sample set. In other words, the classifications for training samples 1-11 generated from the February pass were compared to the classifications for samples 1-11 generated from the April pass, as well as from the May, June, July, September, and October passes.

The following steps describe how the data were handled for each pass:

Step 1: Upon receipt of the Landsat computer compatible tapes from EROS, the data were reformatted to make them compatible with processing software.

Step 2: The data were corrected for a visual striping effect that occurred every sixth scan line due to a difference in gains for the MSS detectors of a given band.

Step 3: Each Landsat pass was georeferenced to Universal Transverse Mercator (UTM) coordinates. This process involves the identification of control points on U.S.G.S. 7½' series (1:24,000) topographic maps and the transfer of their precise locations onto the Landsat data. Georeferencing the data ensured spatial consistency for the delineation of the training samples on the Landsat passes and the eventual comparison of their classifications.

Step 4: Data from bands 5 and 7 were combined for a high contrast display tape. Viewing the tape with an image display device interactive with the minicomputer, the locations of the training samples were transferred interactively onto the georeferenced Landsat data. Sample size averaged about 25 elements. Transfer of the training sample locations onto the georeferenced data by reading their universal transverse mercator coordinates into the computer was attempted, but proved too imprecise for project requirements.

Step 5: A spectral signature was developed for each training sample based on the average reflectivity response and standard deviation derived from all elements in the sample for each of the four bands of data. The statistics from training samples of similar vegetative composition were combined to produce spectral signatures for five classes, or dominant marsh species, from the original 11 samples.

Step 6: A scaled Euclidean distance was generated for each class pair. This value indicated the relative pair-wise distance of each class to all other classes in conceptual multidimensional space (ref. 4).

Step 7: Based on the multispectral response statistics generated for each class, the digital elements within the training samples were classified. The results represented the accuracy of the pattern-recognition technique in classifying the training samples against their known composition.

CONCEPT

The average percent classification accuracy of the training samples has been a traditional indicator for the over-all classification success of a data set using the supervised pattern recognition technique. However, this value considers only the accuracy of classifying each training sample against the individual spectral signatures of all other training samples. Modifying the derivation of accuracy so that each training sample is classified against the spectral signatures of all classes may improve the use of that value as an indicator. The drawback of this second approach is that training sample classification accuracy represents the success of classification of data points included in only a portion of the space defined by the class spectral signatures. This is in accordance with the hyperspace concept of maximum likelihood theory.

The analysis of this investigation depended on a dispersion index (DI), defined as the ratio of separability among class spectral means to variability within classes, to predict classification success. In other words, to determine the time of year at which a group of classes best classifies from a comparison of data sets acquired at different times, the average DI is calculated for each data set:

$$\text{DI Class} = \frac{\text{Separability}}{\text{Variability}} = \frac{\text{Av Scaled Distance/Class}}{\text{Av Coefficient of Variation/Class}}$$

and

$$\text{DI Av} = \frac{\Sigma\text{DI Class}}{n\ \text{classes}}$$

The time of year of the data set associated with the highest DI is optimum for mapping the classes involved.

Separability among classes relates to the scaled Euclidean distance between the spectral means in four dimensions (four bands) for each pair of classes.

The following illustrates the measurement for the distance D between Class A and Class B:

Given:

Class A with spectral means X_1, X_2, X_3, X_4

Class B with spectral means Y_1, Y_2, Y_3, Y_4

Then:

$$D(A, B) = \sqrt{(X_1 - Y_1)^2 + (X_2 - Y_2)^2 + (X_3 - Y_3)^2 + (X_4 - Y_4)^2}$$

Distance D is then scaled to adjust for a disproportionate increase in D as the relative values of the spectral means increase, a situation created by the decompression of the Landsat MSS data when down-linked. Thus, the final measurement is a scaled Euclidean distance.

Variability within classes denotes the relative "spread" of a class and is a function of the coefficient of variation, or the ratio of standard deviation to mean spectral response.

Theoretically, high separability (high scaled distance) and low variability (low coefficient of variation) create a situation with the least amount of spatial intersection of classes. The dispersion index simply ratios separability to variability to provide a relative estimator for overall classification success. The index can be used, then, to evaluate the optimum time of year for classification. For passes occurring at different times, conditions at the time of the pass with the highest dispersion index should be optimum for classification.

Finally, the relationship of training sample classification accuracy to separability and variability can be analyzed. Figure 2 illustrates hypothetical cases for the average training sample classification accuracy, separability, and variability within a data set. As illustrated by the "Case 2" diagram, a high training sample classification accuracy may not relate to optimum classification time. Conversely, the "Case 4" diagram shows that a low training sample classification accuracy may indicate an optimum classification time. A relatively high dispersion index occurs in both cases.

ANALYSIS AND RESULTS

The field record maintained for 2-1/2 years between 1974 and 1976 describes the composition of eleven training samples observed periodically, shown in table I of the appendix. The training samples characterized communities of plant species prevalent in the brackish and saline marshes of Louisiana: <u>Spartina patens</u>, <u>S. alterniflora</u>, <u>Juncus roemericanus</u>, <u>Distichlis spicata</u>, and <u>Baccharis halimifolia</u>. As evidenced in table I, most of the training samples were not 100% monospecific stands, though one species generally dominated. The percent of each species and the amount of water and/or exposed mud within a training sample fluctuated with time.

Multispectral statistics were derived for five classes from the original eleven training samples, grouped according to vegetation type. The five classes, or types, are those mentioned in the previous paragraph. Tables IIa-VIIIa of the appendix list for each pass the mean spectral response, the standard deviation and the % coefficient of variation for each class. Reflectivity response means for the four bands appeared lowest in February, when green vegetation was scarcest and sun elevation lowest. Tables IIb-VIIIb of the appendix present for each pass a scaled distance matrix. The relative values indicate the pairwise scaled distance for all possible class pairs. For the *Juncus roemerianus* class on the June Landsat pass, the MSS data were unobtainable because of cloud interference.

The technique to determine the optimum remote classification time relied on 1) variability within classes and 2) separability among classes. These terms are discussed in the following text.

The variability within classes derived from the % coefficient of variation per class (from tables IIa-VIIIa). This percent was averaged over all four bands for each class and listed according to pass, shown in table IX. Theoretically, high variability within classes could create overlapping multispectral signatures among all classes. This situation is not conducive to an optimum classification. In this investigation, the highest average variability within classes occurred for the months of February and May. Variability (high or low) *within* classes alone is not sufficient to predict optimum classifying time because it bears no relative information about the statistical distance *between* class means.

Separability among class spectral means resulted from the scaled distance data (from tables IIb-VIIIb). For each class, the pairwise scaled distances were averaged and listed for each pass, given in table X.

High average separability among class spectral means occurred for the months of April, May, and June.

Dispersion index values were generated for each class from the ratio of separability to variability and listed according to pass, as shown in table XI. The months of June and September exhibited the highest average DI, indicating optimum mapping time for all classes. Considering the classes individually, April appeared to be the best month to map *Juncus roemerianus*, May - *Spartina alterniflora*, June - *Baccharis halimifolia*, and September - *Spartina patens* and *Distichlis spicata*.

To compare the use of DI vs. training sample classification accuracy, the latter was generated by an ERL software program. Table XII provides classification accuracy data for each sample listed by date of pass. The table shows only the percent of elements within a training sample that actually classified as that training sample using the signatures derived from the sample statistics. The average accuracies presented at the bottom of table XII indicate the overall Landsat classification accuracy for the data set of a given pass month. Data from the months of June and September exhibited the highest accuracies, though the lack of data for three training samples on the June pass leads one to question the validity of the June results.

Figure 3 presents a graph comparing average DI and average percent training sample classification accuracy as a function of time. Values of both indicators were maximum for June and September, though the relationship of DI and training sample classification accuracy with respect to time was not the same for the remaining months.

DISCUSSION

This section of the paper discusses the methods and final results of the investigation. It qualifies some of the assumptions and offers explanations for the results.

The training sample set signifies a critical element of this investigation. Table I indicated that descriptions of percent cover, i.e., exposed mud and water, as well as vegetation in each training sample, varied over the three years of field observations. Thus, the ephemeral presence or absence of surface water due to tide and precipitation played a role in the MSS classification for the same training sample on different pass dates. The spectral quality of the vegetation, alone, did not comprise the spectral characteristics of the training sample. The seasonal sun elevation and atmospheric conditions at the time of each Landsat pass also affected the average reflectivity response of each training sample. This effect is inherent in the results. To extend the findings of this investigation to the classification of data acquired over a much larger geographic area of marsh, represented only in part by the training samples, one must assume that the training samples characterize the natural distribution.

In accepting the investigation procedure, one assumed that the Landsat MSS data, selected for each month of the marsh growing season, represented the vegetation at progressive instants within an annual phenological continuum. In other words, MSS data taken from different years were expected to depict the vegetative spectral qualities of sequential growth within a single year. However, the MSS data were selected from various years because of cloud constraints. One had to assume, for instance, that the April 1976 data exemplified the natural growth stage, but 60 days later, of the same vegetation on the February 1977 data. One also assumed that the data acquired instantaneously on a given pass date typified the spectral characteristics of the vegetation for that entire month. However, the vegetation grew continuously, probably resulting in changing spectral characteristics over a month's time.

The objective of this investigation was to determine optimum classification time within the framework of ERL software. Thus, no major software modification occurred. The factors of separability among class spectral means, variability within classes, and training sample classification accuracy related to the computer processing and analysis of the MSS data via the ERL pattern-recognition programs.

The graph of the average DI and training sample classification accuracy (figure 3) showed June and September data exhibited the highest peaks for both variables. The June data probably typified a vegetative "green peak," providing more separable spectral characteristics among the species. However, the lack of some of the June training sample data reduces the validity of these results. The September data probably typified anthesis for some of the species, where the flowering and fruiting contributed to spectral separation among the species. The five marsh species studied do not emerge simultaneously nor grow at the same rate, however. The results, though they are associated with particular calendar times, actually identify the growth stage and climatic and environmental conditions optimum for classifying the five species within the study area. These findings can probably be extended to the classification of marsh species within the Louisiana, Mississippi, and Alabama Gulf Coasts, where climatic and environmental conditions are similar.

The results were based on a comparison of relative data. Therefore, the term "optimum classification time" does not relate to an absolute, maximum classification accuracy or dispersion index. The determination of these values would require further investigation and additional measurements. Also, these results can only be used to predict optimum time for classification of marsh species with respect to the Landsat MSS. Though the results of this investigation do not relate to an optimum time for producing a composite classification of different land cover types, the same technique could be applied for such a determination.

CONCLUSIONS

1. A technique was used to determine the optimum time for classifying marsh vegetation from computer-processed Landsat MSS data. The technique depended on the analysis of data derived from supervised pattern recognition by maximum likelihood theory. A dispersion index, created by the ratio of separability among the class spectral means to variability within the classes, defined the optimum classification time. This technique should probably be applied to the determination of optimum classification time for a combination of other land cover classes.

2. Data compared from seven Landsat passes acquired over the same area of the Louisiana marsh indicated that June and September were optimum marsh mapping times to collectively classify *Baccharis halimifolia*, *Spartina patens*, *Spartina alterniflora*, *Juncus roemericanus*, and *Distichlis spicata*.

3. The same technique was used to determine the optimum classification time for individual species. April appeared to be the best month to map *Juncus roemericanus*; May, *Spartina alterniflora*; June, *Baccharis halimifolia*; and September, *Spartina patens* and *Distichlis spicata*. This information is important, for instance, when a single species is recognized to indicate a particular environmental condition.

References

1. Federal Register, Vol. 38, Number 229, Part V, Chapter IX, Part 920.20.

2. Chapman, V.J., Salt Marshes and Salt Deserts of the World. Interscience Publishers (New York) 1960, pp. 256-259.

3. Penfound, William T. and Hathaway, Edward S., Plant Communities in the Marshlands of Southeastern Louisiana. Ecological Monographs, Vol. 8, No. 1, Jan. 1938, p.p. 1-56.

4. Whitley, Sidney L., A Procedure for Automated Land Use Mapping Using Remotely Sensed Multispectral Scanner Data. NASA TR R-434, 1975.

Figure 1. Map locations of training samples.

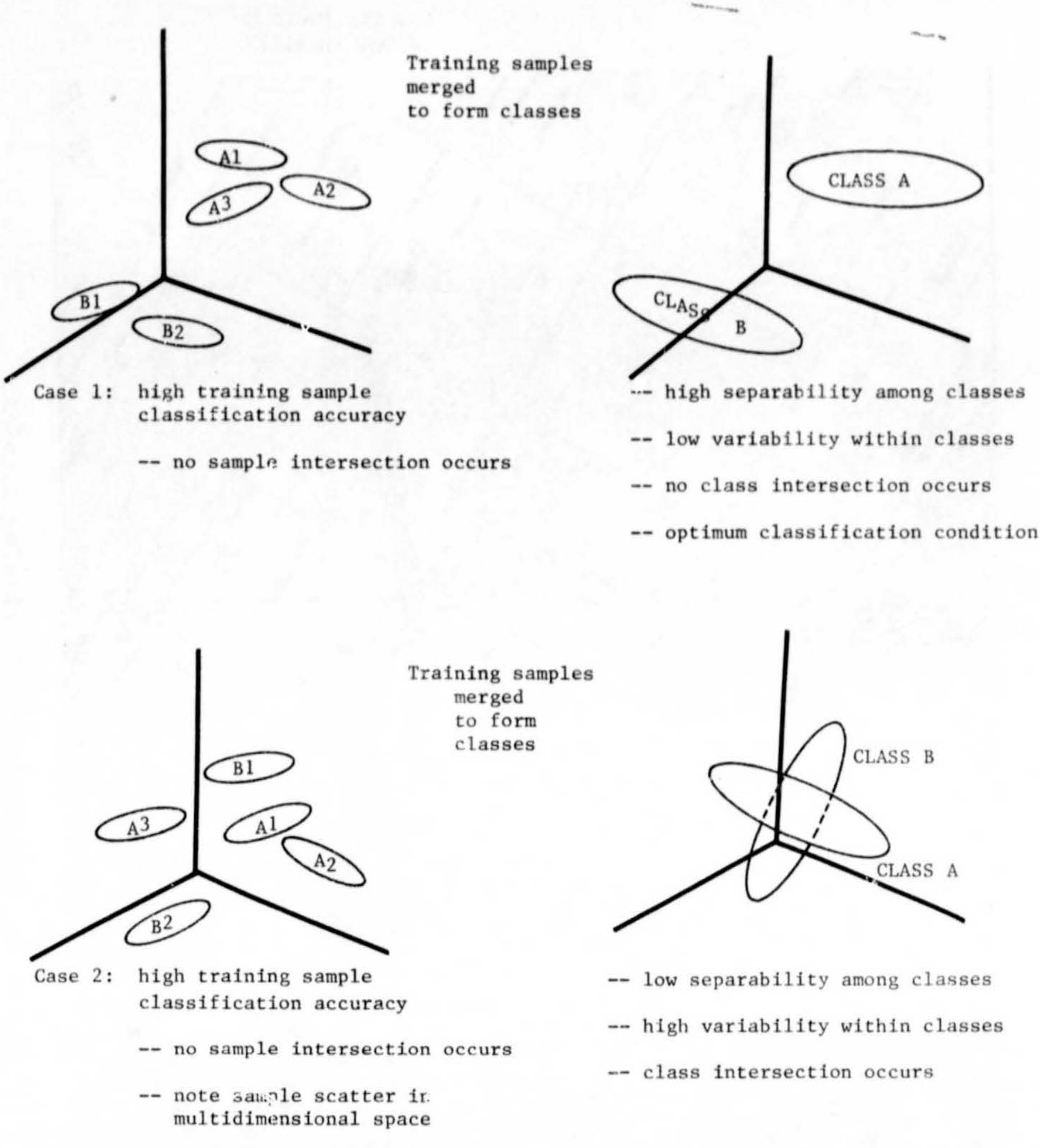
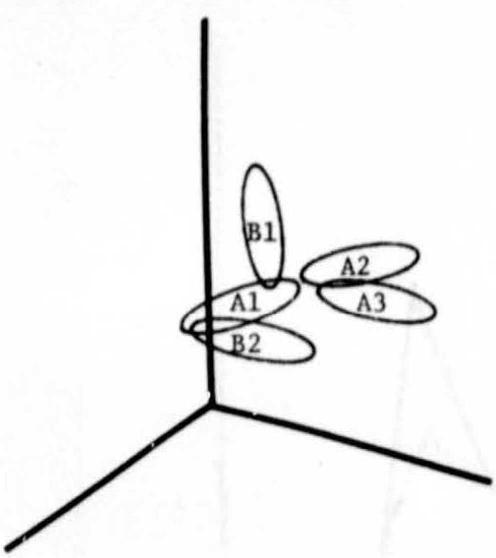
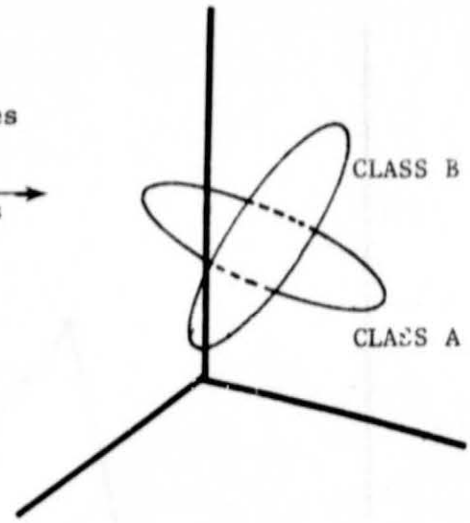


Figure 2. Hypothetical cases of the relationship of training sample classification accuracy to separability among classes and variability within classes. Based on a supervised, pattern-recognition technique for the classification of MSS data. (Three dimensions in space are represented pictorially, though four dimensions are actually involved.)



Training samples
merged

to form classes



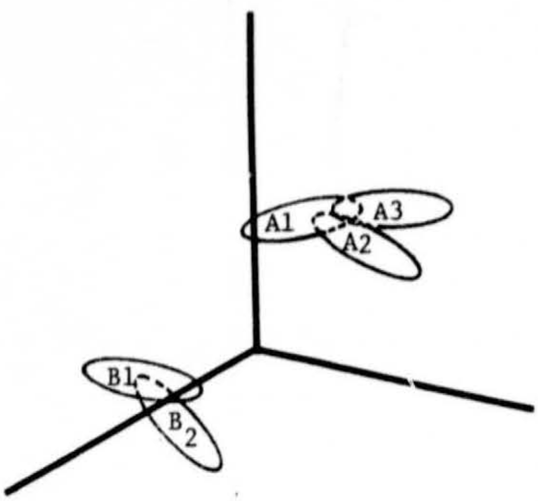
Case 3: low training sample classification accuracy

-- Sample intersection occurs

-- low separability among classes

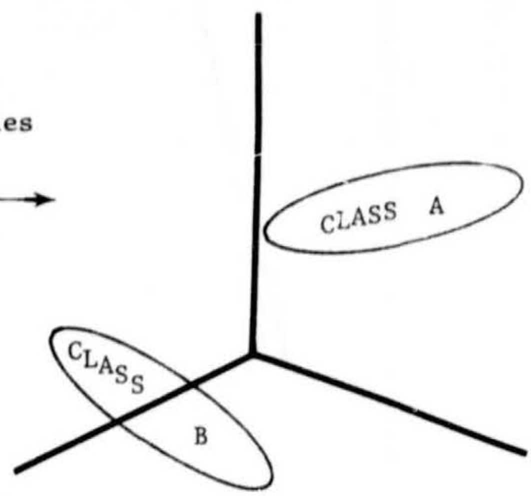
-- high variability within classes

class intersection occurs



Training samples
merged

to form
classes



Case 4: low training sample classification accuracy

-- Sample intersection occurs

-- high separability among classes

-- low variability within classes

-- no class intersection occurs

-- optimum conditions

Figure 2. -Concluded

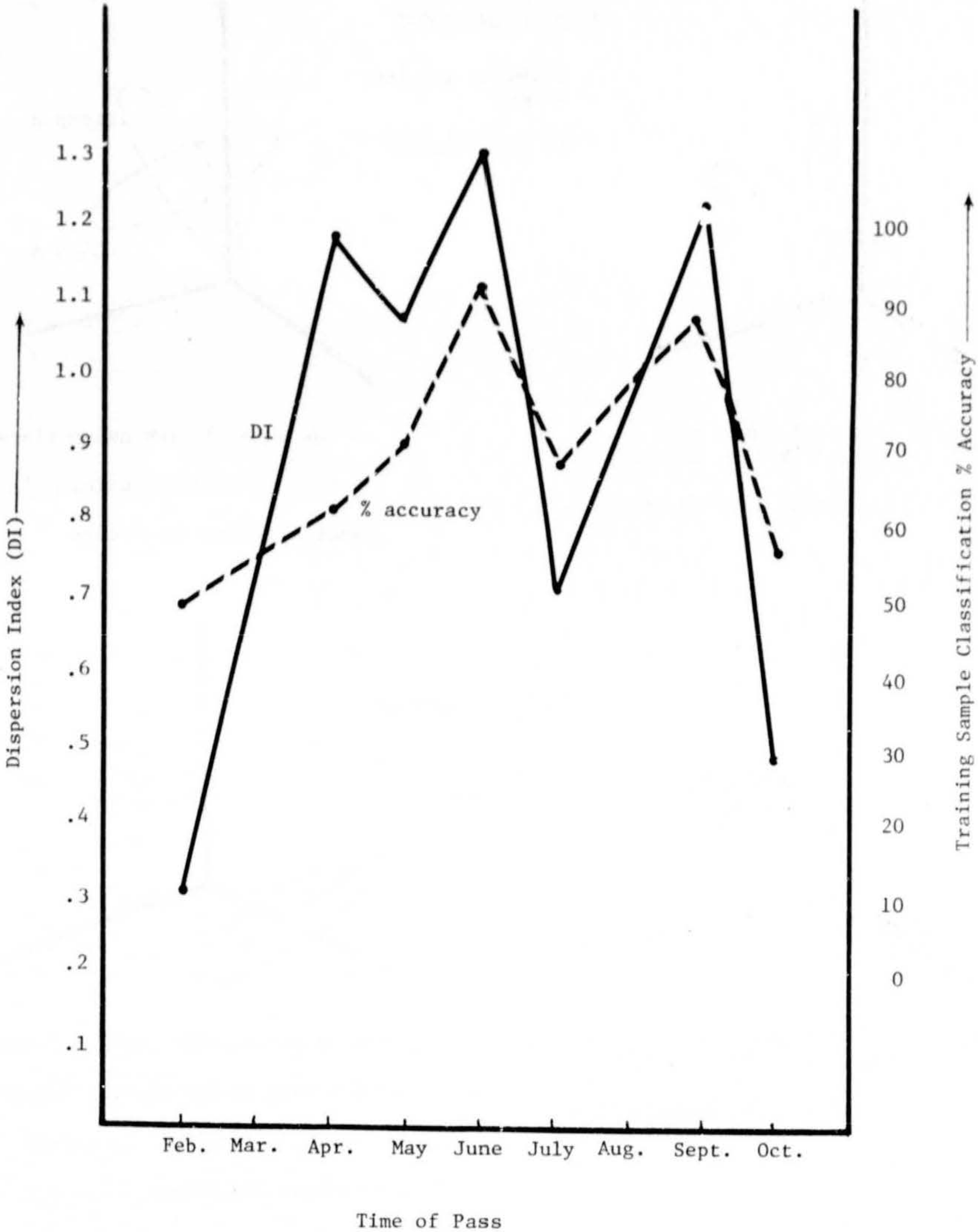


Figure 3. Graph of Dispersion Index and Training Sample Classification Accuracy (%) As a Function of Time of Landsat Pass

These abbreviations are used in the following tables:

BH --- *Baccharis halimifolia*

SP --- *Spartina patens*

JR --- *Juncus roemerianus*

SA --- *Spartina alterniflora*

DS --- *Distichlis spicata*

TABLE IX.- VARIABILITY WITHIN CLASSES (AVE. % COEFFICIENT OF VARIATION)

CALCULATED FROM LANDSAT MSS DATA.

	Time of Pass						
Class	Feb.	Apr.	May	June	July	Sept.	Oct.
BH	9.0	6.1	8.7	6.0	6.1	4.9	8.0
SP	27.8	16.0	17.7	17.7	32.0	11.1	13.8
JR	12.5	9.7	29.0	--	6.7	12.3	11.6
SA	17.0	12.2	12.2	20.6	14.1	12.5	15.1
DS	10.3	5.6	7.5	8.5	7.4	4.3	7.2

TABLE X. - SEPARABILITY AMONG CLASS SPECTRAL MEANS (SCALED DISTANCE) CALCULATED FROM LANDSAT MSS DATA

	Time of Pass						
Class	Feb.	Apr.	May	June	July	Sept.	Oct.
BH	6.3	16.3	19.5	17.0	11.3	10.0	5.5
SP	2.5	9.0	11.8	11.3	5.0	9.8	6.8
JR	2.5	8.0	15.0	--	4.5	9.5	4.0
SA	2.8	7.5	9.5	10.7	4.8	8.0	4.8
DS	4.0	6.8	8.8	10.3	4.0	7.8	4.5

TABLE XI. - DISPERSION INDEX CALCULATED FROM LANDSAT MSS DATA

Class	Time of Pass Feb.	Apr.	May	June	July	Sept.	Oct.
BH	.70	2.75	2.24	2.83*	1.90	2.04	.69
SP	.08	.56	.67	.64	.16	.88*	.49
JR	.20	.82*	.52	----	.67	.77	.34
A	.16	.61	.78*	.52	.34	.64	.32
DS	.38	1.21	1.17	1.21	.54	1.81*	.63
Ave.	.31	1.19	1.08	1.30	.72	1.23	.49

*Indicates optimum classification time for a single species.

TABLE XII. - PERCENT CLASSIFICATION ACCURACY OF THE TRAINING SAMPLES

	Time of Pass						
Sample	Feb.	Apr.	May	June	July	Sept.	Oct.
92BH	52.31	100.00	92.00	98.28	86.15	91.67	80.46
111SP	73.81	78.18	77.36	97.92	100.00	94.00	61.11
133SP	39.22	63.79	67.16	80.33	80.85	96.30	45.45
145SP	93.94	86.36	96.77	87.50	72.41	80.00	66.67
151SP	55.56	58.82	77.78	100.00	73.08	88.00	71.88
142JR	17.65	14.29	100.00	--	40.91	100.00	76.19
214JR	60.00	42.86	50.00	--	51.35	84.85	8.57
135SA	51.52	31.25	43.33	100.00	62.86	70.00	78.38
153SA	7.69	57.14	35.29	93.33	43.75	84.62	40.00
213SA	52.17	78.26	84.00	--	82.14	91.30	31.43
141DS	42.86	78.95	54.55	80.95	63.64	84.21	75.00
Ave.	49.7	62.70	70.70	92.30	68.80	87.70	57.70

Appendix

This section includes table I, the ground truth record of the training samples, tables IIa - VIIIa, the data from which variability within classes was derived, and tables IIb - VIIIb, the data from which separability among class spectral means was derived.

TABLE I. - GROUND TRUTH RECORD FOR MARSH TRAINING SAMPLES
(Percent of Sample Area)

Training Sample	1974		1975		1976	
92	Baccharis halimifolia (flowering)	70%	Baccharis halimifolia	85%	Baccharis halimifolia	80%
	Phragmites communis	8%	Sambucus canadensis		Phragmites communis	
	Solidago mexicana		Myrica cerifera		Salix nigra	
	10/7/74		9/26/75		8/18/76	
111	Spartina patens		Spartina patens	35%	Spartina patens	35%
	Bacopa monieri		Distichlis spicata	15%	Juncus roemerianus	35%
	Phragmites communis		Spartina alterniflora	7%	Baccharis halimifolia	8%
			Bacopa monieri	7%	Phragmites communis	7%
			Cyperus sp.		Water	15%
			Water	30%		
	7/25/74		9/29/75		9/24/76	
133	Spartina patens	100%	Spartina patens	95%	Spartina patens	84%
			Spartina alterniflora		Spartina alterniflora	6%
			Surface water visible		Water	10%
	10/1/74		10/1/75		8/24/76	
135	Spartina alterniflora	50%	Spartina alterniflora	50%	Spartina alterniflora	65%
	Distichlis spicata	40%	Distichlis spicata	30%	Distichlis spicata	25%
	Batis maritima	5%	Water	20%	Water	10%
	7/25/74		10/1/75		8/20/76	
141	Spartina alterniflora	45%	Spartina alterniflora	55%	Spartina alterniflora	60%
	Distichlis spicata	45%	Distichlis spicata	30%	Distichlis spicata	30%
	Batis maritima	5%	Batis maritima	10%	Water	10%
			Water	5%		
	7/25/74		10/1/75		8/20/76	

TABLE I. - CONTINUED

Training Sample	1974		1975		1976	
142	*Juncus roemerianus*	65%	*Juncus roemerianus* (tips are bent & brown)	65%	*Juncus roemerianus*	55%
	Spartina alterniflora	20%	*Spartina alterniflora*	35%	*Spartina alterniflora*	25%
	Distichlis spicata	10%			*Distichlis spicata*	10%
	Borrichia frutescens				Water	10%
	7/26/74		10/1/75		8/20/76	
145	*Spartina patens*	90%	*Spartina patens*	60%	*Spartina patens*	80%
	Spartina alterniflora	5%	*Spartina alterniflora*	3%	*Juncus roemerianus*	10%
			Juncus roemerianus	7%	*Scirpus* Sp.	
			Water	30%	Water	10%
	7/26/74		10/1/75		8/20/76	
151	*Spartina patens*	100%	*Spartina patens*	65%	*Spartina patens*	65%
			Spartina alterniflora	2%	*Spartina alterniflora*	10%
			Water	30%	*Cyperus* sp.	10%
					Water	10%
	7/25/74		9/30/75		9/24/76	
153	*Spartina alterniflora*	50%	*Spartina alterniflora*	25%	*Spartina alterniflora*	55%
	Spartina patens	40%	*Spartina patens*	15%	*Spartina patens*	25%
	Spartina cynosuroides		*Spartina cynosuroides*	10%	*Juncus roemerianus*	10%
			Distichlis spicata	10%	Water	5%
			Scirpus olneyi			
	7/26/74		9/30/75		9/24/76	

TABLE I. - CONCLUDED

Training Sample	1974		1975		1976	
213	*Spartina alterniflora*	30%	*Spartina alterniflora*	70%	*Spartina alterniflora*	75%
	Spartina patens	30%	*Juncus roemerianus*	15%	*Distichlis spicata*	10%
	Distichlis spicata	30%	*Distichlis spicata*	10%	Water	15%
	Juncus roemerianus	15%	Water	10%		
	4/4/75		9/29/75		8/20/76	
214	*Juncus roemerianus*	85%	*Juncus roemerianus*	35%	*Juncus roemerianus*	40%
	Spartina alterniflora	5%	*Spartina alterniflora*	25%	*Spartina alterniflora*	15%
	Borrichia frutescens		*Batis maritima*		*Distichlis spicata*	5%
	Batis maritima		*Distichlis spicata*		Water	30%
	Distichlis spicata		Mud	35%	Dead vegetation	10%
	4/4/75		9/29/75		8/20/76	

TABLE IIa. CLASS MEANS, STANDARD DEVIATIONS AND % COEFFICIENTS OF VARIATION FOR FEBRUARY

Class		Band 4	Band 5	Band 6	Band 7
BH-1	Mean	13.60	15.17	20.08	9.17
	Std. Dev.	.99	1.46	1.99	.83
	% C. of V.	7.3	9.6	9.9	9.1
SP-2	Mean	12.56	14.45	15.81	6.64
	Std. Dev.	1.49	2.89	5.67	2.87
	% C. of V.	11.9	20.0	35.9	43.2
JR-3	Mean	12.96	13.63	14.69	6.75
	Std. Dev.	.88	1.07	2.15	1.39
	% C. of V.	6.8	7.9	14.6	20.6
SA-4	Mean	13.38	14.45	15.08	6.42
	Std. Dev.	1.01	1.73	2.80	1.92
	% C. of V.	7.5	12.0	18.6	29.9
DS-5	Mean	13.05	13.48	12.86	5.62
	Std. Dev.	1.05	1.01	1.42	.82
	% C. of V.	8.0	7.5	11.0	14.6

TABLE IIb. CLASS PAIRWISE SCALED DISTANCE MATRIX FOR FEBRUARY

	BH	SP	JR	SA
SP	5			
JR	6	1		
SA	6	1	1	
DS	8	3	2	3

TABLE IVa. CLASS MEANS, STANDARD DEVIATIONS AND % COEFFICIENTS OF VARIATION FOR MAY

Class		Band 4	Band 5	Band 6	Band 7
BH-1	Mean	17.38	14.34	59.32	32.22
	Std. Dev.	.70	.84	6.95	4.23
	% C. of V.	4.0	5.9	11.7	13.1
SP-2	Mean	19.55	19.04	41.33	19.94
	Std. Dev.	2.08	2.82	8.61	4.86
	% C. of V.	10.6	14.8	20.8	24.4
JR-3	Mean	21.57	21.83	22.66	8.48
	Std. Dev.	3.52	2.84	6.02	5.08
	% C. of V.	16.3	13.0	26.6	59.9
SA-4	Mean	18.81	19.14	29.67	13.51
	Std. Dev.	1.36	2.27	3.58	2.37
	%C. of V.	7.2	11.9	12.1	17.5
DS-5	Mean	18.95	19.68	30.41	14.50
	Std. Dev.	1.16	1.16	2.62	1.37
	% C. of V.	6.1	5.9	8.6	9.4

TABLE IVb. CLASS PAIRWISE SCALED DISTANCE MATRIX FOR MAY

	BH	SP	JR	SA
SP	14			
JR	27	16		
SA	20	9	8	
DS	17	8	9	1

TABLE Va. CLASS MEANS, STANDARD DEVIATIONS AND % COEFFICIENTS OF VARIATION FOR JUNE

Class		Band 4	Band 5	Band 6	Band 7
BH-1	Mean	20.45	17.62	54.43	28.22
	Std. Dev.	1.12	1.13	3.23	1.72
	% C. of V.	5.5	6.4	5.9	6.1
SP-2	Mean	22.48	21.90	41.14	18.72
	Std. Dev.	3.10	3.58	7.46	4.21
	% C. of V.	13.8	16.3	18.1	22.5
SA-3	Mean	29.98	30.00	36.10	14.37
	Std. Dev.	8.00	7.91	4.96	2.26
	% C. of V.	26.7	26.4	13.7	15.7
DS-4	Mean	30.67	29.24	35.67	14.81
	Std. Dev.	1.76	2.57	3.23	1.54
		5.7	8.8	9.1	10.4

TABLE Vb. CLASS PAIRWISE SCALED DISTANCE MATRIX FOR JUNE

	BH	SP	SA
SP	12		
SA	20	11	
DS	19	11	1

TABLE VIa. CLASS MEANS, STANDARD DEVIATIONS AND % COEFFICIENTS OF VARIATION FOR JULY

Class		Band 4	Band 5	Band 6	Band 7
BH-1	Mean	29.97	20.14	40.35	21.28
	Std. Dev.	1.31	1.63	2.47	1.23
	% C of V.	4.4	8.1	6.1	5.8
SP-2	Mean	29.80	21.50	27.31	12.55
	Std. Dev.	1.79	2.80	12.67	7.85
	% C. of V.	6.0	13.0	46.4	62.5
JR-3	Mean	30.00	23.32	27.20	12.64
	Std. Dev.	1.25	1.29	2.16	1.16
	% C. of V.	4.2	5.5	7.9	9.2
SA-4	Mean	31.32	24.58	30.03	14.33
	Std. Dev.	2.79	3.20	4.63	2.71
	% C. of V.	8.9	13.0	15.4	18.9
DS-5	Mean	29.78	23.15	27.93	13.70
	Std. Dev.	1.01	1.24	2.63	1.57
	% C. of V.	3.4	5.4	9.4	11.5

TABLE VIb. CLASS PAIRWISE SCALED DISTANCE MATRIX FOR JULY

	BH	SP	JR	SA
SP	12			
JR	12	2		
SA	10	4	3	
DS	11	2	1	2

TABLE VIIa. CLASS MEANS, STANDARD DEVIATIONS AND % COEFFICIENTS OF VARIATION FOR SEPTEMBER

Class		Band 4	Band 5	Band 6	Band 7
BH-1	Mean	26.86	23.49	44.82	21.54
	Std. Dev.	1.16	1.36	1.99	1.10
	% C. of V.	4.3	5.8	4.4	5.1
SP-2	Mean	27.37	25.95	47.75	21.80
	Std. Dev.	2.25	2.16	5.77	3.45
	% C. of V.	8.2	8.3	12.1	15.8
JR-3	Mean	33.96	31.85	32.85	12.19
	Std. Dev.	3.71	4.30	3.68	1.65
	%C. of V.	10.9	13.5	11.2	13.5
SA-4	Mean	27.90	25.83	30.32	12.68
	Std. Dev.	2.48	2.80	3.57	2.23
	% C. of V.	8.9	10.8	11.8	18.4
DS-5	Mean	29.32	27.16	29.84	12.21
	Std. Dev.	1.03	.86	1.82	.55
	% C. of V.	3.5	3.2	6.1	4.5

TABLE VIIb. CLASS PAIRWISE SCALED DISTANCE MATRIX FOR SEPTEMBER

	BH	SP	JR	SA
SP	2			
JR	14	13		
SA	12	12	6	
DS	12	12	5	2

TABLE VIIIa. CLASS MEANS, STANDARD DEVIATIONS AND % COEFFICIENTS OF VARIATION FOR OCTOBER

Class		Band 4	Band 5	Band 6	Band 7
BH-1	Mean	25.60	17.48	26.92	13.28
	Std. Dev.	1.23	1.50	1.94	1.51
	% C. of V.	4.8	8.6	7.2	11.4
SP-2	Mean	23.92	19.11	29.74	14.62
	Std. Dev.	1.82	2.42	4.45	2.92
	% C. of V.	7.6	12.7	15.0	20.00
JR-3	Mean	24.30	18.20	21.77	10.36
	Std. Dev.	1.45	1.89	2.94	1.69
	% C. of V.	6.0	10.4	13.5	16.3
SA-4	Mean	23.67	17.20	19.96	9.01
	Std. Dev.	1.54	1.99	3.58	2.21
	% C. of V.	6.5	11.6	17.9	24.5
DS-5	Mean	24.42	18.04	20.25	9.50
	Std. Dev.	1.04	1.43	1.29	.95
	% C. of V.	4.3	7.9	6.4	10.00

TABLE VIIIb. CLASS PAIRWISE SCALED DISTANCE MATRIX FOR OCTOBER

	BH	SP	JR	SA
SP	3			
JR	5	7		
SA	7	9	2	
DS	7	8	2	1