Development of an Everglades Vegetation Map Using a SPOT Image and the Global Positioning System

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Abstract
SPOT multispectral imagery captured 10 August 1991, ERDAS image processing software, the Global Positioning System (GPS), and error analysis techniques were used to develop a baseline vegetation map of Water Conservation Area 2A, an impounded portion of the remnant Everglades managed for flood control and water supply. A hybrid unsupervised/supervised classification routine was performed utilizing the GPS for ground truthing and accuracy assessment. Differentially corrected GPS data were an essential part of the overall effort. Cluster busting techniques were utilized to properly refine confused classes, and Kappa statistics programs were used for error analysis. Results suggest a relationship between agricultural nutrient inflow and vegetation changes from sawgrass to cattail and/or willow monoculture in areas closest to the inflow.

Introduction
The South Florida Water Management District (SFWMDd) is developing a detailed land-cover vegetation map of the entire Everglades system. This mapping project will encompass Water Conservation Areas 1, 2A, 2B, 3A, 3B, the Holey Land Wildlife Management Area, and Everglades National Park (Figure 1). These lands comprise approximately 754,000 ha of remnant Everglades habitat.

The requirements for data sources and methods for this effort were such that the resultant maps be defensible in both a scientific and legal context. Methods also had to be reliable, efficient, economical, and, above all, repeatable so that various analysis functions could be performed on a regular basis, possibly by different personnel. Accuracy assessment was required so that the integrity and utility of the resultant maps would be known. After careful consideration of all these requirements, it was determined that remotely sensed multispectral imagery and digital image processing techniques would serve as a first approach to meet the stated goals.

Past Everglades vegetation mapping efforts utilizing digital image processing techniques have been sporadic and limited to selected geographic areas. Capehart *et al.* (1977) found limited applications of Landsat MSS data for mapping the distribution of an exotic nuisance tree, *Melaleuca quinquenervia*, throughout southern Florida. Gunderson *et al.* (1986) depicted vegetation cover types of Shark River Slough in Everglades National Park from Landsat TM data. No accuracy assessment was done for this mapping effort. Richardson *et al.* (1990) mapped the vegetation types of Loxahatchee National Wildlife Refuge (also known as Water Conservation Area 1) from SPOT satellite data. A generalized ground truthing effort was performed using LORAN C. No omission/commission or overall map accuracy assessment was reported. Gilbert (1991) initiated a vegetation mapping project of the Holey Land Wildlife Management Area. Both Landsat TM and SPOT data were available for this mapping project. It was determined that the classified SPOT imagery was more efficient in separating certain land-cover classes than was Landsat. Gilbert (1991) determined that overall map accuracy for ten classes using LORAN C was 83.1 percent based on 59 ground truthed sites.

Compared to the above, this study is unique in that it utilizes the Global Positioning System developed by the Department of Defense. GPS was used to locate field verification sites in addition to providing us with a precise navigational tool for map accuracy assessment. GPS has a greater accuracy than any other navigation system in use today (Gibbons, 1992). Although the system was not fully deployed, it provided a large enough ephemeris window in South Florida to be used as an accurate and convenient geographic positioning tool.

The remnant Everglades has been influenced by an extensive system of levees and canals which have significantly altered the hydroperiod and flow of water (Davis and Ogden, 1993; Worth, 1988). Much of the area has been impounded into Water Conservation Areas. The geographic focus of this study was Water Conservation Area 2A (WCA2A) (Figure 1), a 42,707 ha impoundment managed by the SFWMD.

The objective of this study was to define the dominant species composition, distribution, and spatial extent of the existing Everglades macrophyte communities in order to produce a baseline vegetation map. Once completed, this digital data set could act as a benchmark against which future conditions can be compared. The future changes that may result from various management scenarios, such as possible hydroperiod manipulations or nutrient inflow changes, will be documented utilizing image processing change detection techniques. This documentation will provide researchers with one analysis tool for determining the relationships between management practices and plant community structure.

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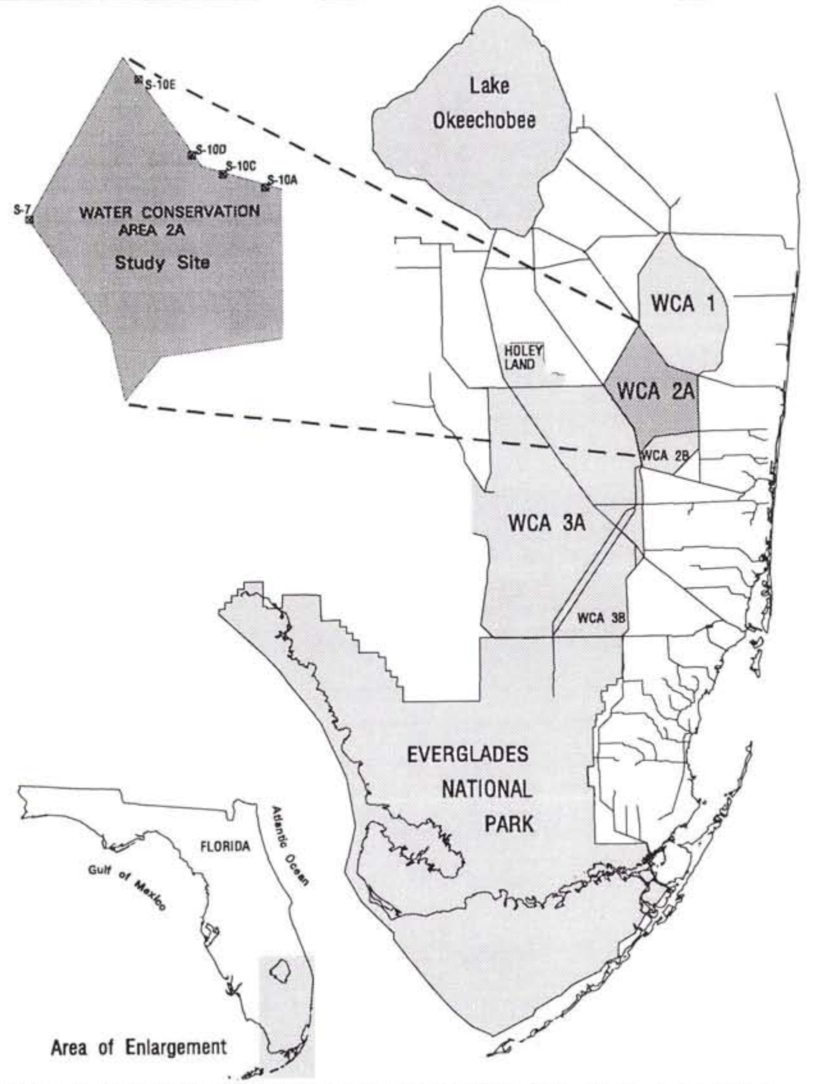

Figure 1. Area of Florida showing remaining Everglades system and location of study area. Note that S-10 stands for structure 10. All structures shown are inflow structures.

Materials and Methods

Vegetation mapping was accomplished by utilizing SPOT (HRV2) 20-metre multispectral digital satellite imagery collected on 10 August 1991. All image processing was performed on a Sun Sparc 2 (Mountain View, California) workstation using ERDAS (Atlanta, Georgia) image processing software. The area of interest (Water Conservation Area 2A) was extracted from the total scene and all background pixels were set to a value of zero. A small portion of the very southern tip of Water Conservation Area 2A was not available from the satellite data for this study.

An initial unsupervised classification was performed on the unrectified Water Conservation Area 2A image using the minimum spectral distance formula (ERDAS, 1991). Arbitrary cluster means were chosen by default and allowed to shift through an iterative process until a maximum percentage (95 percent) of unchanged pixels had been reached between the final two iterations. A number of initial clusters (e.g., 25, 50, 75, 100) were examined in this unsupervised classification. A final number of 30 clusters was chosen based on the ability to find homogeneous areas that could be field verified within each cluster using the GPS.

The image was then rectified to a Universal Transverse Mercator (UTM) map projection using 20 well distributed ground control points. Ground control point selection was based on the ability to find a corresponding pixel within the image. Ground control data and corresponding image pixel locations were then used to compute a transformation matrix. A coefficient file was generated. A first-order transformation was performed with a resultant root-mean-square error of 0.4 pixels. The coefficient file was then used to rectify both the unsupervised subset as well as the original extracted subset of the WCA2A image using a nearest neighbor resampling method.

Field verification and ground control data for this study were gathered by airboat or helicopter. Navigation to field site locations was accomplished with a Trimble (Sunnyvale, California) Pathfinder Basic GPS unit, and positions were differentially corrected using satellite ephemeris data collected by a Trimble Pathfinder Community Base Station. Multiple points were collected at each site so that averaging algorithms could be applied to the data once it was differentially corrected. Trimble software packages PFBASIC (Version 1.0), PFCBS (Version 1.0), and PFINDER (Version 1.42) were used. GPS position accuracy was periodically verified at a 1990 National Geodetic Survey North American Datum 1983 adjusted benchmark. Ground control data were differentially corrected, averaged, and checked against this benchmark. Data accuracy ranged between three and seven metres. This level of accuracy was essential to the mapping effort so that the pixel locations within the image could be identified with spatial precision.

Wherever possible, five points were selected for ground truthing from each of the 30 unsupervised spectral classes of the rectified image. Optimally, field verification data were collected at distributed geographical regions throughout the spectral class. Points also had to be within the center of a minimum 3 by 3 homogeneous pixel block. This procedure allowed room for any positional errors inherent in the rectification process (total root-mean-square error of 0.4 pixel = 8 m) and the inaccuracy of the GPS unit collecting the data (3 to 7 m), and it resulted in 129 points being selected from the image.

Each of the data points selected from the image were field verified. Field verification was accomplished by navigating to a point using the GPS and having a single observer visually estimate the percent cover of each of the plant species located within an approximated 20- by 20-metre grid square. The same observer was used throughout the study in order to maintain consistency and uniformity. Every attempt was made to evaluate percent coverage of vegetation based on a vertical view of the grid cell (i.e., understory species were not taken into account if they were not visible from a vertical perspective).

After performing differential GPS correction routines, each point was then rechecked to verify that its exact location was still within the center of a minimum 3 by 3 homogeneous pixel block of the correct spectral class. Evaluation of this ground truth data resulted in the composition of the 19 vegetation classes listed in Table 1 (as discussed below, a twentieth class was added after subsequent analysis routines were performed). Each of the 129 field verified data points were assigned to a vegetation class and used as seed locations for generating training samples.

Ellipses were created by using the mean and standard deviation of each training sample band combination. Training samples were viewed simultaneously by class to find and eliminate signatures that were not visually representative of the class distribution. All remaining training statistics for each class were combined, resulting in one file containing signature statistics for 19 vegetation classes. Ellipses for all 19 vegetation classes were viewed simultaneously, and it was determined that each was spectrally unique enough to represent a separate class.

A maximum-likelihood (Bayesian) supervised classification was performed using the vegetation signature statistics file and the original unrectified extracted WCA2A subset image. All bands were utilized with no change to *a priori* probabilities for any one class.

Each vegetation class generated from the maximum-likelihood classification was viewed individually. From 1:24,000-scale color infrared photography obtained 10 October 1991 and field observation, it was determined that all the resultant classes appeared reasonable except Sawgrass/Cattail Sparse and Tree Islands.

In the case of the Sawgrass/Cattail Sparse class, it was concluded that this class was accurate in the northern parts of the project area, but within the southern region the signature was heavily influenced by periphyton reflectance. The lack of uniformity within this class was addressed by first masking out all other classes from the original unrectified subsetted WCA2A image, creating a single class image file. An unsupervised classification was then performed on this data similar to the procedure described earlier for the parent image. The original Sawgrass/Cattail Sparse class was broken down into five new spectral classes. Each of these classes was viewed individually, and it was determined from large-scale aerial photography and from field experience that these five classes could be reduced to two—Sawgrass/Cattail Sparse and Periphyton. The resulting two-class image file was then mosaicked back into the maximum-likelihood classification output data set. Thus, one additional class (Periphyton) was added, making a new total of 20 vegetation classes.

The problem of misclassification of tree islands was dealt with by digitizing the outline of the tree islands from the original unrectified subsetted WCA2A image. A total of 31 tree islands were digitized and extracted out of the data set as a new image. In a "cluster busting" (Jensen, 1987) technique similar to that described for the Sawgrass/Cattail Sparse class above, an unsupervised classification was performed, resulting in ten classes. These classes were then collapsed into four of the already existing classes and mosaicked back into the maximum-likelihood classification output data set to create a vegetation map with 20 classes.

A rectification of this final hybrid unsupervised/supervised classification was then performed using the coefficient file described earlier and a nearest neighbor resampling technique. The resultant map was color coded and a legend was added in preparation for hard copy output (Plate 1).

Accuracy Assessment

Map accuracy assessment was initiated by generating 241 random points from the final classification using a random sampling technique stratified by class. The number of points selected was based on the required minimum number of 204 points for an 85 percent map accuracy level with an error of ± 5 percent. This minimum required number was based on binomial probability formulas (Snedecor and Cochran, 1978).

Map accuracy assessment points were field verified. During this phase of the study the Department of Defense had implemented Selective Availability (SA), degrading the GPS signal and positional accuracy in the navigation mode. After each site was visited, position data were differentially corrected and site locations were rechecked. Depending on the extent of SA, many points were geographically located at different pixel/class locations than originally determined. However, these new locations were considered valid because random sampling was still maintained.

Each site was then evaluated for majority pixel status. Data were deemed acceptable as long as there was a 5-pixel class majority within the center of a 3- by 3-pixel block with the site being the center pixel. Field verification data were checked against the map vegetation class pixel block and

TABLE 1. CLASS DESCRIPTIONS FOR WATER CONSERVATION AREA 2A 20- CLASS MAP.

Class	Description
1 - SAWGRASS - DENSE	dense to moderately dense *Cladium jamaicense*; areal coverage ≥70%, evenly distriubted; balance in open water
2 - SAWGRASS - MODERATE	dense to moderately sparse *Cladium jamaicense*; >30% to <70% coverage; balance in open water
3 - SAWGRASS - SPARSE	Evenly distributed, sparse or clumps of moderately dense to dense *Cladium jamaicense*; ≤30% coverage; balance in open water
4 - SAWGRASS/CATTAIL - DENSE	mixture of *Cladium jamaicense* and *Typha domingensis*; vegetative cover excluding aquatics ≥60%
5 - SAWGRASS/CATTAIL - SPARSE	mixture of *Cladium jamaicense* and *Typha domingensis*; vegetative cover excluding aquatics <60%
6 - SAWGRASS/CATTAIL/BRUSH	≥70% coverage of *Cladium jamaicense*; ≥30% coverage of *Typha domingensis* and brush (*Myrica cerifera, Salix caroliniana*, and/or *Cephalanthus occidentalis*)
7 - SAWGRASS/BRUSH 1	*Cladium jamaicense* at ≥70%; balance in *Myrica cerifera, Salix caroliniana*, and/or *Cephalanthus occidentalis*
8 - SAWGRASS/BRUSH 2	≥30% and <70% coverage of *Cladium jamaicense*; balance in *Myrica cerifera, Salix caroliniana*, and/or *Cephalanthus occidentalis*
9 - SAWGRASS/BROADLEAF/CATTAIL	≥50% coverage of *Cladium jamaicense*; >30% and <70% coverage of broad leaf emergents (typically *Sagittaria* spp. and/or *Pontederia* spp.); ≤30% coverage of *Typha domingensis*
10 - CATTAIL - DENSE	dense to moderately dense *Typha domingensis*; ≥70% coverage; balance in open water
11 - CATTAIL - MODERATE	dense to moderately sparse *Typha domingensis*; >30% and <70% coverage; balance in open water
12 - CATTAIL - SPARSE	sparse distribution or small clumps of moderately dense to dense *Typha domingensis*; coverage of ≤30%; balance in open water
13 - CATTAIL/BRUSH	≥50% coverage of *Typha domingensis*; balance in *Salix caroliniana, Myrica cerifera*, and/ or *Cephalanthus occidentalis* and open water.
14 - BRUSH MIXTURE	dominated by *Salix caroliniana, Myrica cerifera*, and/or *Cephalanthus occidentalis*; associated species are *Lemna* spp., *Sagittaria* spp., *Pontederia* spp., *Mikania scandens, Acrostichum* spp., and/or *Hibiscus grandiflorus*
15 - BRUSH/CATTAIL	≥50% areal coverage of *Salix caroliniana, Myrica cerifera*, and/or *Cephalanthus occidentalis*; balance in *Typha domingensis* at a ≤30% areal coverage and/or open water
16 - TREE ISLAND	*Ilex cassine* and *Persea borbonia* as overstory plants; *Myrica cerifera* occupying lower tier and outside edges; *Salix caroliniana, Myrica cerifera*, and/or *Cephalanthus occidentalis* at southern end
17 - SLOUGH/OPEN WATER	large pools or sloughs of open water; may also include *Nymphaea odorata, Eleocharis* spp., and/or algal mats; other plants occupy <5% of the area (See Class 20 - PERIPHYTON)
18 - BROADLEAF EMERGENT/BRUSH	dominated by broad-leaved emergents, typically *Sagittaria* spp. and/or *Pontederia* spp.; areal extent ≥70%; balance in brushy species
19 - POLYGONUM/BRUSH	uncommon; ≥70% areal coverage of *Polygonum* spp.; balance in brushy species
20 - PERIPHYTON	large pools or sloughs of open water; thick and heavy algal mats of periphyton; sparse *Cladium jamaicense* and/or *Typha domingensis* may be present; bright spectral reflectance of algal mats dominates signature

deemed correct if they fell within the pixel majority class and incorrect if they did not.

A final consolidation of classes was performed. The 13 density dependent classes from the 20-class map were selectively merged into five more generalized vegetation classes -- Sawgrass, Sawgrass/Cattail, Sawgrass/Brush, Cattail, and Cattail/Brush. This resulted in a vegetation map with 12 classes (Plate 2, Table 2). A map accuracy assessment was then performed utilizing the same field verified data and procedures used for the 20-class vegetation map.

Overall map accuracy was computed by taking the total number of correctly classified samples (diagonal cells of the matrix) and dividing by the total number of samples.

Kappa coefficient of agreement was computed by running the KAPPA (Congalton *et al.*, 1981: 1982) FORTRAN program. Variance of the Kappa statistic has been corrected in this program as documented in Hudson and Ramm (1987). The Kappa coefficient of agreement is a measure of the actual agreement (indicated by the diagonal elements of the matrix) minus chance agreement (indicated by the product of row and column marginals) (Fung and Ledrew, 1988). It takes into account both commission and omission errors (Rosenfield and Fitzpatrick-Lins, 1986) and is a measure of how well the classification agrees with the reference data (Congalton *et al.*, 1983).

A pairwise test of significance was performed utilizing the Kappa coefficients from the 12- and 20-class vegetation maps to determine if the two error matrices were significantly different (Cohen, 1960; Congalton *et al.*, 1983; Congalton and Mead, 1986). The formula used to test for significance between the two independent Kappas was

$$Z = (K_1 - K_2)/[V(K_1) + V(K_2)]^{1/2}$$

where K is the Kappa coefficient, V is the large sample vari-

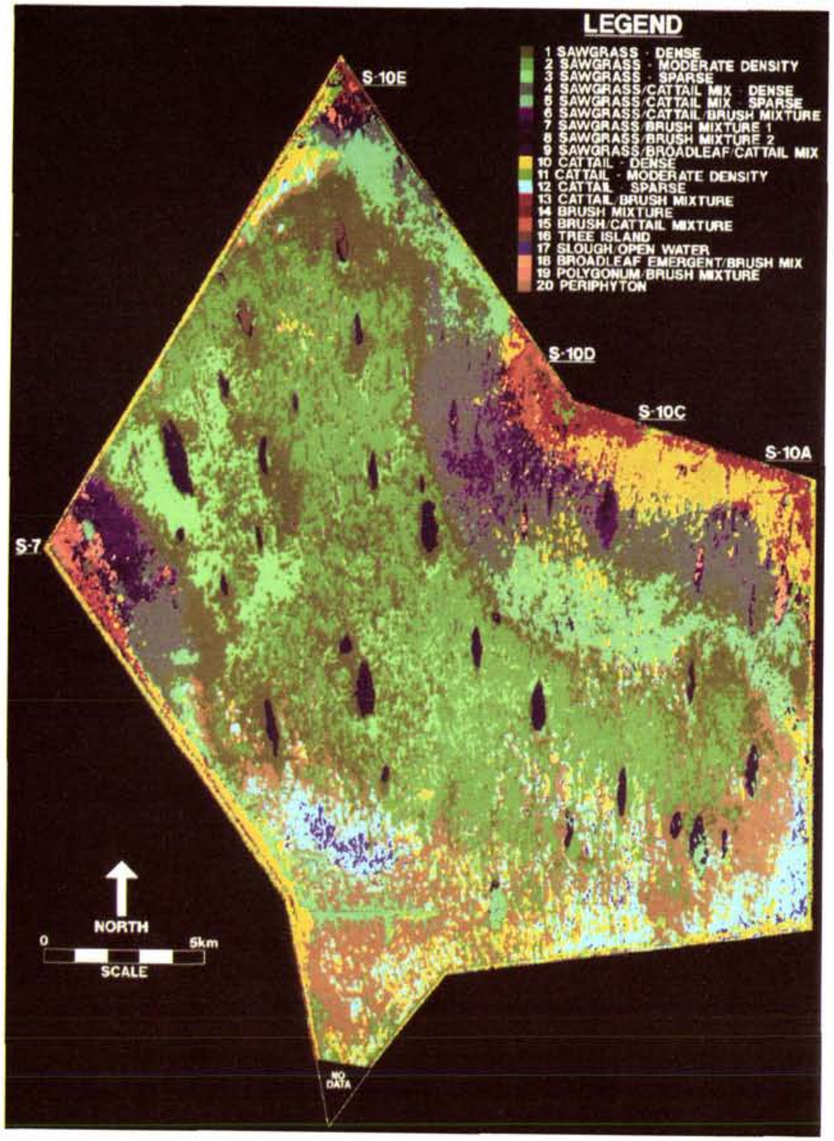

Plate 1. Twenty-class vegetation map resulting from the classification process. Note that the pattern and composition of vegetation communities surrounding inflow structures appears to be different from the interior marsh areas.

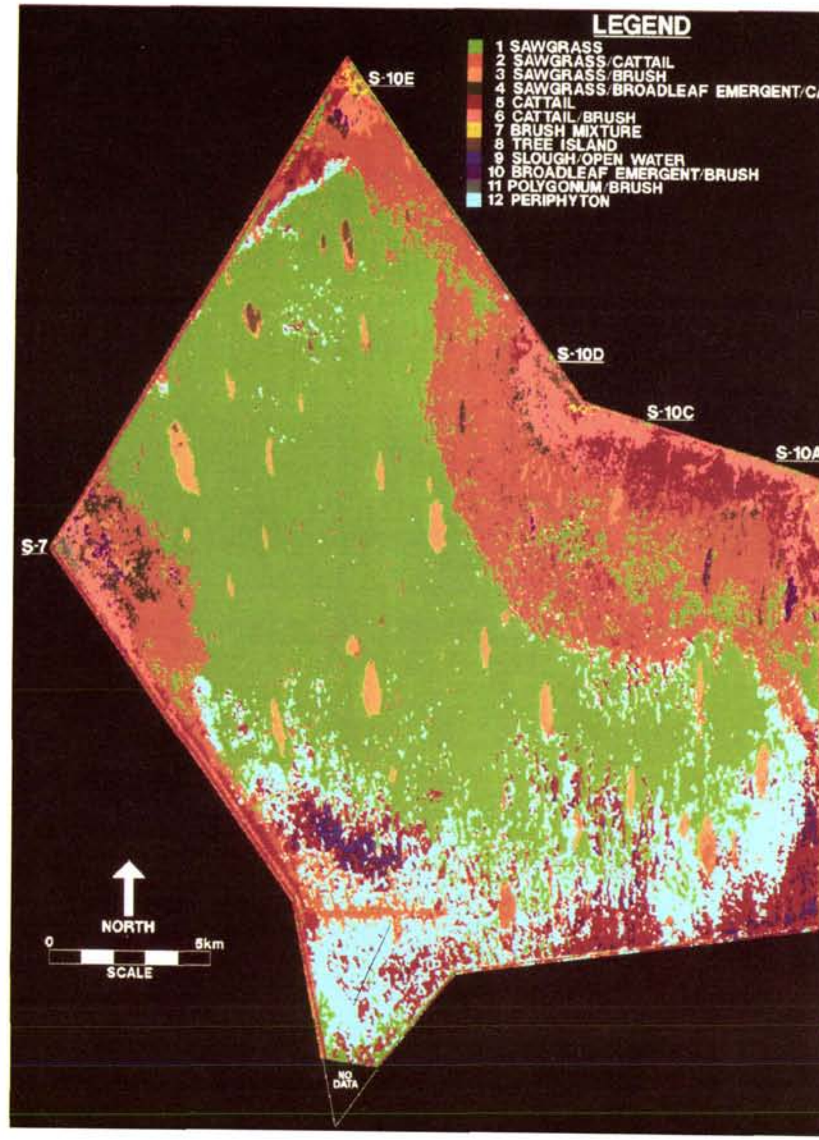

Plate 2. Vegetation map produced by combining the plant density characteristics of individual species from the 20-class vegetation map to make a more accurate map consisting of 12 vegetation classes.

TABLE 2. MIGRATION PATH FROM TWENTY TO TWELVE VEGETATION CLASSES.

TWENTY-CLASS MAP	TWELVE-CLASS MAP
1 - SAWGRASS - DENSE (8280) 2 - SAWGRASS - MODERATE (7908) 3 - SAWGRASS - SPARSE (3344)	1 - SAWGRASS (19532)
4 - SAWGRASS/CATTAIL MIXTURE - DENSE (3819) 5 - SAWGRASS/CATTAIL MIXTURE - SPARSE (4645) 6 - SAWGRASS/CATTAIL/BRUSH MIXTURE (756)	2 - SAWGRASS/CATTAIL MIXTURE (9220)
7 - SAWGRASS/BRUSH MIXTURE 1 (1139) 8 - SAWGRASS/BRUSH MIXTURE 2 (268)	3 - SAWGRASS/BRUSH MIXTURE (1407)
9 - SAWGRASS/BROADLEAF/CATTAIL MIXTURE (682)	4 - SAWGRASS/BROADLEAF/CATTAIL MIXTURE (682)
10- CATTAIL - DENSE (3141) 11- CATTAIL - MODERATE (126) 12- CATTAIL - SPARSE (1632)	5 - CATTAIL (4899)
13- CATTAIL/BRUSH MIXTURE (874) 15- BRUSH/CATTAIL MIXTURE (336)	6 - CATTAIL/BRUSH MIXTURE (1210)
14- BRUSH MIXTURE (62)	7 - BRUSH MIXTURE (62)
16- TREE ISLAND (234)	8 - TREE ISLAND (234)
17- SLOUGH/OPEN WATER (473)	9 - SLOUGH/OPEN WATER (473)
18- BROADLEAF EMERGENT/BRUSH MIXTURE (255)	10 - BROADLEAF EMERGENT/BRUSH MIXTURE (255)
19- POLYGONUM/BRUSH MIXTURE (53)	11 - POLYGONUM/BRUSH MIXTURE (53)
20- PERIPHYTON (5092)	12 - PERIPHYTON (5092)

NOTE: NUMBERS IN PARENTHESIS REPRESENT HECTARES

ance of the Kappa coefficients, and Z is the standard normal deviate. If Z is less than or equal to 1.96, then there is no significant difference between the two independent Kappa coefficients at the 95 percent confidence level.

Producer's accuracy was computed by taking the number of correctly classified samples of a particular class and dividing by the total number of reference samples for that class. Producer's accuracy indicates the probability of a reference pixel being correctly classified and is really a measure of omission error. User's accuracy was computed by taking the number of correctly classified samples of a particular class and dividing by the total number of samples being classified as that class. User's accuracy, or reliability, is indicative of the probability that a pixel classified on the map actually represents that class on the ground and is really a measure of commission error.

Results

Error matrix and statistical results for both the 20- and 12-class maps are found in Table 3. Overall accuracy for the 20- and 12-class maps was 70.9 and 80.9 percent, respectively. The Kappa coefficients of agreement for the 20- and 12-class maps were 67.0 and 73.5, respectively.

Six of the 20 and five of the 12 classes provided reliable data for calculating the conditional Kappa coefficient for individual class accuracy assessment (Table 3). This was based on a minimum sample size of 19 for a single category at the 95 percent confidence level with assumed probability of 85 percent and error of estimate of 10 percent (Rosenfield *et al.*, 1982).

Results of the pairwise test of significance (Table 4) utilizing the Kappa coefficients show that there was no significant difference between the overall accuracy of these two maps despite the overall accuracy of the 20-class map having been ten percent less than the 12-class map.

Both of the vegetation maps generated for this project depict an area dominated by large expanses of sawgrass (Plates 1 and 2, Table 2). This species was found throughout the study area and had an areal coverage of 19,532 ha. Mixed sawgrass/cattail communities covered 9220 ha with monotypic cattail contributing an additional 4899 ha. Cattail/brush mixture comprised 1210 ha and was found almost exclusively downstream of the S-10D control structure with the exception of a number of small patches along the levee adjacent to and south of the S-7 structure. Six-hundred-and-eighty-two ha of sawgrass/broadleaf emergent/cattail mixture were found east of the S-7 along with many small patches south of the S-10s. As previously stated, most of the cattail and cattail mixes were found in close proximity to inflow structures. Several canopied tree islands comprising 234 ha still existed in the northeast portion of the study area. Sloughs and open water areas had an areal coverage of 473 ha and were found almost exclusively in the south end of the impoundment. Periphyton coverage was 5092 ha, also in the south end. Many of the periphyton areas were sloughs dominated by these microfloral communities. The broadleaf emergent/brush mixture was found primarily on remnant tree islands south of the S-10s, east of the S-7, and in one small patch in the very north end of the study area. The polygonum/brush mixture class was small with an areal coverage of only 53 ha. It was restricted to two areas east of the S-7 and in one small patch in the very north end.

Discussion

Classification Procedures

Consideration was given to the use of Landsat TM data due to its greater ability to discriminate the spectral characteristics of vegetative features. A case can also be made in support of SPOT data because of the greater spatial resolution that it offers. The final deciding and consequently overriding factor was the availability of a current cloud-free scene. There was none available from Landsat.

There was concern that rectifying the original cut image file before performing the classification routines would corrupt the brightness values of the data set. Thus, all supervised/unsupervised classifications were run prior to rectification. However, use of the nearest neighbor method of resampling would eliminate this concern. (John R. Jensen, personal communication). This sampling technique does not alter the pixel brightness values during resampling (Jensen, 1986). Future mapping routines could include pre-classification rectification as long as the nearest neighbor resampling method is used.

The initial strategy for this mapping project was to perform an unsupervised classification of the original cut data set and to collapse the classes into the appropriate categories. However, a new course of action had to be taken after evaluation of the field verification sites for homogeneity within each of the unsupervised classes. Only five unsupervised spectral classes were homogeneous based on field verified data. Field verified data for three unsupervised spectral classes were unobtainable within the minimum 3- by 3-pixel block because no homogeneous areas could be found for these classes within the scene. There was only one field verified site available for each of two unsupervised spectral classes. All other unsupervised spectral classes exhibited heterogeneity based on field verified data. As a result, field verified data from the unsupervised classification was used in a supervised classification. Thus, a hybrid unsupervised/supervised classification was performed utilizing the field verified data set.

Accuracy Assessment

The accuracy level of the 20-class vegetation map was less than expected with an overall accuracy of 70.9 percent and a Kappa coefficient of 67. Because much of the inaccuracy

TABLE 3. ERROR MATRICES SHOWING STATISTICAL RESULTS FOR TWENTY- AND TWELVE-CLASS MAPS.

TWENTY-CLASS MAP

MAP CLASS	GROUND TRUTHED CLASS 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	ROW TOTAL	USERS ACCURACY	CONDITIONAL KAPPA (X100)
1	41	2		1							1										45	91	88
2	5	37																			42	88	85
3	2	4	8																		14		
4	2			13		1	3	2													21	62	58
5	3	1		4	15		2						1								26	58	55
6						2	1														3		
7				1			5		1						1						8		
8								3							1						4		
9								1	3												4		
10			3							13	1	2									19	68	66
11																					0		
12	4	1		2						1	2	7									17		
13													9								9		
14																					0		
15															3						3		
16																					0		
17																	1				1		
18																					0		
19																					0		
20	8	2		3						1										11	25	44	41
COLUMN TOTAL	65	47	11	24	15	3	11	6	4	15	4	9	10	0	5	0	1	0	0	11	241		
PRODUCERS ACCURACY	63	79		54	100					87										100			

POINTS SAMPLED	241
OBSERVED MISCLASSIFICATIONS	70
OVERALL ACCURACY	70.9%
KAPPA (X 100)	67.0

TWELVE-CLASS MAP

MAP CLASS	GROUND TRUTHED CLASS 1	2	3	4	5	6	7	8	9	10	11	12	ROW TOTAL	USERS ACCURACY	CONDITIONAL KAPPA (X100)
1	99	1			1								101	98	96
2	6	35	8			1							50	70	64
3		1	8	1		2							12		
4			1	3									4		
5	8	2			26								36	72	69
6						12							12	100	100
7													0		
8													0		
9									1				1		
10													0		
11													0		
12	10	3			1							11	25	44	41
COLUMN TOTAL	123	42	17	4	28	16	0	0	1	0	0	11	241		
PRODUCERS ACCURACY	80	83			93	80						100			

POINTS SAMPLED	241
OBSERVED MISCLASSIFICATIONS	48
OVERALL ACCURACY	80.9%
KAPPA (X 100)	73.5

came from errors within the density classes of a single vegetation community, an attempt was made to collapse these categories into a single class for each plant community. This affected the class density categories for Sawgrass, Sawgrass/Cattail, Sawgrass/Brush, Cattail, and Cattail/Brush and resulted in a 12-class vegetation map with an overall accuracy of 80.9 percent and a Kappa coefficient of 73.

In the authors' view, going from the 20- to 12-class map produced a visual impression that there are large stands of monotypic cattail in the south end of WCA2A along the levee. The 20-class vegetation map depicts sparse cattail coverage for the same region. By collapsing the density categories of cattail into one class, there is a visual impression of much more cattail in the south end of WCA2A.

Much of the inaccuracy depicted by the error matrices was in the southern region of the image. This was due to the presence of periphyton which exhibited unique spectral reflectance characteristics. Periphyton is the term used to describe the microfloral growth upon substrata (Wetzel, 1983). The microfloral colonies tend to rise to the surface in the late summer and frequently form large floating masses on the water's surface and around the stems of wetland macrophytes (Craighead, 1971). The signature of periphyton outcompeted the signature of associated species within the same class. This was reflected in the low user's accuracy for periphyton of 44 percent in both the 12- and 20-class maps. Imagery could be captured during the infrequent times when periphyton is absent or submerged enough to mask its bright signature, but this would be an unrealistic limitation on the data acquisition window.

Interpretation of Final Maps

The pattern and composition of the vegetative communities surrounding all WCA2A inflow structures appeared to be different from the interior marsh areas. The most obvious disparity was the presence of monotypic and/or mixed stands of cattail. Phosphorus inputs to the Water Conservation Areas have increased from 167 tonnes annually under predrainage conditions to 455 tonnes currently (Davis and Ogden, 1993). Davis and Ogden (1993) and Davis (1991) have shown that

TABLE 4. RESULTS OF KAPPA ANALYSIS FOR COMPARISON BETWEEN 20- AND 12-CLASS ERROR MATRICES.

Test of Significant Differences between Error Matrices		
Comparison	Z Statistic	Result
20 Class vs. 12 Class	1.3747	NS[1]

[1] NS = not significant at the 95% confidence level

areas affected by high nutrient influx undergo a change in plant community coverage. These studies show that sawgrass has a limited capacity to tolerate higher nutrient inputs and is subject to displacement by a more competitive species such as cattail when nutrient inflow is excessive. Richardson *et al.* (1991) concluded that loadings of water, nutrients (N, P), and other chemical constituents into the northern part of WCA2A are probably contributing to the replacement of sawgrass with cattail. Debusk *et al.* (1993) concluded that the occurrence of cattails at WCA2A soil sampling stations closely corresponds to the zones of phosphorus enrichment.

Many remnant tree islands near inflow structures may have also been affected by high nutrient levels and exhibit a luxuriant growth of willow along with a mixture of cattail. Remnant tree islands within the interior marsh area of WCA2A and spatially distant from the input structures are comprised mainly of sawgrass with a scattering of brushy species (willow, buttonbush, wax myrtle, and saltbush). This abnormal vegetative composition was the result of the artificial lengthening of hydroperiods as well as increased water depths (Worth, 1988). Dineen (1972; 1974) concluded that the loss of trees and woody vegetation on tree islands was the result of prolonged high water stages. Several large tree islands in the northern reaches of WCA2A still exhibited a well developed and healthy tree canopy and are good examples of what these drowned tree islands once looked like.

Conclusion

It was concluded that heterogeneity within unsupervised spectral classes was the result of too few unsupervised classes being selected initially. However, tests were conducted to determine the appropriate number of clusters to be used in the unsupervised classification. It was determined that if the initial number of clusters was larger, then the minimum 3- by 3-pixel requirement for GPS navigation would not be found within many of the classes. Based on this knowledge, it was apparent that Everglades vegetation communities were too spatially heterogeneous for performing an unsupervised classification utilizing a large enough number of classes to overcome heterogeneity. Attempts to ground truth unsupervised classes utilizing GPS would not be possible without the minimum number of required homogeneous pixels. It may be desirable in future mapping efforts to perform an unsupervised classification by choosing enough classes to overcome heterogeneity and then collapsing these classes into the appropriate categories. The GPS could still be utilized to ground truth vegetation pattern boundaries resulting from the unsupervised classification. However, it would not be possible to ground truth each class individually using the GPS due to the problems just discussed. Thus, the hybrid unsupervised/supervised classification used for this study may have been unnecessary had enough initial clusters been chosen for the unsupervised classification.

The lower accuracy levels exhibited by the 20-class map versus the 12-class map was indicative of the subtle signature changes between similar species with differing densities. Choosing a larger number of initial clusters for the unsupervised classification routine may have also reduced the confusion caused by density differences within classes. Obtaining digital data with a greater pixel resolution may have alleviated this problem.

The increase in overall accuracy from 70.9 percent to 80.9 percent resulting from collapsing the 20-class map into 12 classes was appreciable. The loss of specific density breakdowns for the Sawgrass, Sawgrass/Cattail, Sawgrass/Brush, Cattail, and Cattail/Brush classes was justified considering the greater level of accuracy obtained using more generalized classes. However, a pairwise test of significance using Kappa coefficients revealed that the error matrices of the 20- and 12-class maps were not significantly different.

Overall, the map accuracy results were modest for this type of classification. Considering the highly mosaicked nature of the Everglades and the limited range of feature types (100 percent wetland), this may be the best that can be expected using these data and analyses. Future work should investigate other data sources such as Landsat TM, low altitude aircraft multispectral scanner data at various scales of resolution, and aerial photography.

Periphyton was used as a vegetation class through the normal classification process while accepting the fact that the spectral returns of some vegetation types, especially in sparse concentrations, may be masked.

It was concluded that the cluster busting routine used to refine the Sawgrass/Cattail Sparse and Tree Island classes was an appropriate method to break down confused classes into smaller, more defined vegetation categories. Of course, had a greater number of clusters been chosen for the initial unsupervised classification, these cluster busting methods would have probably been unnecessary.

During a review of the methods used to process the WCA2A imagery, it was learned that all image rectification resampling methods do not necessarily corrupt the original digital values of the data set. The algorithms used in the nearest neighbor resampling method do not rely on averaging data values as other methods do. Thus, the original digital values are maintained.

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