Inland Wetland Change Detection in the Everglades Water Conservation Area 2A Using a Time Series of Normalized Remotely Sensed Data

John R. Jensen, Ken Rutchey, Marguerite S. Koch, and Sunil Narumalani

Abstract

l

Recent and historical satellite remote sensor data were used to inventory aquatic macrophyte (especially cattail and sawgrass) changes within the Florida Everglades Water Conseruation Area 2A using Landsat Multispectral Scanner (MSS) data (1973, 1976, and 1982) and SPOT High Resolution Visible (HRV) multispectral data (1987 and 1991). The method required a single base year of remotely sensed data with adequate ground reference information (1991). Historical remotely sensed dota were "normalized" to the base year's radiometric characteristics. Statistical clusters extracted from each date of imagery were found in relatively consistent regions of multispectral feature space (using red and near-infrared bands) and labeled using a "core cluster" approach. Wetland classification maps of each year were analyzed using "post-classification comparison" change detection techniques to produce maps of (1) cattail change and (2) change in the "sawgrass/cattail mixture" class. The amount of hectares in each wetland class was tabulated by year. The spatial distribution of the wetland was then overlaid onto a soil porewater phosphorus statistical surface obtained through in situ investigation. The cattail and cattail/sawgrass mixture classes appear to be spatially associated with the distribution of relatively high concentrations of porewater phosphorus in Water Conservation Area 2A.

lntroduction

In the mid-1970s, there were an estimated 105.9 million acres of wetlands in the conterminous United States. In the mid-1980s, an estimated 103.3 million acres of wetlands remained. An estimated 1.1 percent of estuarine wetlands and 2.5 Dercent of inland wetlands were lost from the lower 48 states during this period. Of the remaining wetlands acreage

J.R. Jensen is with the Department of Geography, University of South Carolina, Columbia, SC 29208.

K. Rutchey is with the South Florida Water Management District, Box 24680, West Palm Beach, FL 33416-4680.

M.S. Koch is with the Rosenstiel School of Marine & Atmospheric Science, University of Miami, 4600 Rickenbacker Causeway, Miami, FL 33149-1098.

S. Narumalani is with the Department of Geography, University of Nebraska, Lincoln, NE 68588.

in the conterminous United States, 97.8 million acres (95 percent) were freshwater {inland) wetlahds and 5.5 million acres (5.0 percent) were estuarine (coastal) wetlands (Dahl and Johnson, 1991). Thus, inland wetlands make up the vast majority of the precious wetland resources in the conterminous United States. They improve water quality, provide flood control, assist groundwater recharge, and provide habitat for fish and wildlife (Koeln, 1992). They represent a significant natural resource which must be preserved.

The Everglades represent the largest freshwater system in Florida (SFWMD, 1992). These wetlands are influenced by an extensive system of levees and canals, which have significantly altered the hydroperiod (duration and depth of surface water that covers an area), flow of water, and water quality (Worth, 1988; Davis and Ogden, 1993). Much of the area has been impounded into Water Conservation Areas, as shown in Figure 1. This study focused on the inland wetland conditions found within Water Conservation Area 2A. Sawgrass [a perennial sedge and not actually a grass as the common name implies) is one of the dominant vegetation community types found throughout the freshwater (palustrine) Everglades ecosystem. The loss of sawgrass (Cladium jamaicense) and the apparent replacement by cattail (Typha domingensis) appears to be taking place in Water Conservation Area 2A. (wcA-2A).

This study focused on the analytical inventory and mapping of the aquatic macrophyte communities in WCA-zA (especially cattail and sawgrass). The goal was to inventory the cattail distribution using historical remotely sensed data to document whether the cattail distribution was decreasing, stable, or increasing. Several recent studies document how to identify changes in inland wetland using satellite remote sensor data (Jensen et al., 1991; 1992; 1993b; Rutchey and Vilchek, 1994). The methods usually involve (Jensen, 1986; Jensen et al., 1987)

- o the selection of a minimum of two dates of remotely sensed data:
- holding sensor system variables as constant as possible (e.g., spatial, spectral, temporal, and radiometric resolutions, Iook angle);

Photogrammetric Engineering & Remote Sensing, Vol. 61, No. 2, February 1995, pp. 199-209.

0099-1112/95/6102-199\$3.00/0 O 1995 American Society for Photogrammetry and Remote Sensinq

- o holding environmental variables as constant as possible (time of year, time of day, soil moisture, phenological cycle); and
- o the extraction of thematic information from each date of imagery and the application of a change detection algorithm.

Ideally, scientists also collect unbiased "ground reference" wetland information at the time of each remote sensing data acquisition. Unfortunately, many agencies have only recently discovered the utility of remote sensing data for inland wet-Iand change detection. Therefore, while it may be possible to collect ground reference information for the most recent remotely sensed data, it is impossible to go back in time and collect the historical ground reference information. This research summarizes the results of image "radiometric normalization" and "core cluster" feature space partitioning techniques used to analyze four historical remotely sensed images (1973, 1976, 1982, and 1987) without ground reference data in conjunction with a single date of imagery (1991) with accurate ground reference information. The study focused on Water Conservation Area 2A in the Florida Everglades (Figure 1).

The Remotely Sensed Data

It is often difficult to acquire cloud-free, remotely sensed data in subtropical south Florida. Nevertheless, six predominantly cloud free dates of satellite remote sensor data were collected by two sensor systems for Water Conservation Area 2A from 1973 to 1991. Landsat Multispectral Scanner (MSS) data were obtained in 1973, 1976, and 1982, and sPoT High Resolution Visible (Hnv) multispectral (xs) data were col-Iected in 1987 and 1991. The specific date, type of imagery, bands used in the analvsis, and nominal spatial resolution of the various sensor systems are summarized in Table 1. Colorinfrared color composite images of the individual dates are shown in Plate 1.

Collection of 1991 In Situ Reference Data

Rutchey and Vilchek (1994) inspected 129 ground plots during 1991 using a helicopter and the Global Positioning System (cps). The GPS data were "differentially corrected" to a planimetric accuracy of \pm 3 to 7 m which was compatible with the spatial resolution of the SPOT 20- by 20-m multis-

pectral data and superior to the 79- by 79-m Landsat MSS data. Field verification was accomplished bv navigating to a point using the GPS and having a single observer estimate the percent cover of each of the plant species located within an estimated 2O-by zo-m grid square. The same observer was used throughout the study 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). All data were reduced and placed in digital format for statistical analysis.

lmage Preprocessing

Inland wetland change detection using multispectral remote sensor data involves preprocessing, classification, and change detection procedures. The following sections document the preprocessing required to perform the multiple date change detection using satellite remotelv sensed data. The most

I x,y coordinate root-mean-square error.

southern portion of the 1987 and 1991 SPOT scenes did not encompass all of Water Conservation Area 2A' (Plate 1). Also, a small amount of cloud cover was present in the 1987 SPor data. These conditions are accounted for in the statistical analvsis (Table a).

Table 1.

lmage Rectification

Twenty ground control points (crs) were obtained in map (metres northing and easting) and image space (row and column) coordinates and used to rectify the 10 August 1991 remote sensor data to a Universal Transverse Mercator (UTM) map projection having 20- by 20-m pixels using a nearestneighbor resampling algorithm and a root-mean-square error (RMSE) of \pm 0.4 pixel (\pm 8 m) (Rutchey and Vilchek, 1994). All other images were resampled to 20- by 20-m pixels using nearest-neighbor resampling and registered to the 1991 SPor data for change detection purposes (Plate 1). The RMSE statistic for each image is summarized in Table 1.

The boundary of Water Conservation Area 2A was digitized from U. S. Geological Survey 7.5-minute, 1:24,000-scale topographic maps. The polygon boundary file was "rasterized" to a UTM map projection resampled to 20- by 20-m pixels, producing a binary "mask" of the wcA-za. The mask was applied to each of the rectified images. Thus, only land within Water Conservation Area 2A was allowed to contribute to the cluster development in the classification phase of the project. The mask also maintained a constant amount of hectares in each image, which was important for computing the change in wetland between dates.

lmage Normalization

A problem associated with using historical remotely sensed data for change detection is that the data are usually "nonanniversary" dates with varying sun angle, atmospheric, and soil moisture conditions. Ideally, the multiple dates of remotely sensed data should be "normalized" so that these effects can be minimized or eliminated (Eckhardt et al., 1990; Hall et al., 1991).

The ability to use remotely sensed data to classify wetland is contingent upon there being a relationship between remotely sensing brightness value (BV) and actual surface conditions. However, factors such as sun angle, Earth/sun distance, detector calibration differences between the various sensor systems, atmospheric condition, and sun/target/sensor (phase angle) geometrv will also affect pixel brightness value (Eckhardt et al., 1990). Image normalization was performed to reduce pixel BV variation caused by non-surface factors, so that variations in pixel brightness value between dates could be related to actual changes in surface conditions.

Differences in direct beam solar radiation due to variation in sun angle and Earth/sun distance can be calculated accurately, as can variation in pixel BVs due to detector calibration differences between sensor systems. However, removal of atmospheric and phase angle effects require information about the gaseous and aerosol composition of the atmosphere and the bi- directional reflectance characteristics of elements within the scene (Eckhardt et al., 1990). Because atmosoheric and bi- directional reflectance information were not available for any of the five scenes, an "empirical scene normalization" approach was used to match the detector calibration, astronomic, atmospheric, and phase angle conditions present in a reference scene. The 10 August 1991 SPOT HRV scene was selected as the reference scene to which the 1973, 1976, 1982, and 1987 scenes were normalized. The 1991 SPOT image was selected because it was the only year for which quality in situ ground reference data were available.

Image normalization was achieved by applying regression equations to the 1973, 1976, 1982, and 1987 imagery which predict what a given BV would be if it had been acquired under the same conditions as the 1991 reference

scene. These regression equations were developed by corre-Iating the brightness of "normalization targets" present in both the scene being normalized and the reference (1991) scene. Normalization targets were assumed to be constant reflectors, so any changes in their brightness values were attributed to detector calibration, astronomic, atmospheric, and phase angle differences. Once these variations were temoved, changes in BV could be related to changes in surface conditions.

The acceptance criteria for radiometric "normalization targets" were (Eckhardt et al., 1990)

- . The target should be at approximately the same elevation as the other land within the scene. Selecting a mountain top normalization target would be of little use in estimating atmosoheric conditions near sea level because most aerosols in the atmosphere occur within the lowest 1000 m.
- o The targef should contain only minimal amounts of vegetation. Vegetation spectral reflectance can change over time due to environmental stresses and plant phenology.
- The target must be in a relatively flat area so that incremental changes in sun angle from date to date will have the same proportional increase ot decrease in direct beam sunlight for all normalization targets.
- e When viewed on the image display screen, the patterns seen on the normalization targets should not change over time. Changing patterns indicate variability within the target which could mean that the reflectance of the target as a whole may not be constant over time. For example, a mottled pattern on what had previously been a continuous tone dry lake bed may indicate changing surface moisture conditions, which might eliminate the dry lake bed from consideration as a normalization target.

Multiple wet (water) and dry (e.g., unvegetated bare soil) targets were found in the base year image (1991) and in each of the other dates of imagery (e.g., 1987 SPOT data). A total of 21 radiometric control points were used to normalize the 1973, 1976, 1982, and 1987 data to the 1991 SPOT data. It is useful to summarize the nature of the normalization targets used and identifv adiustments which had to be made when trying to identify dry soil targets in a humid-subtropical environment.

Radiometric normalization targets found within the 1987 and 1991 sPor data consisted of three wet points obtained just to the north of WCA2A within WCA-1 and three dry points extracted from an excavated area, a dry lake area, and a limestone road area. The brightness values of the early image targets (e.g., 1987) were regressed against the brightness values of the base image targets (e.9., 1991) for each band (Figure 2). The coefficients and intercept of the equation were used to compute a normalized 1987 SPOT dataset which had approximately the same spectral characteristics as the 1991 SPOT data. Each regression model contained an additive component that corrected for the difference in atmospheric path radiance between dates, and a multiplicative term that corrected for the difference in detector calibration, sun angle, Earth/sun distance, atmospheric attenuation, and phase angle between dates.

The 1982 MSS data were normalized to the 1991 data using (1) three "common" wet targets found within wCA-1 and (2) two dry points extracted from a bare soil excavation area in 1982 which progressed northward about 300 m (15 pixels) in the y dimension by 1991 (i.e., the x dimension was held constant). Thus, two "non-common" dry radiometric control points were extracted for this date. Hall et al. (1991) suggest that the members of the radiometric control sets may not be the same pixels from image to image in contrast to geometric

Figure 2. (a) Relationship between the same wet and dry regions found in both the 4 April 1987 and 10 August 1991 SPoT band 1 (green) dataset. The equation was used to normalize the 4 April 1987 data to the 10 August 1991 sPoT data as per methods described in Eckhardt et al. (1990). (b) Relationship between wet and dry regions found in both the 4 April 1987 and 10 August 1991 SPoT band 2 (red) dataset. (c) Relationship between wet and dry regions found in both the 4 April 1987 and 10 August 1991 SPoT band 3 (near-infrared) dataset.

control points for spatial image rectification, which are composed of identical elements in each scene. Furthermore, they suggest that "using fixed elements inevitably requires manual selection of sufficient numbers of image-to-image pairs of suitable pixels, which can be prohibitively labor intensive, particularly when several images from a number of years are being considered." Such conditions were definitely a factor in this study.

The 1976 MSS data were normalized to the 1991 data using three wet targets located in WCA-1 and two dry points extracted along a bare soil road and a limestone bare soil area. The 1973 MSS data were normalized to the 1991 data using two wet and three dry targets. The greater the time period between the base image (e.g., 1991) and the earlier year image (e.g., 1973), the more difficult it is to locate unvegetated, dry normalization targets. For this reason, analysts sometimes use man-made, "pseudo-invariant" features such as concrete, asphalt, rooftops, parking lots, and roads when normalizing historical remotely sensed data (Schott et al., 1988; Caselles and Garcia, 1989; Hall et al., 1991).

The normalization equations for each of the individual dates are summarized in Table 2. The gain (slope) associated with the SPOT data were minimal while the historical MSS data required significant gain and bias adiustments (because some MSS data were not originally acquired as 8-bit data). The methodology, applied to all images, minimized the differences in sun angle, atmospheric effects, and soil moisture conditions between the dates. Rectified, standardized, and masked remote sensor data are shown in Plate 1.

lmage Classification

Rutchey and Vilchek (1994) classified the 10 August 1991 sPor data into 20 classes. These data were "recoded" into the more general classes summarized in Table 3 and shown in Plate 2. This section reviews the methodology used to classify the 1991 base image and documents the techniques used to classify the historical remotely sensed data.

Classification of the 1991 5P0T Base lmage

First, a standard statistical unsupervised classification of the study area was performed, yielding 30 clusters. One hundred twenty-nine ground reference locations within the initial classification were then visited in the field (in sifu) using Global Positioning System (cps) technology. The planimetric locations of the field sites were located in the imagery, and the mean and variance-covariance matrices of these data

'All regression equations were significant at the 0.001 level.

were used to "seed" a supervised maximum-likelihood classification. Rutchey and Vilchek (1994) documented the thematic accuracy of the 1991 SPoT wetland classification map by analyzing an additional 241 stratified random ground reference locations surveyed using GPS instruments. The overall map accuracy was 81 percent with a Kappa coefficient of agreement of 73,5,

Unfortunately, such accurate ground reference information was not available for the historical 1973 to 1987 classifications; therefore, no error assessment was made for these dates. Nevertheless, the valuable 1991 data were used to understand where the important wetland classes were located in multispectral feature space.

Measurement vectors were extracted from the 1991 SPOT data at the GPS locations and plotted in red (band 2) and near- infrared (band 3) feature space. Thirteen of the cPS verified 1991 measurement vectors for sawgrass, cattail, and

brush are shown in Figure 3 along with slough/water and bare soil measurement vectors. Slough/water absorbed most of the red and near-infrared incident radiant flux, causing these vectors to be located near the origin at approximately 30,30 (in red, near- infrared feature space). Sawgrass was found above water in feature space, up and to the left of the water-dry soil line. Cattail absorbed about the same amount of red radiant flux but reflected more near-infrared radiant flux. This caused the cattail measurement vectors to be located above the sawgrass vectors away from the water-dry soil line, as expected. Mixtures of cattail and sawgrass were found situated between the cattail and sawgrass classes. Dense brush absorbed even more red radiant flux and reflected even more near-infrared radiant flux, moving the measurement vectors further from the soil line up and to the left in a unique portion of the feature space. Dry soil reflected much of the incident red and near-infrared radiant

flux and was found in the top right quadraat of the feature space. The dry soil vectors exhibited the greatest variance of all classes.

Labeling Clusters Extracted from Historical Remote Sensor Data

With the historical remotely sensed data (1973, 1976, 1982, and 1987) normalized to the 1991 image data, it was hypothesized that the feature space relationships for the major wetland classes would be relatively constant between the various dates of imagery. Therefore, each historical remote sensing dataset was analyzed using statistical unsupervised pattern recognition techniques to yield 75 clusters (Jensen, 1986). In order to label the 75 clusters on each date of imagery into information classes as accurately as possible, four types of information were used: (a) an individual plot of the cluster mean vectors in red versus near-infrared feature space for each date of imagery; (b) a 24-bit color infrared color composite display $(RGB = near\t- infrared, red, and green)$ bands) of the study area for visual analysis of the true color characteristics of the scene; (c) a display "highlighting" the individual cluster under investigation in the green image plane of a 24-bit color infrared color composite (a typical "class overlay" operation); and (d) a map showing the geographic distribution of an individual cluster under investigation {e.g., highlighted in red) in relationship to other clusters already evaluated. This was accomplished using two 24-bit color displays at one time with stable items 'a' and 'b' on one display and dynamic items 'c' and 'd' on the second display.

Identifying Sawgrass "Core" Clusters

Those clusters in each date having >25,000 pixels (1000 ha) were identified because it was believed that these could possibly be sawgrass clusters based on the still large total number of sawgrass pixels reported in the 1991 SPoT classification map. Three representative clusters meeting this criteria were selected for each date. For example, in the 1973 Mss dataset clusters #22, #18, and #33 were selected and contained approximately 1a5K, 105K, and 90K pixels, respectively. These 1973 clusters were found to be located in approximately the same red versus near- infrared feature space location (i.e., cluster #22 43.95,68.78; cluster #18 45.O7,64.73; and cluster #33 42.69, 64.26; respectively) as the 1991 SPOT GPS sawgrass brightness values (Figure 3). These 1973 clusters were also evaluated on the CRT screen by overlaying the geographic distribution of each cluster on top of a color-infrared image of the study area (display 'c' above) and were found to occupy interior regions of the conTABLE 3. CLASS DESCRIPTIONS FOR WATER CONSERVATION AREA 2A.

'Rutchey and Vilchek (1994) inventoried individual sparse, moderate, and dense cattail classes using the 10 Aug 91 SPOT XS data. The 1991 classification map (Plate 2) depicts the spatial distribution of a "merged" dense, moderate, and sparse cattail class. '?Rutchey and Vilchek (1994) inventoried individual sparse, moderate, and dense sawgtass classes as well as beds of periphyton, sawgrass/brush, and slough/water using the 10 Aug 91 SPOT XS data. ' Slough/water was found consistently on each date of imagery just outside of WCA-2A near structure S-10C (Figure 1).

servation area which were mapped as sawgrass in 1991. Therefore, these were considered "core" 1973 sawgrass clusters.

Identifying Cattail and Brush "Core" Clusters

Because of the relatively good "fit" between the 1973 "core" sawgrass clusters and the 1991 SPOT GPS sawgrass brightness values, the analyst proceeded to locate "core" cattail clusters. Cattail "core" clusters had to satisfy three criteria: (1) they had to be relatively large clusters (containing > 1000 pixels) which were located in the 1973 dataset feature space region which corresponded generally with the 1991 SPor GPS cattail red versus near-infrared region; (2) the "core" cattail clusters should be distant in geographic space from the "core" sawgrass cluster distributions when evaluated on the color infrared display'c' above; and (3), if present, they should normally be geographically located on the brighter magenta vegetated areas near the water control structures as was demonstrated in the field verified 10 August 1991 sPOT geographic distribution of cattail. Three cattail "core" clusters meeting these criteria were selected on each date. For the 1973 dataset, the three clusters selected were $#12, #13$, and #57 (containing approximately 5K, 7K, and 2K pixels, respectively) and had red versus near-infrared brightness values of 44.92, 101.27; 46.84, 96.23; and 49.44, 101.28; respectively. Thus, they were considered cattail "core" clusters. Brush "core" clusters were identified using similar logic, except that thev could be any size and also occur on tree islands. Three brush "core" clusters were identified for each date despite the relatively few brush pixels in each scene. Figure 3 depicts the distribution in two- dimensional feature space of the sawgrass, cattail, and brush "core" clusters for each date of imagery. A dashed line simply bounds all the core clusters and was not used to partition feature space when labeling individual clusters on each date of imagery.

Labeling "Non-Core" Clusters

Having analytically "fine-tuned" each date's feature space by identifying a triad of sawgrass, cattail, and brush "core" clusters, it was possible to use the "core" clusters as "anchor points" to subjectively evaluate and label surrounding "noncore" clusters using the information provided in the four displays 'a to d' described above. Because the individual date's $(e.g., 1973)$ feature space was now analytically "fine-tuned," the 1991 SPOT GPS brightness value feature space distributions for each class were no longer used.

Those clusters which were "relatively" near the "core" sawgrass clusters in the feature space and/or geographic space on an individual date (e.g., 1973) were assigned to the

¹ The 1991 sawgrass class also includes 5092.56 ha of periphyton, 1406.68 ha of sawgrass/brush, and 472.8 ha of slough/water as described in Rutchey and Vilchek (1994).

'? The most southern extent of WCA-2A was not recorded bv the SPOT HRV sensor svstem on these dates.

TABLE 5. RECODED VALUES FOR CATTAIL AND SAWGRASS/CATTAIL CLASSES FOR EACH OF THE CLASSIFICATION MAPS DERIVED FROM REMOTELY SENSED DATA

Recoded File & Date	Cattail	Sawgrass/Cattail
File 1 22 Mar 73		
File 2 02 Apr 76		
File 3 17 Oct 82		8
File 4 04 Apr 87		9
File 5 10 Aug 91		10

sawgrass class. Using the same subjective logic, clusters which were relatively near the "core" cattail clusters in feature space and geographic space were assigned to the cattail class. Those clusters which were relatively near the "core" brush clusters in feature space and geographic space were assigned to the brush class using the same logic.

Identifying Mixed Clusters

Clusters which were intermediate between the maior "core" sawgrass, cattail, and brush clusters were sometimes believed to contain "mixed" land cover. These were systematicallv evaluated using displays 'a to d' described above and where appropriate labeled as "sawgrass/cattail" and "brush/cattail." The subiective density (e.g., compact, diffuse) of a cluster pixel distribution throughout a geographic area was another important diagnostic characteristic when labeling all clusters, especially potential mixed clusters.

All burn scars, slough/water, and cloud shadow were assigned to sawgrass. Clouds were relatively easy to identify and label as they occupied distinct regions of multispectral feature space. It appears that the technique may be used to extend field verified feature space signatures (in this case, data obtained in 1991) back through time using "core" cluster logic for image classification and change detection purposes. The procedure involves both analytical and subjective methods.

Wetland classification maps of the study area for each of the dates of remote sensor data are shown in Plate 2. Statistics for each of the classification maps are summarized in Table 4. In 1973, there were relatively little cattail in Water Conservation Area 2A (920 ha), the majority adiacent to water control structures S-10A, S-10C, and S-10D. Significant growth in cattail took place by 1976 (1,533 ha) and 1982 (2,381 ha), primarily in this same region. The cattails continued to expand southward below structure S-10C as evidenced in the 1987 map $(3,125$ ha) with a major expansion near structure S-7. By 1991, there were 4,898 hectares of cattail in WCA-2A.

Change Detection

It was a straightforward task to compare the individual wetland classification maps using "post-classification comparison" change detection techniques. The goal was to identify the change in the spatial distribution of the Cattail and the Sawgrass/cattail class through time from 1973 to 1991. Therefore. the spatial distribution of these two classes were extracted from each of the classification maps and recoded into a new file according to the logic shown in Table 5.

A map showing the change in Cattail distribution per year is shown in Plate 3a. This map was produced using a GIS "minimum dominate" overlay function applied to values 1 to 5 (Table 5) using all five of the recoded files. In this way, even the smallest amount of cattails present in an individual year (1973) show up in the change map. A map showing the change in the "sawgrass/cattail" mixture class from 1973 to 1991 is shown in Plate 3b. This map was produced using a cIS "minimum dominate" overlay function applied to values 6 to 10 (Table 5) using all five of the recoded files. Significant expanses of sawgrass/cattail mixture below S-10A. S-10C. and S-10D. and adiacent to structure S-7 were recorded in the 1982, 1987, and 1991 datasets. The progression of cattail growth in Water Conservation Area 2.A from 1973 to 1991 in five time periods is graphed in Figure 4. Fig-

Water Conservation Area 2A from 22 March 1973 to 10 August 1991 as measured using Landsat MSS and SPOT HRV satellite remote sensor data. The 1991 Sawgrass class includes all periphyton and water in the study area (Table 4).

ure 5 summarizes the growth of cattail and sawgrass/cattail mix, and the decline of sawgrass hectares from 1973 to 1991.

Discussion

What agent(s) are responsible for the expansion of the cattail and the sawgrass/cattail mixed classes in WCA-2A during this time period? Research in south Florida has suggested that the spread of cattail may be linked to increased phosphorus (P) Ioading or extended hydroperiod, or a combination of these factors (Toth, 19BB; Davis, 1991). Only the possible impact of increased P will be briefly reviewed here. The Hillsboro and North New River canals, which drain the Everglades Agricul-

tural Area, border WCA-2A on the northeast and southwest, respectively (Figure 1). Surface water inflow to WCA-2A occurs through the four S-10 control structures on the Hillsboro Canal and pump station S-7 on the North New River Canal. Outflow of surface water occurs through six control structures located at the south end of wcA-2A, although virtually all of the outflow is routed through the three S-11 structures into WCA-3A. A field study was conducted to determine the spatial distribution of P and related physical-chemical parameters in the peat soil of WCA-2A (DeBusk et al., 1993). Field sampling of the top 30 cm of soil was performed at 74 sites across WCA-24 in July, 1990. An isarithmic plot of P in the top 10 cm of soil revealed widespread enrichment of P (Figure 6), especially in areas proximal to surface inflows importing nutrient-laden water from the Everglades Agricultural Area into wCA-2A. Soluble reactive P in the porewater varied from ≤ 50 ug L⁻¹ in the interior marsh to greater than 1,000 μ g L⁻¹ near inflow structures.

The porewater P data were converted from state plane coordinates to UTM coordinates and interpolated to a 20- by 20-m grid which was registered to the remote sensing derived wetland classification maps. Plate 4a depicts the 1991 SPOT HRV color composite scene (Plate 1e) draped ovet a three-dimensional representation of the P statistical surface for orientation purposes. The 1991 classification map (Plate 2e) was draped over the P statistical surface in Plate 4b. It

appears that the additional porewater P is available for plant uptake because the cattail and sawgrass/cattail distributions are located in the same region as the greatest porewater P concentrations. However, phosphorus loading may not be the only factor controlling vegetation distribution.

References

- Caselles, V., and M.J.L. Garcia, 1989. An Alternative Simple Approach to Estimate Atmospheric Correction in Multitemporal Studies, International Journal of Remote Sensing, 10(6):1127-1134.
- Dahl, T.E., and C.W. Johnson, 1991. Status and Trends of Wetlands in the Conterminous United States, Mid-1970's to Mid-1980's, U.S. Dept. of Interior, U.S. Fish & Wildlife Service, Washington, D.C., 28 p.
- Davis, S.M., 1991. Sawgrass and Cattail Nutrient Flux: Leaf Turnover, Decomposition, and Nutrient Flux of Sawgrass and Cattail in the Everglades, Aquatic Botany, 4O:2O3-224.
- Davis, S.M., and J.C. Ogden, 1993. Everglades: The Ecosystem and its Restoration, St. Lucie Press, Delray Beach, Florida.
- DeBusk, W.F., K.R. Reddy, M.S. Koch, and Y. Wang, 1993. Spatial Distribution of Soil Nutrients in a Northern Everglades Marsh: Water Conservation Area 2A, Soil Science Society of America lournal, 58(2):543-5 52.
- Eckhardt, D.W., I.P. Verdin, and G.R. Lyford, 1990. Automated Update of an Irrigated Lands GIS Using SPOT HRV Imagery, Photogrammetric Engineering & Remote Sensing, 56(11):1515-1522.
- Hall, F.G., D.E. Strebel, J.E. Nickeson, and S.J. Goetz, 1991. Radiometric Rectification: Toward a Common Radiometric Response among Multidate, Multisensor Images, Remote Sensing of Environment, 35:11-27.
- Jensen, J.R., 1986. Introductory Digital Image Processing: A Remote Sensing Perspective, Prentice-Hall, Inc., Englewood Cliffs, New jersey, 278 p.
- Jensen, I.R., and S. Narumalani, 1992. Improved Remote Sensing and GIS Reliability Diagrams, Image Genealogy Diagrams, and Thematic Map Legends to Enhance Communication, International Archives of Photogrammetry and Remote Sensing, 6(B6):125-L32.
- Jensen, J.R., E.W. Ramsey, H.E. Mackey, E. Christensen, and R. Sharitz, 1987. Inland Wetland Change Detection Using Aircraft MSS Data, Photogrammetric Engineering & Remote Sensing, 53(5): 527-529.
- Jensen, J.R., S. Narumalani, O. Weatherbee, and H.E. Mackey, 1991. Remote Sensing Offers An Alternative for Mapping Wetlands, Geo Info Systems, October, pp. 46-53.
- fensen,].R., S. Narumalani, O. Weatherbee, and K.S. Morris, Jr., 1992. Predictive Modeling of Cattail and Waterlily Distribution in a South Carolina Reservoir Using GIS, Photogrammetric Engineering & Remote Sensing, 58(11):1561-1568.
- lensen, 1.R., D. Cowen, S. Narumalani, O. Weatherbee, and J. Althausen, 1993a. Evaluation of CoastWatch Change Detection Protocol in South Carolina, Photogrammetric Engineering ε Remote Sensing, 59(6):1039-1046.
- Jensen, J.R., S. Narumalani, O. Weatherbee, and H.E. Mackey, 1993b. Measurement of Seasonal and Yearly Cattail and Waterlily Changes Using Multidate SPOT Panchromatic Data, Photogrammetric Engineering & Remote Sensing, 59(4):519-525.
- Koch, M.S., and K.R. Reddy, 1992. Distribution of Soil and Plant Nutrients along a Trophic Gradient in the Florida Everglades, Soil Science Society of America Journal, 56:1492-1499.
- Koeln, G., 1992. How Wet Is that Wetland? Earth Obseruation Magazine, July/August) , pp. 36-39.
- Rutchey, K., and L. Vilchek, 1994. Development of an Everglades Vegetation Map Using a SPOT Image and the Global Positioning

System, Photogrammetric Engineering & Remote Sensing, 60(6): $767 - 775.$

- Schott, J.R., C. Salvaggio, and W.J. Volchok, 1988. Radiometric Scene Normalization Using Pseudoinvariant Features, Remote Sensing of Environment, 26:1-16.
- SFWMD, 1992. Surface Water Improvement and Management Plan for The Everglades, SFWMD, W. Palm Beach: (March), 472 p. and Appendices.
- Toth, L.A., 1988. Cattail Nutrient Dynamics, Technical Pub. DRE-255, SFWMD. West Palm Beach, Florida.
- Worth, D.F., 1988. Environmental Response of WCA-2A to Reduction in Regulation Schedule and Marsh Drawdown, Technical Pub. DRE- 250. SFWMD. West Palm Beach, Florida.

fReceived 14 Mav 1993; accepted 6 October 1993; updated 11 May 1994)

John R. Jensen

Dr. Tohn R. Jensen received his M.A. from Brigham Young University in 1972 and a Ph.D. in geography from U.C.L.A. in 1976. He is a **Carolina Distinguished Research Professor in the Department of Geography at the University of** Carolina Distinguished Research Professor in the

South Carolina. His current research involves the development of digital image processing algorithms to extract bioohvsical wetland information.

Ken Rutchey

Ken Rutchey received his B.S. degree from Palm Beach Atlantic College with a major in Biology and a minor in Chemistry. He has worked for the South Florida Water Management District as a Research Environrnentalist since 1981. He has

been involved in a number of research projects studying the ecosystems of South Florida. His maior research interests have been in the Everglades. He currently is using remote sensing and cIS applications for environmental studies, specifically for mapping the vegetation of the Everglades.

Marguerite S. Koch

Marguerite S. Koch received a B.S. degree in Biology from Tulane University (1981) and an M.S. degree in Marine Sciences from Louisiana State University (1988). Her research has beer' focused on anaerobic stress and nutrient limita-

tion in wetland macrophytes. Secondary interests include biogeochemistry and nutrient cycling in anaerobic sediments. Marguerite is currently pursuing a Ph.D. at the Rosenstiel School of Marine and Atmospheric Science, University of Miami, investigating factors controlling zonation and succession in marsh-mangrove transitions in relation to sea level rise.

Sunil Narumalani

Dr. Sunil Narumalani is an Assistant Professor at the University of Nebraska, Department of Geography. He received his M.A. from the University of Georgia and a Ph.D. from the University of South Carolina. His research interests are

directed toward the use of remote sensing and GIS techniques for environmental applications. At present he is involved in several projects that focus on evaluating biodiversity, ecological mapping, ecosystem based assistance, and wetland resources manaqement across the U.S.