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Estimating Vegetation Coverage in St. Joseph Bay, Florida with an Airborne Multispectral Scanner

Qualitative comparison of the classification results with ground-truth information shows the classification maps to be both detailed and generally accurate.

ABSTRACT: *A four-channel multispectral scanner (MSS) carried aboard an aircraft was used to collect data along several flight paths over St. Joseph Bay, Florida. Various classifications of benthic features were defined from the results of ground-truth observations. The classes were statistically correlated with MSS channel signal intensity using multivariate methods. Application of the classification measures to the MSS data set allowed computer construction of a detailed map of benthic features of the bay. Various densities of seagrasses, various bottom types, and algal coverage were distinguished from water of various depths. The areal vegetation coverage of St. Joseph Bay was not significantly different from the results of a survey conducted six years previously, suggesting that seagrasses are a very stable feature of the bay bottom.*

INTRODUCTION

SUBMERGED MACROPLANT VEGETATION is a characteristic feature of the benthos of many coastal marine environments. Macroalgae play an important role in marine food webs along both coasts of North America (Mann, 1973). Seagrasses are widely distributed along coasts, particularly in tropical and subtropical latitudes where low-energy conditions prevail (Den Hartog, 1970). Seagrass beds stabilize sediments (Scoffin, 1970) and provide habitat for juvenile fish (Livingston, 1975) and invertebrates (Heck, 1976). The beds support detritus-based food webs, including those leading to shrimp production in the Gulf of Mexico (Parker, personal communication).

Estimates of seasonal primary productivity of macroplants are an important component of marine carbon-balance computations for some coastal environments. Measurements of specific productivity combined with areal biomass estimates are necessary constituents of macroplant productivity calculations. Seagrass beds can be surveyed from boats (Young and Kirkman, 1975); however, this method yields discrete sample data sets of variable levels of resolution. Surface-based surveys can be expensive

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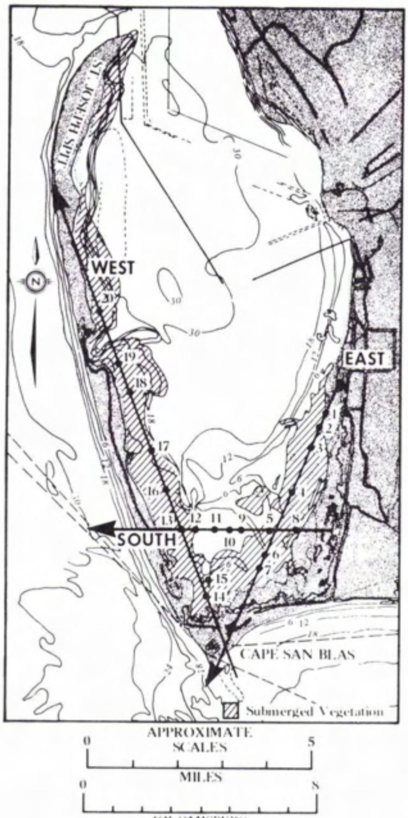

FIG. 1. Flight lines and station locations in St. Joseph Bay, Florida.

if large ships are used as platforms and if extensive areas must be surveyed. The general areal coverage of submerged vegetation can be estimated from aerial photography; however, it is difficult to characterize and make quantitative estimates of different macroplant constituents of the cover from photographs.

With spacecraft scanner data readily available on a regular, repetitive basis, it would be highly desirable to develop a technique that would permit a uniform, repeatable, objective analysis of this type data. A standard technique applied to data acquired at intervals over a period of years would make possible the evaluation of natural and anthropogenic factors causing changes to benthic vegetation.

A research project was therefore undertaken to determine if it were possible to use computer implemented spectral pattern recognition algorithms to distinguish benthic vegetation. The first efforts were made with an airborne multispectral scanner rather than with satellite data that present the complexities of relatively coarse resolution, coordination of surface-truth data acquisition with fixed spacecraft schedules, atmospheric considerations relative to the schedule of spacecraft passages, and the optical density of the atmosphere as viewed from the orbiting platform.

During the summer of 1978, the use of remote multispectral scanning sensors for surveying submerged marine macroplant distribution was investigated. The project was designed to characterize the fine-scale features of submerged vegetation in St. Joseph Bay, Florida. The general features of the bay, including an estimate of bottom coverage of *Thalassia testudinum*, had been determined during a survey of the near-shore region of the Gulf of Mexico (McNulty *et al.*, 1972) (Figure 1). St. Joseph Bay receives negligible fresh water input and contains very small populations of phytoplankton. The sediments are primarily sand, or muddy sand, and settle out of the water column rapidly, so the water is usually very clear. Broad expanses of nearly monospecific stands of *Thalassia* are located around the periphery of the bay. Drift algae accumulate in portions of the bay during spring and fall, with some stands of attached macroalgae present throughout the growing season.

The goal of this research was to develop methods for distinguishing seagrass and macroalgal coverage from bare bottom in St. Joseph Bay by computer analysis of electronic scanner imagery data acquired with a multispectral scanner carried aboard an aircraft. We wished to use the methods for assessing changes in arenal coverage of vegetation in St. Joseph Bay since the investigation of McNulty *et al.* (1972).

METHOD DEVELOPMENT

A Texas Instruments RS-18 multispectral scanner, originally built as a thermal scanner, was modified by the addition of four visible and near-infrared wavelength bands: 400 to 500 nm (channel 1); 500 to 600 nm (channel 2); 600 to 700 nm (channel 3); and 800 to 1000 nm (channel 4). The instantaneous field of view of the scanner was 2.5 milliradians, corresponding to a spot 2.5 m wide for an instrument altitude to 1000 m. The scan width was 100°, giving a total scan of approximately 2400 m at that altitude. The signal from the scanner was recorded in a pulse code modulation format after digitization. The instrument was operated in an uncalibrated mode, so that signal level was a measure of relative radiance within each spectral band.

Data for the investigation were acquired at an altitude of 1520 m on 19 May 1978. The picture-element width was 3.8 m and the total scan width was 3630 m. The extreme angles of the scan introduced problems in analysis caused by geometric distortion, variation of target reflectivity, and atmospheric problems; therefore, only the data from the central 70° were used, giving a total scan width of 2130 m.

Data were of excellent quality in channels 2, 3, and 4, but the information content of channel 1 was very low. This was not unexpected and was a consequence of inadequate detector sensitivity for that channel, leading to a poor signal-to-noise ratio. Atmospheric effects for channels 2 and 3 can be significant, but restricting the field of view to $\pm 35°$ reduces the variation in optical thickness to less than 15 percent. The subject data set was acquired on a very clear day when effects were minimum. As expected, the near-infrared channel provided no information related to the submerged vegetation, but did provide the capability to discriminate readily between water and land or emergent vegetation.

Sun elevation and azimuth are important considerations when collecting imaged data over water bodies. Specular reflection of the solar disk (sun glint) may be orders of magnitude greater in intensity than the light reflected from the bottom or from vegetation covering the bottom of the water body. The ideal situation for remote sensing with a scanning sensor is for the sun to be directly in front of, or directly behind, the aircraft, at a maximum elevation determined to some extent by surface roughness (and, therefore, windspeed), but generally time of data collection was less than optimum and severe sun-glint contamination made some of the data on the eastern side of the bay unusable.

A 9-inch format Zeiss RMK 15/23 camera equipped with a 6-inch lens and 2A and AV filters was flown on the data acquisition mission. The Zeiss photography, using standard color film SO397, provided a record of almost the entire scene imaged by the RS-18 scanner and included nearly the entire area of the bay having significant bottom vegetation cover. Variations in depth and density of vegetation could be observed in the photographs (Plate 1), so photography was used to extend the observations made at various sampling locations by divers to almost all the area imaged with the electronic sensors. This method extended the ground-truth data primarily for the purpose of evaluating the classification.

Locations at which ground-truth data had been acquired by the divers were easily identified in the aerial photographs and in the scanner data when the latter were displayed on the image-processing system. Sheets of styrofoam (1.22 by 2.44 m) deployed at these locations were visible at each sampling station. Training samples were selected from the imagery only at these locations so that spectral signatures could be associated with the ground-truth information. When the scanner image near the marker appeared heterogeneous, care was taken to include only the area in the direction from the marker at which the ground-truth sampling was done. Picture elements (pixels) that appeared inconsistent with the truth information were eliminated. For example, if the ground-truth data indicated a dense growth of *Thalassia* and if there were several bright pixels in contrast to the darker pixels typical of dense benthic vegetation in the imagery, the bright pixels were identified as bare sand spots and were excluded from the training data being developed for dense vegetation. Channels 2 and 3 were used to select the training fields at 20 ground-truth stations. When a sampling station was imaged under two flight lines, training fields were selected for that location from both imagery data sets and were coded by station number and flight line (east, south, and west).

The relative mean radiance upwelling and standard deviation were computed for each spectral channel for each training field. Standard deviations were examined to determine whether a training field was contaminated by variation of the bottom cover, or whether an electronic problem had caused recording of erroneous data. If the deviation exceeded 10 percent of the mean, the training field was again viewed, any "spurious" points were eliminated, and the statistics were recomputed.

After analysis of the training field statistics, it became evident that there were features along the flight lines that were not represented in the ground-truth data. Consequently, additional training fields were taken in areas identified from the photographs. These areas were located in deep water where the bottom was not visible and in intermediate-depth areas (approximately 2 to 4 m) where the bottom was visible but had no significant vegetation cover. No vegetated areas were involved in the expanded set of training data.

Two analytical techniques were used to process the scanner data. The first used spectral information from the training fields and a discriminate function analysis computer program (Dixon, 1977) to develop algorithms for use in a supervised pattern-recognition approach. The second technique consisted in using spectral data from the training fields combined with unsupervised data groupings in a hybrid supervised/unsupervised maximum-likelihood pattern-recognition approach.

Discriminant Function Supervised Technique

The first step in this process was the grouping of training fields into meaningful classes. The initial grouping was subjective, based on uniformity of ground-truth information about vegetation density, the presence or absence of algae, the depth of water, and the uniformity of the remotely measured upwelling light radiance. The ground-truth information separated into eleven classes. Four depth ranges were identified: very shallow (less than 1 m), shallow (1-2 m), deep (2-3 m), and very deep (greater than 3 m). The rooted-vegetation density was partitioned into four classes: bare (no appreciable *Thalassia*), sparse (less than 20 percent cover), medium (20 to 40 percent cover), and dense (greater than 40 percent cover). The floating algal associations were identified as dense red algae, sparse red algase, cream algae, and no algae.

The first approach was to classify data for each of

TABLE 1. TRAINING SAMPLE CLASSES OBTAINED FROM GROUND TRUTH INFORMATION AND TRAINING SAMPLE SPECTRAL DATA FOR DISCRIMINANT FUNCTION CLASSIFICATION

Class Description	Training Samples (No. of pixels used)
Flight Line 1	
Dense Grass	2E (132)
Medium Grass	19W (58)
Sparse Grass	13W (40), 14W (31), 16W (48), 17W (37)
Bare Bottom Visible 1	18W (100)
Bare Bottom Visible 2	23W (1019), 24W (626)
Bare Bottom Visible 3	26W (84), 27W (144), 28W (567)
Bottom Not Visible	15W (146), 21W (3057), 22W (2743), 25W (1030)
Red Algae	20W (79)
Flight Line 2	
Dense Grass	2E (132)
Medium Grass	5S (88), 6S (28), 8S (79)
Sparse Grass	10S (27), 12S (29), 13S (69)
Bare Bottom Visible 1	9S (125)
Bottom Not Visible	11S (178), 15S (276)
Flight Line 3	
Dense Grass	1E (301), 2E (132), 3E (30), 7E (228)
Medium Grass	5E (212), 6E (121), 8E (144)
Sparse Grass	12S (29)
Bare Bottom Visible 1	9S (125)
Bottom Not Visible	11S (178)

the three flight lines, using training-field data from the corresponding line. Flight line 1 (west side of St. Joseph Bay) was selected to be classified first because of the diversity of water depths, vegetation types, and vegetation densities. Statistics used to classify the data from flight line 1 came from this line, except for one dense-grass training field from flight line 3 (east side of St. Joseph Bay) that was included to complete the vegetation range. Means of radiance intensity values from channels 2 and 3 for each training field for each class and flight line (Table 1) were used as input to the discriminant function program, providing an analysis of individual training-field separability and producing a classification algorithm for each final class. Classification algorithms were of the form $A_i\,C_2 + B_i\,C_3 = C_i$ where $i = 1$, the number of classes. The A_i's, B_i's, and C_i's were the coefficients for channel 2, channel 3, and constant terms generated for each class. Training-field statistics from channel 1 and channel 4 were not included because of the low information content revealed in the initial data review.

The next step in the process was to combine algorithms, produced by the discriminant function software for each class with a land/water classifier, in order to classify the RS-18 data from each flight line. A classification program was developed to check the data from each flight line. A classification program was developed to check the data value from channel 4 to determine if the pixel contained land or water. If the pixel contained land (if the radiance intensity value level for water was exceeded), it was classified as land and the program proceeded to the next pixel. If the pixel contained water, then the data from channel 2 and channel 3 for that pixel were processed through the classification algorithms and it was put into one of the remaining classes. The resulting classifications for the three flight lines are shown in the color-coded computer-generated image (Plate 2). The area for each class in each line was computed and is shown in Table 3. The most dramatic problem in the classification was the confusion of the classes Red Algae and Botton Not Visible. While the Red Algae class was separable from the various densities of seagrass (*Thalassia*) and the different Bare Bottom Visible classes, it appeared to have an overlapping spectral signature with the deep water (Bottom Not Visible). This caused a significant part of the deep-water area on the west side of the bay to be classified as Red Algae, a feature clearly evident in Plate 2. An additional problem was the classification of the area to the left on the east line as Bare Bottom Visible 1. This area is primarily deeper water and should have been classified as Bottom Not Visible. Severe sun glint in the area raised the recorded radiance intensities in each channel, making it appear as a Shallow Bare Bottom class. A review of the signatures in all four channels for all training fields, grouped into eight classes, was made to see if further separability could be achieved by using channels 1 and 4. Channel 1 and channel 4 were limited with respect to separability of any of the classes (Figure 2). A display of class means, located as center points and vertical and horizontal lines depicting plus or minus one standard deviation, shows that Red Algae and deep water (Bottom Not Visible) data overlap in a part of the data range

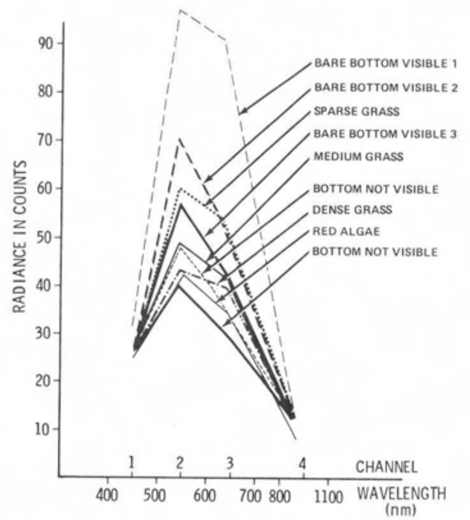

FIG. 2. RS-18 multispectral scanner channel spectral characteristics.

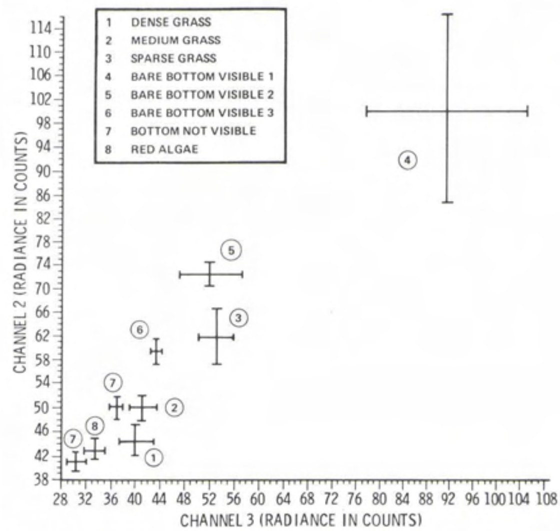

FIG. 3. RS-18 multispectral scanner response to different bottom classification types in St. Joseph Bay, Florida.

in channels 2 and 3 (Figure 3). Rather than expending further computer time to select and refine classification statistics for the Bottom Not Visible and Red Algae classes, the problem was addressed in the hybrid supervised/unsupervised classification effort without using additional training statistics. The supervised classification effort was redirected to classifying the data from each of the three flight lines using algorithms developed with class statistics from a composite of all training fields, excluding the Red Algae training field. This approach permitted the development of more information on the importance of training-field variability from one flight line to another caused by aircraft flight path relative to sun position, vegetation bottom-cover heterogeneity along flight lines, difference in aircraft altitude between flight lines, and the relationship of training variability to classified scene results.

It was not clear whether better results would be achieved by grouping training fields into composite classes for use in classifying all lines or by using classes developed from training fields from each line to classify the data from the same line. A composite training-field set (excluding Red Algae) was prepared with the procedure described earlier to answer that question. The classification obtained with the composite training-field set (Plate 3) yielded a more uniform classification from one flight line to another, as can be seen by comparing the west and south lines with corresponding flight-line classification in Plate 2. Classifications obtained with training fields from individual flight lines provided more detail in specific areas, as demonstrated in the medium seagrass line that ran almost the full length of the east line and in the breakdown of the seagrass beds into medium and sparse grass in the lower section of the west line (Plate 2), a feature that did not appear in Plate 3. Both of these details were present in St. Joseph Bay and were verified by ground-truth operations. The best classification results can be achieved by selecting from each flight line a set of training fields which completely defines all classes found on that line and then classifying the data from that line with the unique set.

HYBRID TECHNIQUE

The hybrid analysis of RS-18 sensor data used statistics computed from training-field imagery taken at the surface-truth locations together with results of a statistical analysis of the entire data set. The two sets of statistics were merged and the entire data set was classified with the merged set.

The training fields were grouped into classes similar to those developed previously, but varied in number and definition as established by a second analytical team. The ground-truth information was separated into 12 classes. Three depth ranges were identified: shallow (less than 1 m), deep (1 to 2 m), and very deep (over 2 m). The rooted-vegetation density was broken into bare (no appreciable *Thalassia*), very sparse (less than 10 percent cover), sparse (10 to 25 percent), medium (25 to 35 percent), and dense (over 35 percent). The floating algal associations were identified as dense red algae, sparse red algae, cream algae, and no algae. The classes derived from grouping the spectral data from the RS-18 training-field statistics, based on the signal level in channels 2 and 3, were similar, but not identical, to classes derived from visual examinations of benthic characteristics.

The final choice for classes was made considering both the imagery data and ground-truth data. Classes were chosen separately for each of the three

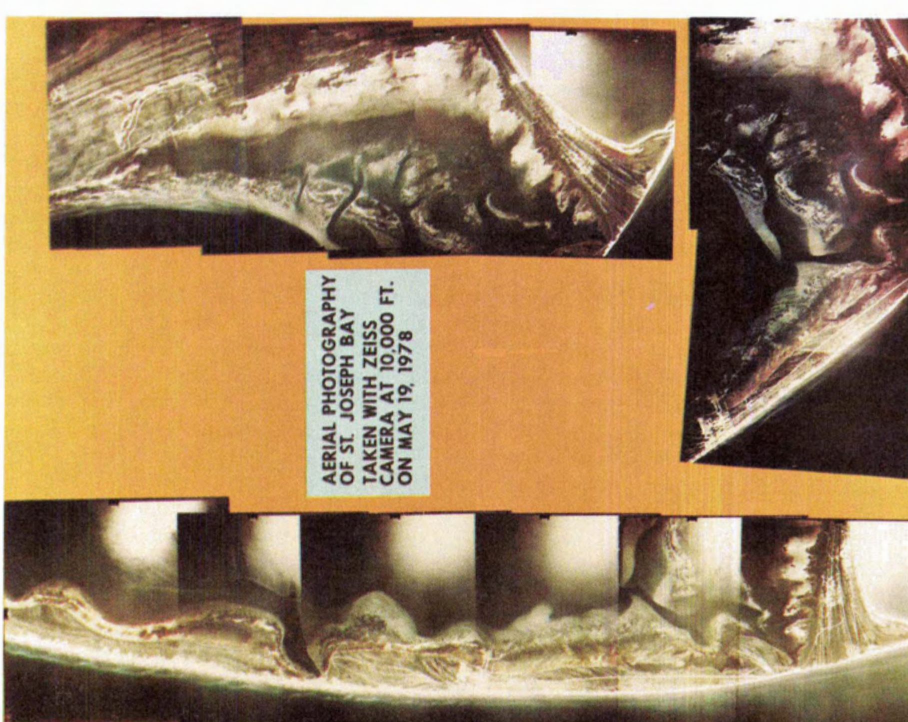

PLATE 1. Aerial photography of St. Joseph Bay, Florida, taken with a Zeiss camera at 10,000 feet on May 19, 1978.

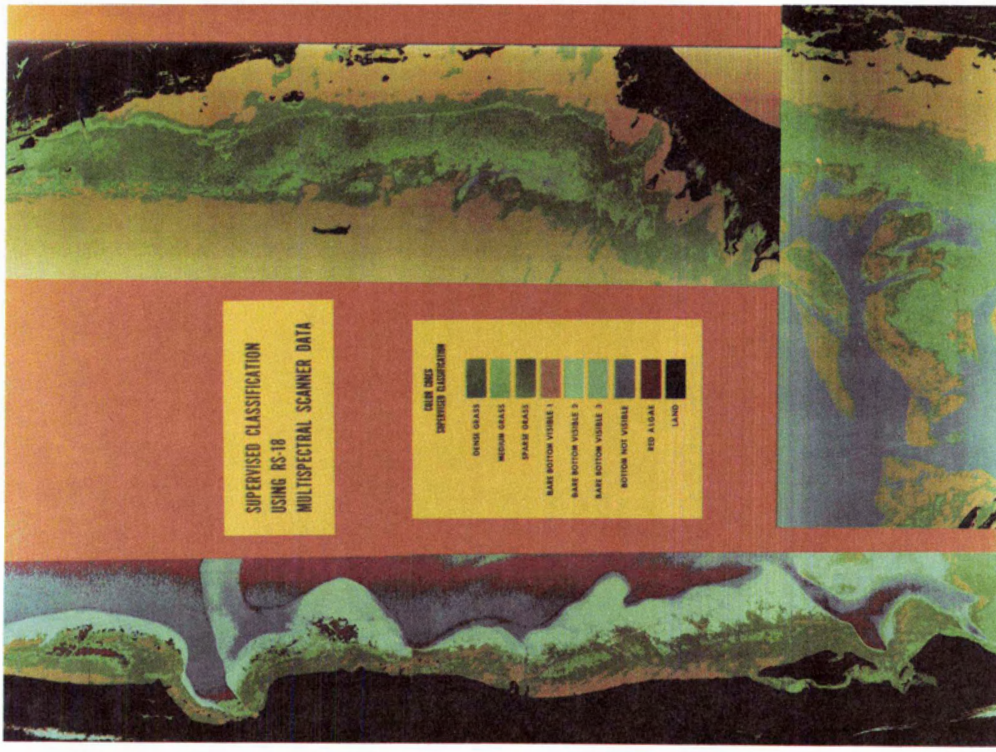

PLATE 2. Submerged features of St. Joseph Bay, Florida, produced from a supervised classification process using an inadequate training class set.

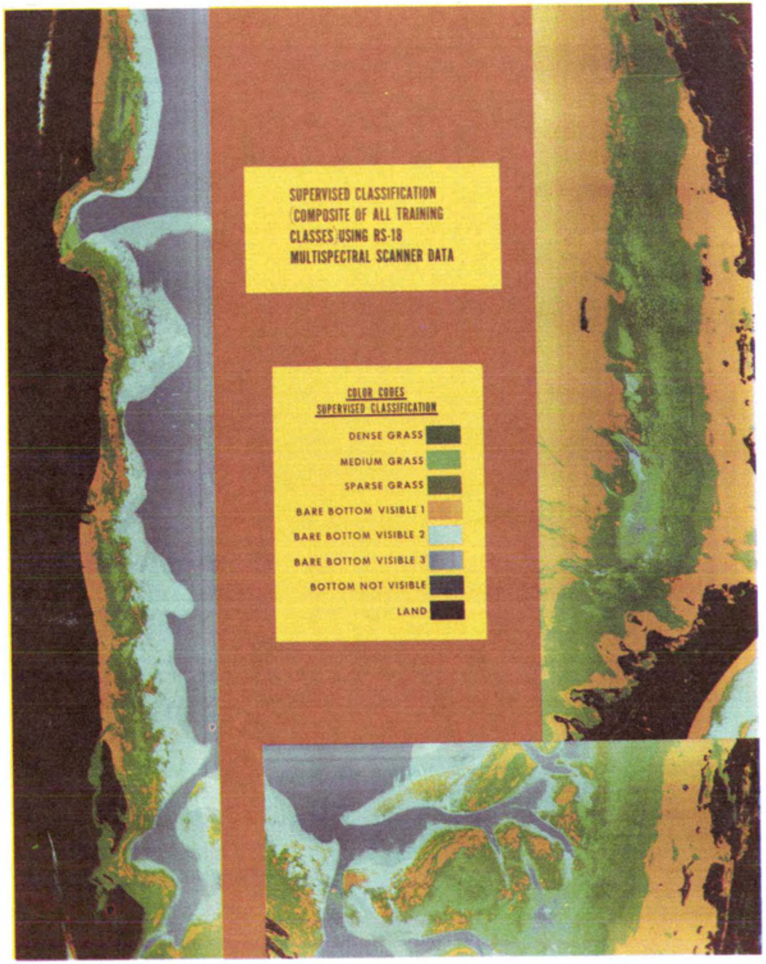

Plate 3. Results of the supervised classification process using a composite of all training classes.

Plate 4. Results of the hybrid classification process using training classes for individual flight lines.

flight lines are listed in Table 2. A class corresponding to bare bottom was not developed at this stage of analysis.

The RS-18 data were also subjected to statistical analyses using an unsupervised training-field selection algorithm implemented in the computer program named SEARCH (Junkin *et al.*, 1980). This technique scanned the data set (or subset as specified) with a six-element scan-line window and located all areas of that size that met specified criteria for homogeneity. The standard deviation and coefficient of variation were computed for each spectral channel in each 36-element area and were compared with a specified criterion for homogeneity. These 36-pixel areas were grouped into classes based only on spectral separability, regardless of the physical characteristics leading to the spectral signatures. The classes represented spectrally separable combinations of depth, water color, surface reflection, and vegetation density, type, and color. Land features were included in two of the flight lines and were therefore included in the statistical analysis for those flight lines. No land was included in the analysis of the remaining flight line, although some land appeared in the imagery.

While the unsupervised training-sample selection provided a statistical analysis of a major subset of the data, the supervised training-field statistics represented a narrow range of well-determined surface characteristics in terms of water depth ranges and benthic characteristics. Consequently, the unsupervised data set was merged with the supervised data set before calculation of classification statistics. Each of the three flight lines was then classified on the NASA Earth Resources Laboratory image-processing system, using a maximum likelihood classifier, MAXL4 (Savastano *et al.*, 1981). The resulting product was analyzed to identify the classes developed by SEARCH. Initially, the SEARCH classes were categorized on the basis of surface-truth information and aerial photography. The unsupervised training-field analysis subdivided the desired categories too finely, identifying classes that could not be identified based on existing information. To correct this problem, less detailed information over more of the study area was collected in a second visit. Using these data, the initial classes were grouped into larger groups that more closely met the study objectives, namely, to map the density of benthic vegetation and discriminate between dense algal communities and seagrasses. The individual classes resulting from the SEARCH spectral analysis subdivided the general classes by depth, water color, and surface reflection. The additional ground-truth data made it possible to weight the SEARCH analysis so that class provided an accurate map of the bay (Plate 4).

The final classes for each flight line formed by combining training-field classes and unsupervised classes are listed in Table 3, along with the area in each class. The overlap between flight lines was eliminated from the area computation, so the figures represent the actual area in each category of vegetation density in the surveyed portion of St. Joseph Bay.

Results and Discussion

Quantitative evaluation of classification accuracy is a difficult problem, both conceptually and technically. It is neither clear how to unambiguously define accuracy criteria, nor how to measure such criteria. It is not usually feasible to obtain ground-truth information with spatial resolution that will provide information as dense as the remote imagery. Use of photography to test the classification results

Table 2. Training sample classes obtained from ground truth information and training sample spectral data for hybrid classification

Class Description	Training Samples (No. of pixels used)
Flight Line 1	
W1 Shallow, medium grass, no algae	12S (29), 14W (31)
W2 Shallow, dense grass, dense red algae	13W (40), 16W (48)
W3 Deep, sparse grass, dense algae	17W (37)
W4 Intermediate depth, medium grass, some algae	5E (212), 6E (121), 8E (144), 19W (58)
W5 Deep, medium grass, dense red algae	20W (74)
W6 Shallow, sparse grass, no algae	10S (27)
Flight Line 2	
S1 Shallow, medium grass	12S (29), 13S (69), 14W (31)
S2 Deep, sparse grass	17W (37)
S3 Shallow, very dense grass	1E (301), 2E (132), 7E (228)
S4 Shallow, sparse grass	10S (27)
Flight Line 3	
E1 Shallow, medium grass	12S (29), 14W (71)
E2 Intermediate depth, medium grass	3E (30), 4E (39), 6E, 8E (144), 19W (58)
E3 Shallow, very dense grass	1E (301), 2E (132), 7E (228)
E4 shallow, sparse	10S (27)

TABLE 3. CLASSES AND AREAS OBTAINED FROM CLASSIFICATIONS

Class Description	Hybrid Classification Area (hectares)	Supervised Discriminant Function Classification (Individual Line Training Fields) Area (hectares)
Flight Line 1		
Dense Grass	183.3	37.4
Medium Grass	165.9	152.4
Sparse Grass	285.3	468.7
Bare Bottom Visible 1 (Sand shallow)	248.5	210.3
Bare Bottom Visible 2	453.3	254.9
Bare Bottom Visible 3		220.3
Bottom Not Visible	763.3	678.4
Land	2105.7	2112.9
Red Algae	244.0	374.5
Flight Line 2		
Dense Grass	55.0	24.4
Medium Grass	229.5	151.3
Sparse Grass (deep water)	9.7	
Sparse Grass	29.7	174.9
Very Sparse Grass	5.7	
Bare Bottom Visible 1 (Sand shallow)	122.6	98.6
Bare Bottom Visible 2	173.2	
Bottom Not Visible	232.3	409.3
Flight Line 3		
Dense Grass	482.4	468.5
Medium Grass	269.9	152.9
Sparse Grass	339.1	333.4
Very Sparse Grass	133.1	
Bare Bottom Visible 1	238.4	511.1
Bare Bottom Visible 2	53.0	
Bottom Not Visible		19.8
Land	414.0	460.4
Severe Glint Contamination	—	—

introduces uncertainty caused by subjectivity in the photointerpretation process. We have evaluated the quality of maps generated from the classification process by comparing field observations at ground-truth sample locations with corresponding benthic projections for those locations on the maps. Plate 5 shows an example of a classification evaluation. In the discriminant function classification, location 1 (emergent marsh grass) was classified as a vegetated area and was not broken out as a separate class of vegetation because no training fields were selected from this area. Location 2 was found to be sparse *Thalassia* and was classified correctly. Location 3 (classified correctly) was discolored sand with no vegetation. Location 4 was a small stand of dense *Thalassia* located in a larger stand of sparse *Thalassia* and was classified correctly. Location 5 was a broad band of sparse *Thalassia* and was classified correctly. Location 6 was a band of medium-density *Thalassia*, classified as sparse *Thalassia* in the composite class-discriminant function classification and as medium-density *Thalassia* in the within-line class-discriminant function classification. Location 7 was a wide area of very dense, tall *Thalassia*, and Location 8 was at the edge of a bare spot in the midst of the dense *Thalassia*. Both 7 and 8 were classified correctly.

In the hybrid classification, Location 1 was an area of very shallow water with marsh grasses (not *Thalassia*), and was classified as a vegetated area. It was not broken out as separate class of vegetation because the unsupervised training sample selection was not performed on this part of the flight line, and given the signatures developed over only the bay itself, the most likely classification of the emergent grasses was an intermediate-density *Thalassia*. The misclassification of the land evident in the product also results from limiting the SEARCH analysis of the flight line to the bay area. Location 2 was found to be sparse *Thalassia* and was classified correctly. Location 3 had no vegetation, but was discolored sand; this area was correctly classified as well. Location 4 was a small stand of dense *Thalassia* located in a larger stand of sparse *Thalassia*. Location 5 was a broad band of sparse *Thalassia*, Location 6 was a band of medium density *Thalassia*, and

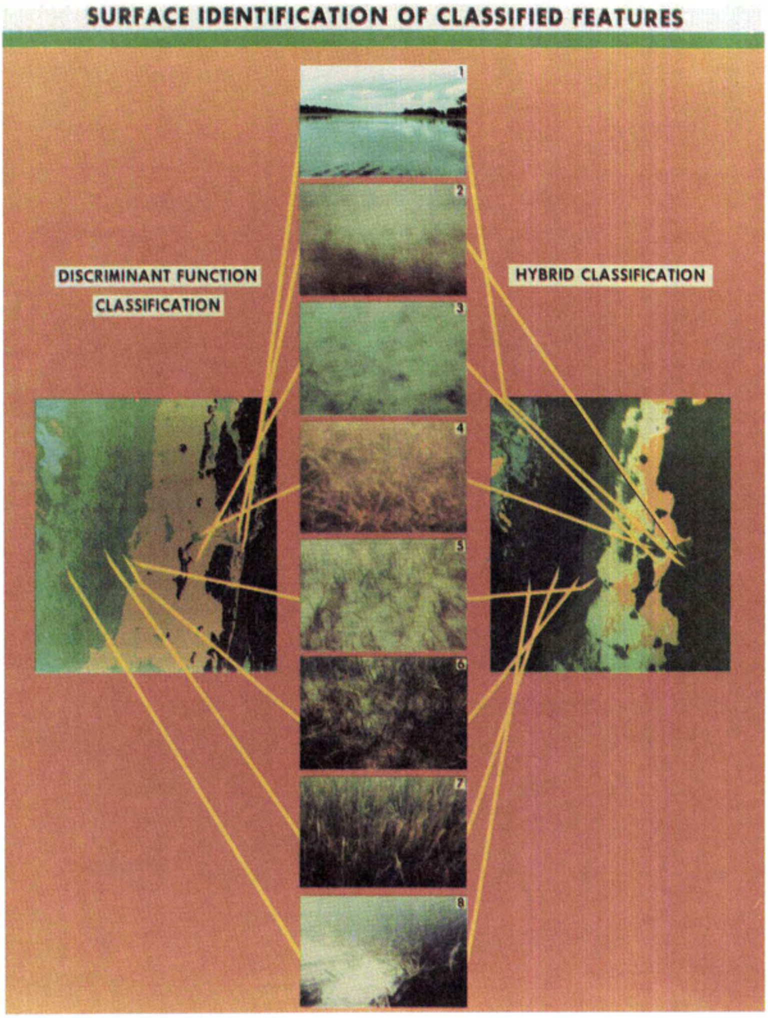

PLATE 5. Various bottom features of St. Joseph Bay, Florida, used in classifications together with their relative locations in submerged vegetation maps of the bay produced with the classification process.

Location 7 was a wide area of very dense, tall *Thalassia*. Location 8 was at the edge of a bare spot in the midst of dense *Thalassia*. Locations 4 through 8 were correctly identified in the remotely sensed product.

Qualitative comparison of the classification results with ground-truth information shows the classification maps to be both detailed and generally accurate. Details such as holes in the seagrass beds along the eastern shore were detected and their bare or sparsely vegetated states were correctly identified. There were some imperfections in the maps. Dense seagrass, which also contained large quantities of red algae, was confused with deep relatively clear water where the bottom was not visible. The very turbid water in the deep channel behind Pig Island, at the southwest corner of the bay, was misclassified as shallow water over dense vegetation. Sun-glint effects were particularly strong offshore on the east flight line. The hybrid classification was performed on data not significantly contaminated with sun glint. Using the model developed by Cox and Munk (1956), one can estimate the contamination of the data via emergent, upswelling radiance, by specular reflection of the solar disc from the surface. Attempts have been made to reduce the effects of glint on scanner data by subtracting from the measured upwelling radiance a term which is a function of scan angle based on the probability of the sea-surface slope being such that the specular reflection of the sun would be seen by the scanner, but the data processed here were not so corrected. When contamination was not negligible, the data were omitted; in the case of the discriminant function analysis, the data were misclassified.

Seagrasses are perennial in St. Joseph Bay and

TABLE 4. SUMMARIZED COVERAGE CLASSIFICATION RESULTS OBTAINED WITH DIFFERENT CLASSIFICATION TECHNIQUES

Class Description	Supervised Classification (Composite Training Fields) Area (hectares)	Supervised Classification (Individual Line Training Fields) Area (hectares)	Hybrid Classification Area (hectares)
A. Subcategories			
Land	2574	2574	2520
Dense Grass	608	530	720
Medium Grass	436	457	665
Sparse Grass	871	977	664
Very Sparse Grass			
Bare Bottom Visible 1	891	819	640
Bare Bottom Visible 2	334	255	680
Bare Bottom Visible 3	363	221	
Bottom Not Visible	1230	1108	996
Red Algae		375	244
B. General Categories			
Land	2574	2574	2520
Vegetation	1915	2339	2432
Bare Bottom Visible	1598	1295	1290
Bottom Not Visible	1230	1108	996

local observers report that seagrass distribution appears not to have changed for many years. To test that hypothesis, we compared the area of vegetated bottom observed by McNulty *et al.* (1972) with the area obtained from this analysis.

The area in each class for the three flight lines computed by the three classification techniques are different because the number of classes differed among classification techniques (Table 4a). The major difference was that elimination of the Red Algae class in the supervised classification, using composite training fields, caused a decrease in vegetation coverage and an increase in water coverage. A general summary, which combined all plant types, indicated reasonable agreement on vegetation coverage for the individual-line training field and hybrid classifications (Table 4b). There were between 2300 and 2400 hectares of vegetation covering the part of St. Joseph Bay surveyed in this investigation. Some of the bay was excluded in this study; there was no flight-line coverage of the extreme northern area along the west shoreline and the northeastern portion of the bay (Figure 1). Seagrass beds and attached algal stands are not as well developed in these areas in the part of the bay through which the flight line passes, but they are present. Therefore, the results of this investigation would be expected to yield a lower estimate of the area covered by vegetation coverage than the estimate of 2560 hectares by McNulty *et al.* (1972). The vegetation map prepared by these investigators also showed simplified vegetation distribution patterns, probably a consequence of problems in interpreting the aerial photography used in that investigation. The similarity in vegetation coverage observed during 1972 and during 1978 supports local impressions about the stability of bay macroplant communities.

The successful mapping of the St. Joseph Bay benthic vegetation demonstrates the capability of automated analysis of remotely sensed data. The Landsat multispectral scanner includes sensors at approximately the same wavelengths as the RS-18 bands 2 and 3. The results of the project, therefore, indicate that the more complex task of satellite mapping of submerged vegetation for trend analysis should be investigated.

The analysis of the scanner data by computer has several advantages over classical photointerpretation. First, and perhaps most important, discrimination is objective, although density slicing of multispectral photography does provide a means for achieving objectivity. However, normal photointerpretation with as fine a resolution as is available in aircraft and spacecraft scanner data is not always practical, and use of density slicing techniques reduces the practicality further. Finally, the availability of Landsat MSS, and possibly Thematic Mapper data on regular intervals, should make feasible short- and long-term analysis of the trends of change of benthic vegetation.

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REFERENCES

Cox, C., and W. Munk, 1956. Slopes of the sea surface deduced from photographs of sun glitter. *Bulletin of* *the Scripps Institution of Oceanography of the University of California, La Jolla, California*. Vol. 6, No. 9, pp. 401-488.

Den Hartog, C., 1970. *The seagrasses of the world*. North Holland Publishing Co., Amsterdam, 275 p.

Dixon, W. J. (ed.), 1977. *BMD biomedical computer programs*. Univ. Cal. Press, Los Angeles, 733 p.

Heck, K. C. J., 1976. Community structure and the effects of pollution in seagrass meadows and adjacent habitats. *Marine Biology* 35, pp. 345-354.

Junkin, B. G., R. W. Pearson, B. R. Seyfarth, M. T. Kalcic, and M. H. Graham, 1980. *Earth Resources Laboratory applications software*. NASA Report No. 183, 5-68-5-70.

Livingston, R. J., 1975. Impact of kraft pulp-mill effluents on estuaries and coastal fishes in Apalachee Bay, Florida USA. *Marine Biology* 32, pp. 19-48.

Mann, K. H., 1973. Seaweeds: their productivity and strategy for growth. *Science* 182, pp. 975-981.

McNulty, J. K., W. N. Lindall, Jr., and J. E. Sykes, 1972. *Cooperative Gulf of Mexico estuarine inventory and study, Florida: phase 1, area description*. NOAA Technical Report NMFS CIRC-368, 126 p.

Savastano, K. J., K. H. Faller, and L. McFaden. 1981. *Mapping of submerged vegetation using remote sensing technology*. NOAA Technical Memorandum NMFS-SEFC-73, 70 p.

Scoffin, T. P., 1970. The trapping and binding of subtidal carbonate sediments by marine vegetation in Bimini Lagoon sediments. *Journal of Sedimentary Petrology* 40, pp. 249-273.

Young, P. C., and H. Kirkman, 1975. The seagrass communities of Moreton Bay, Queensland. *Aquatic Botany* 1, pp. 191-202.

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