PROFESSIONAL PAPER SJ2009-PP2

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Palatka, Florida

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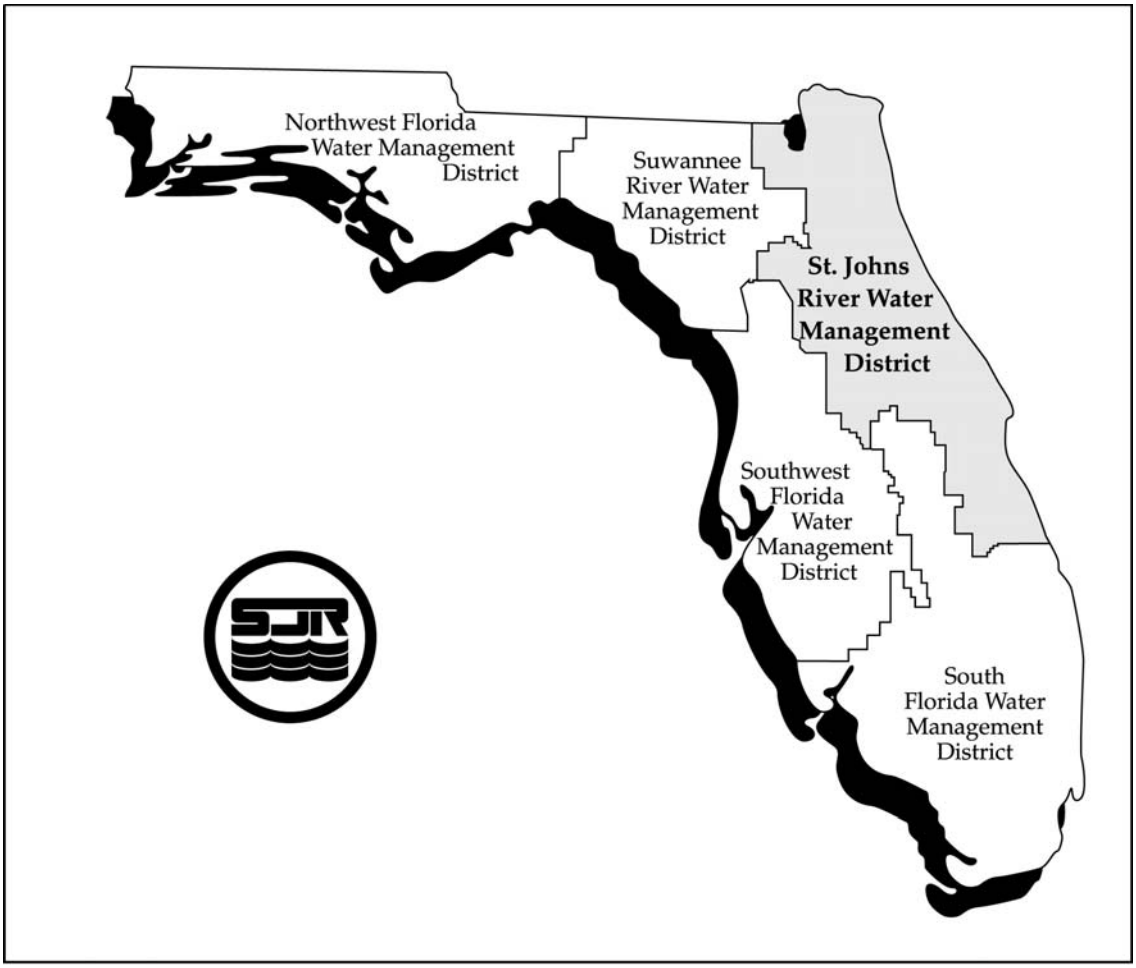

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ABSTRACT

This atlas contains Lower St. Johns River Basin submerged aquatic vegetation (SAV) data for 2006. Ground-truthing transects and ground-truthing polygons from field-collected data were mapped and assessed, and hyperspectral imagery was collected and analyzed. Hyperspectral imagery classification was generally successful and appeared to identify a greater proportion of the existing SAV than previous attempts using true-color photo interpretation. Based on the imagery classification, 1,273 acres of SAV were mapped within the mainstem of the lower basin and Doctors Lake. In some cases, imagery classification and transect data gave divergent bed-size estimates. Reasons for those discrepancies are briefly discussed.

INTRODUCTION

Submerged aquatic vegetation (SAV) plays an important role in many aquatic ecosystems, particularly in shallow lakes (Sheffer 1998). It is important for anchoring sediment, sequestering nutrients, serving as a food resource and as nursery habitat (Dennison et al., 1993). SAV is an important food source and habitat for a number of organisms in the Lower St. Johns River Basin (LSJRB). Manatees graze the deepwater edge of the SAV beds and use the shallow areas for cover (reviewed in Burns et al. 1997). Fish rely on SAV beds for predator evasion and increased foraging opportunities (Rozas and Odum 1988, Heck and Crowder 1991, Jordan et al. 1996), as do insects (Batzer and Wissinger 1996, Lombardo 1997, Solimini et al. 1997). SAV beds in the LSJRB have three-fold-higher fish abundance and 15-fold-higher invertebrate abundance than do adjacent sand flats (D. Dobberfuhl, unpublished data). Thus SAV-based production rates are disproportionately higher than unvegetated areas of the river and are critically important to the overall health of the system.

SAV mapping efforts began in 1995 to evaluate the quality and distribution of estuarine and freshwater submerged habitats. This ongoing effort is designed to quantify ecosystem change in response to restoration efforts and to provide information necessary for the development of pollutant load reduction goals and total maximum daily loads.

True-color aerial imagery was obtained in 1998 and 2001. Photo interpretation and delineation of the grass beds in the 1998 imagery underestimated grass bed extent at approximately 50% of the ground-truthing transects (Dobberfuhl 2002). Photo interpretation and delineation of the 2001 imagery was performed by on-screen digitizing SAV identified from scanned orthorectified true-color aerial photographs. This methodology was unsuccessful and failed to identify SAV in many areas of the river (Dobberfuhl and Trahan 2003). In 2003, the decision was made to obtain hyperspectral imagery, focusing on those spectral bands thought to be characteristic of important vegetative and benthic features. This imagery appears to be more sensitive than the true-color imagery previously obtained and better characterizes grass bed features. Imagery was again collected in 2006, with the bands for data collection altered somewhat from the 2003 band selection in order to provide more spectral separation between features. In fact, fewer bands were selected in 2006, but the selected bands had narrower bandwidths and their placement along the electromagnetic spectrum allowed for better targeting of desired features.

This edition of the SAV atlas includes ground-truthing SAV extent for 2005 and ground-truthing SAV extent and SAV presence and absence as identified by hyperspectral imagery analysis for 2006. Two independent measures of SAV spatial extent were performed in 2006 and compared to provide an accuracy estimate for hyperspectral imagery classification. These maps are presented as a continuing series of atlases documenting the distribution and change of SAV in the LSJRB.

METHODS

Ground-Truthing Transects

In 2005 and 2006, 75 sites were selected to ground-truth actual SAV conditions. At each site, one transect was run from the shoreline to beyond the terminus of the SAV bed. The line-intercept method (Canfield 1941) was used to record species present and percent cover; transect length was recorded, and the two end points for each transect were recorded by using global positioning system (GPS). Transect length and the georeference of end points were entered into GIS. Transect length was compared to the spatial coverage derived from hyperspectral image classification to assess the relative accuracy of the classified images. Of the 75 ground-truthing transects, 50 overlapped the hyperspectral images spatially and were used to assess spatial accuracy of the classified imagery.

Ground-Truthing Polygons

In 2006, 107 polygons along the shoreline were delineated and surveyed. Data included species present, aggregate percent coverage, plant foliar density, water depth, mean plant height, and substrate type. These polygons were then randomly split into two groups — 54 to be used as training data in developing a classification scheme to apply towards all images and 47 polygons were to be used during the accuracy assessment. Six polygons were not used at all: three polygons were collected outside of the imagery extent and three polygons that identified emergent vegetation were not examined in the study.

Hyperspectral Image Analysis

Imagery — The LSJRB received 87 hyperspectral swaths that covered the lower St. Johns River shoreline (Figure 1). The imagery was collected April 13–16, 2006 (HIL, Elmsdale, N.S., Canada), using a compact airborne spectrographic imager (CASI) sensor (ITRES, Calgary, Alberta, Canada). The resulting images have 1.2-meter (m) pixels and a swath width of 512 pixels (or 614.4 m) and swath length generally ranging from 5 to 8 kilometers (km) (Figure 2). Data collection was timed to prevent shadows from riverside trees from interfering with the sensor's view of the water and SAV near shore. Twelve of the 87 images were used to develop the classification methodology and 75 images were used in the final classification (12 images were excluded completely because of image overlap and redundancy).

Several processes were run on the images before delivery by the vendor, including image data processing, attitude data processing, GPS data processing, merging attitude and position data, atmospheric correction, and geocorrection. Image data processing involves a radiometric correction of the raw sensor image data that compensates for variations in optical transmission ("noise") and sensor sensitivity. Attitude data and GPS data processing are necessary to standardize the images. These two data files are then merged, synchronized, and corrected if necessary. The imagery is then atmospherically corrected to remove the effects of scattering and absorption of sunlight by particles in the air. This process permits comparisons between images and allows spectral signatures collected from one image to be applied to other images. The final step is to apply the GPS navigation data to the radiometrically and atmospherically corrected imagery to create a geocorrected version of the

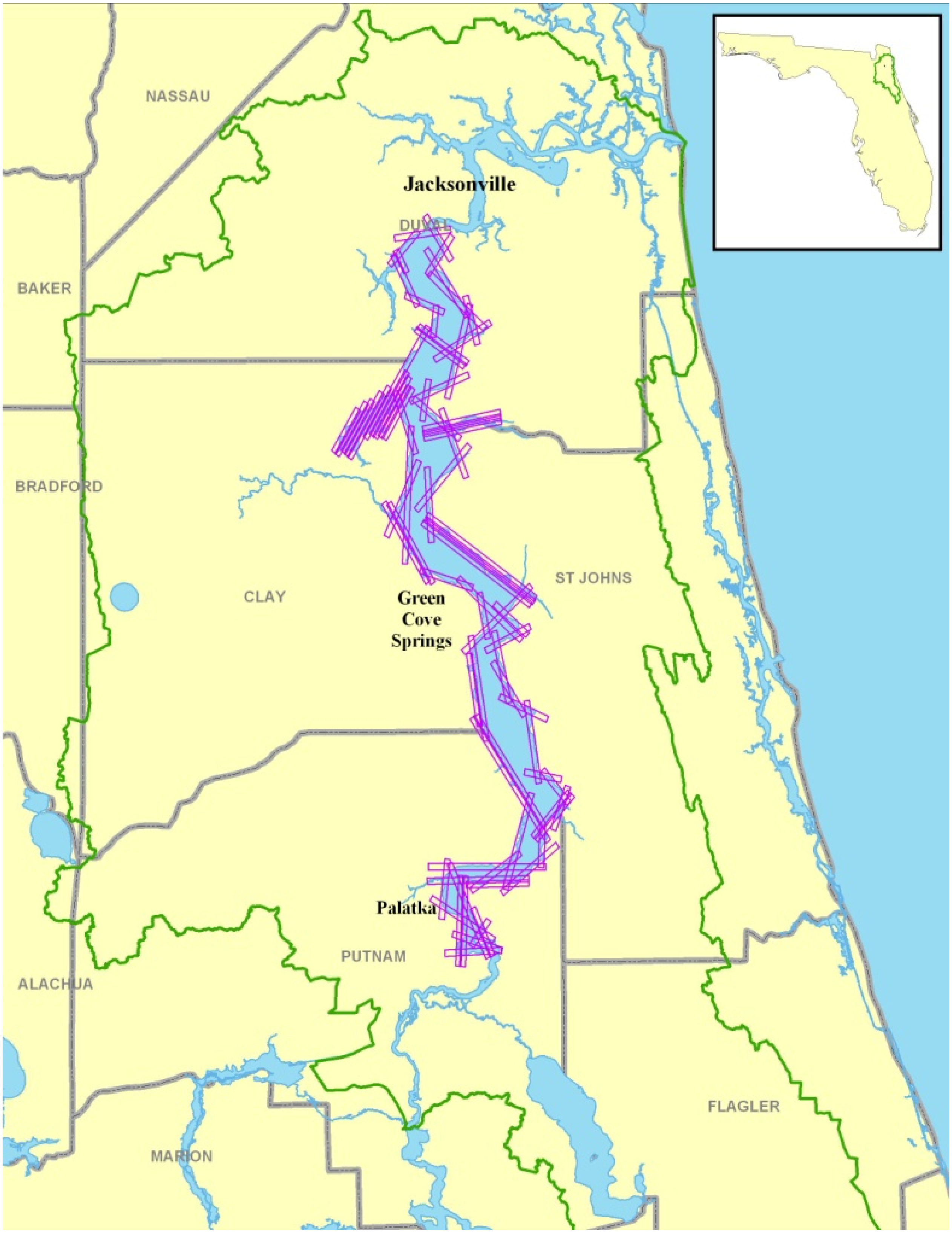

Figure 1. Location of 87 raw images

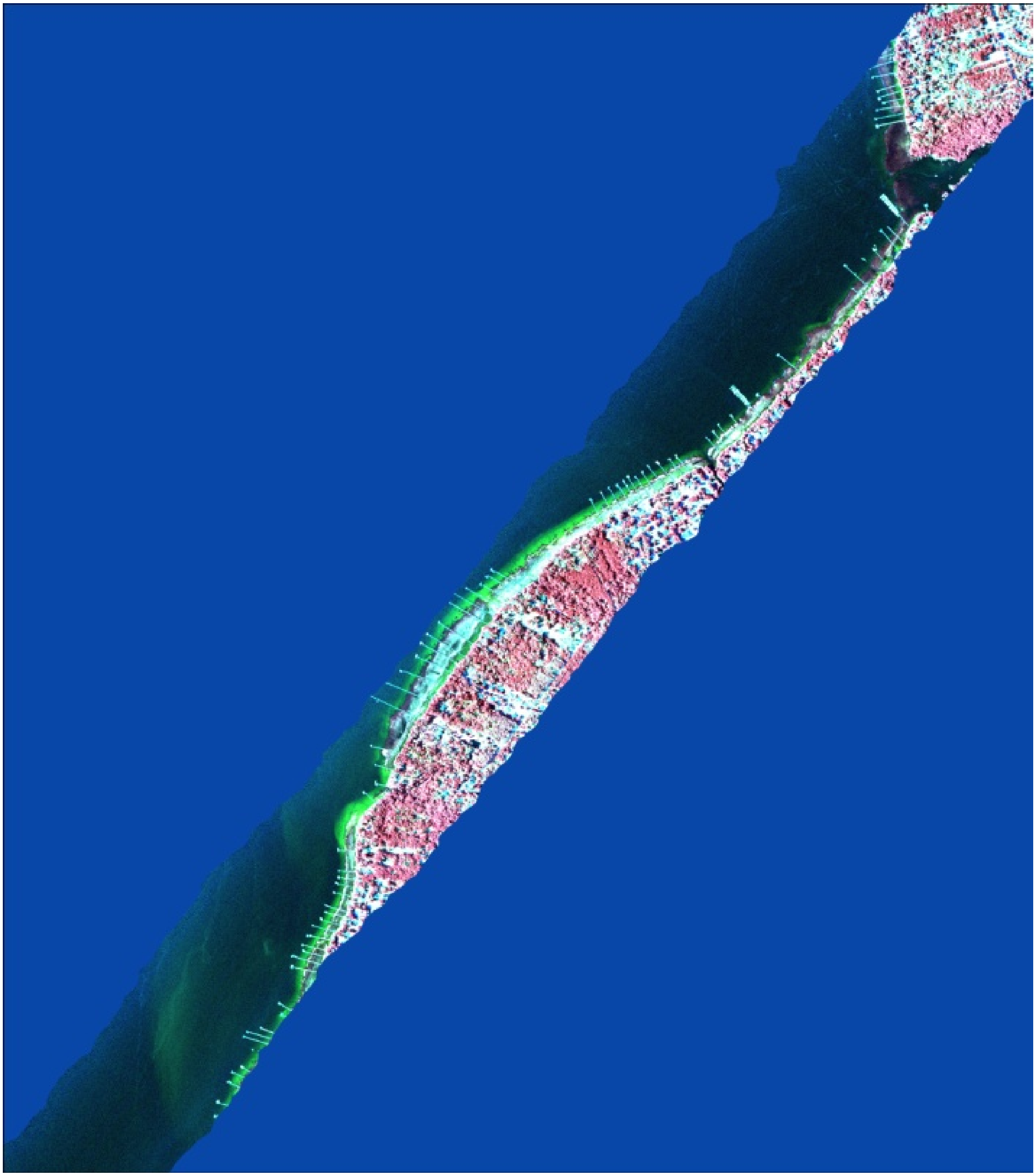

Figure 2. Image 61

imagery. The images were geocorrected by using data collected from onboard inertial measurement unit (IMU) and surface collected ground control points (GCPs) bringing the geocorrected images within a 2-pixel, or approximately 2.4-m, spatial accuracy (HIL 2006).

Spectral Resolution — Spectral resolution describes "the number and width of the portions of the electromagnetic spectrum measured by the sensor" (Govender 2007). For this study hyperspectral data was collected in 17 different bands of varying widths across the visible (400 nanometer [nm] to 750 nm) and near infrared (750nm to 2,500 nm) range of the electromagnetic spectrum (Table 1). Each band collects information in a different part of the electromagnetic spectrum and, therefore, may be able to contribute to identifying unique features on the earth's surface. Most objects reflect energy in unique patterns across the electromagnetic spectrum, and bands and bandwidths should be selected to allow that variation to appear without creating unmanageable amounts of data. Water absorbs most wavelengths in the near infrared, so the majority of the most useful information regarding SAV will come from the visible range.

Table 1. Band ranges and bandwidths

Band	Range	Bandwidth (nm)
1	453.6 +/– 5.8 nm	11.6
2	465.7 +/– 6.7 nm	13.5
3	480.6 +/– 4.8 nm	9.6
4	491.7 +/– 4.8 nm	9.6
5	542.0 +/– 4.8 nm	9.6
6	572.7 +/– 3.9 nm	7.8
7	581.1 +/– 3.0 nm	6.0
8	589.5 +/– 2.0 nm	4.0
9	681.7 +/– 2.0 nm	4.0
10	693.0 +/– 2.0 nm	4.0
11	698.7 +/– 2.1 nm	4.2
12	710.2 +/– 2.1 nm	4.2
13	720.6 +/– 3.0 nm	6.0
14	736.0 +/– 3.0 nm	6.0
15	750.4 +/– 4.0 nm	8.0
16	762.9 +/– 5.0 nm	10.0
17	787.1 +/– 4.0 nm	8.0

nm = nanometers

Image Processing — ENVI Geospatial Software (ITT Visual Information Solutions, Boulder, Colo.) was used for image processing. ENVI has the ability to process and analyze geospatial imagery including spectral signature selection and image classification. ArcGIS (Environmental Systems Research Institute, Redlands, Calif.) was used for Geographic Information Systems (GIS) work.

Classification — Classifying an image involves giving each pixel in the image a class designation based on its value across all bands, known as its spectral signature. There are two major types of classification schemes: unsupervised and supervised. Unsupervised classifications allow the computer that processes the data to identify classes based purely on the digital number (DN) of each pixel in each band. Each individual pixel is compared to other pixels, and they are then divided into clusters based on the similarity of their DN combination values. The objective is to group spectral response patterns into clusters that are statistically separable. Supervised classifications are generally more accurate because they include analyst-specified spectral information developed from specified locations in the image. Training sites are identified by the user, and the spectral signatures from those areas guide the model as it classifies the remaining pixels in the image into the designated class types.

For this project, we selected a type of supervised classification scheme uniquely developed for use with hyperspectral data — the spectral angle mapper classification scheme or SAM. SAM is a physically based spectral classification scheme that uses an *n*-dimensional angle to match pixels to reference spectra. The algorithm used in the SAM scheme determines the similarity between two spectra by determining the "spectral angle" between them. It uses the direction of the spectra and not its length or magnitude; therefore, all illumination possibilities are treated equally. When used with calibrated data this method is relatively insensitive to illumination and albedo effects. With SAM, smaller angles represent closer matches of pixels to reference spectra; however, any pixels that do not fall into the angle range of any of the classes will remain unclassed.

Training Data — Training data for the SAM classification scheme were created with the use of ground-truthing polygons that were collected along the shoreline over several days in April 2006 and within 2 weeks of the image acquisition. These polygons were overlaid onto the imagery and pixels were selected from within the polygons that represented areas of medium-to-high density SAV or bare bottom areas with no SAV. Additional pixels were selected from several of the images to capture the spectral signatures of other class types including urban areas, tree cover, and open water. The signatures from the selected pixels were then included in the spectral library.

Spectral Signatures — The spectral signatures of all pixels across 17 bands for the four class types (SAV, bare, urban, terrestrial vegetation) can be compared, and distinct differences can be seen in the shape of the signature curve between class types (Figure 3). Urban areas and areas with tree cover are spectrally distinct and are easily distinguished. However it is more important, and more difficult, to find spectral separability between water and SAV.

Spectral Library — A spectral library is a collection of reflectance spectra for natural and/or man-made materials for use in identifying unknown spectra. A unique spectral library for the lower basin of the St. Johns River consisting of 63 signatures for both aquatic and terrestrial features was developed (Figure 4). This spectral library was referenced by ENVI to classify the each individual image using the SAM model.

RESULTS AND DISCUSSION

The accuracy of the hyperspectral imagery classification was assessed with the use of the two different ground-truthing data sets. First, the remaining 47 ground-truthing polygons were examined and the classification accuracy for each polygon was determined by comparing the polygon's class designation to the image's classification. If an area was classified as SAV in the polygon but only 95% of the same area was classified as SAV in the imagery, the accuracy for that polygon was 95%. Several metrics were useful in evaluating the overall accuracy of the classification based on these polygons. The average of the presence/absence accuracy for all 47 polygons is 78%, but the median value of the accuracy values is 95%. The average of the presence/absence accuracy of the 50% trimmed mean of the measured values is 90% (Table 2).

Table 2. Accuracy assessment

Accuracy Metrics	Ground-Truthing Polygons	Ground-Truthing Transects
Mean	78%	82.1%
Median	95%	89.9%
50% trimmed mean	90%	86.0%

The second method used to determine accuracy involved a comparison between SAV bed length as identified by the classified hyperspectral imagery to bed lengths measured from ground-truthing transects in the river. Fifty of the 75 ground-truthing transects were found to be within the extent of collected imagery and were used for measuring classification accuracy. A comparison of bed length measurements at the 50 transect sites shows that the hyperspectral imagery classified an average of 82.1% of the SAV extent measured by the ground-truthing transects, a median accuracy value of 89.9%, and the average of the 50% trimmed mean of measured values is 86%. These results suggest that the hyperspectral classification generally underestimated bed length. Closer examination reveals that the deep end of the SAV bed was more often the underestimated area. Deep overlying water attenuates the reflected light energy available to the sensor, and it is possible that there may not be sufficient sensor sensitivity under those conditions. These results suggest that the hyperspectral sensor had more difficulty detecting SAV in deeper water condition, especially if those plants were short.

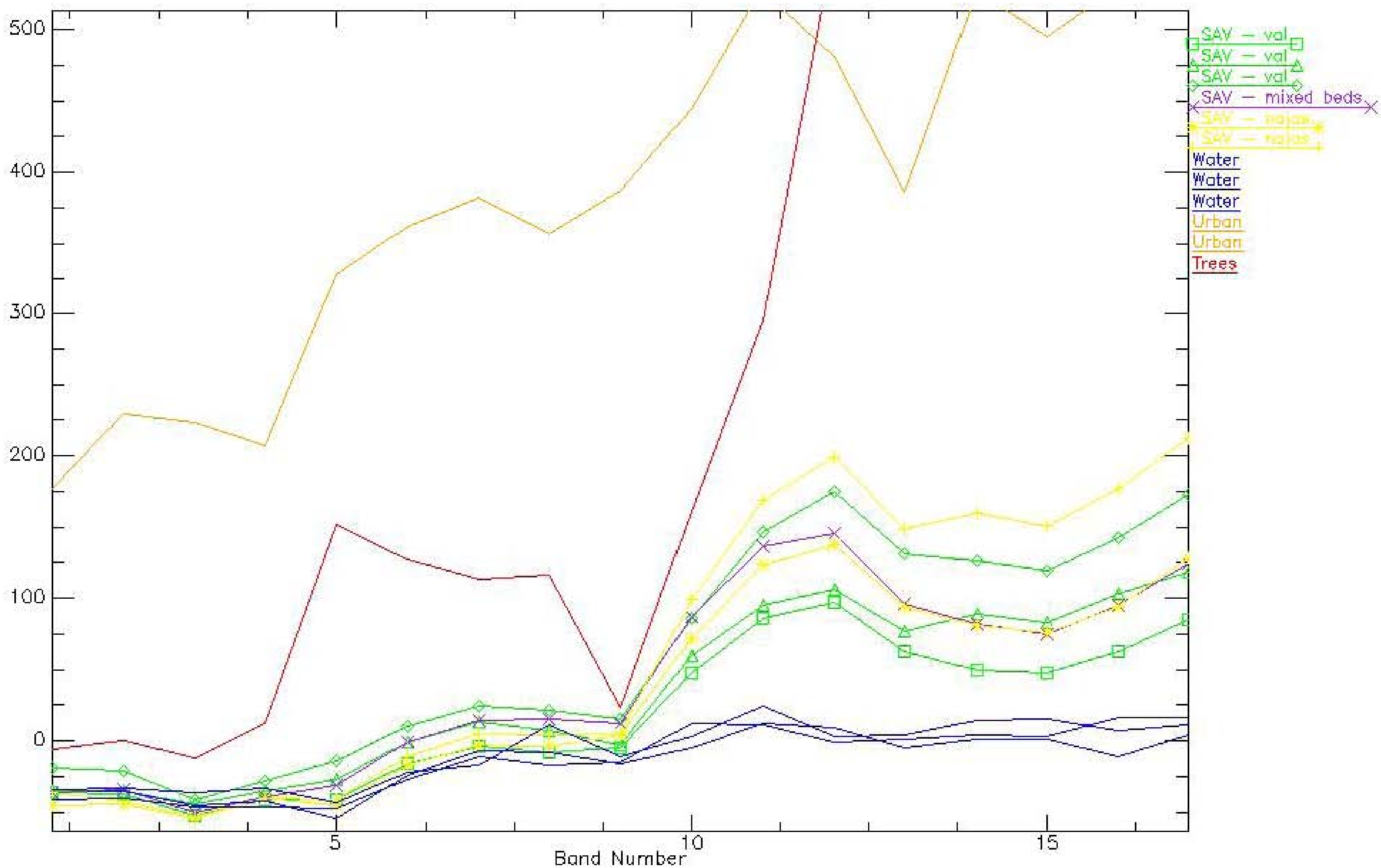

Figure 3. Spectral signatures for image 25

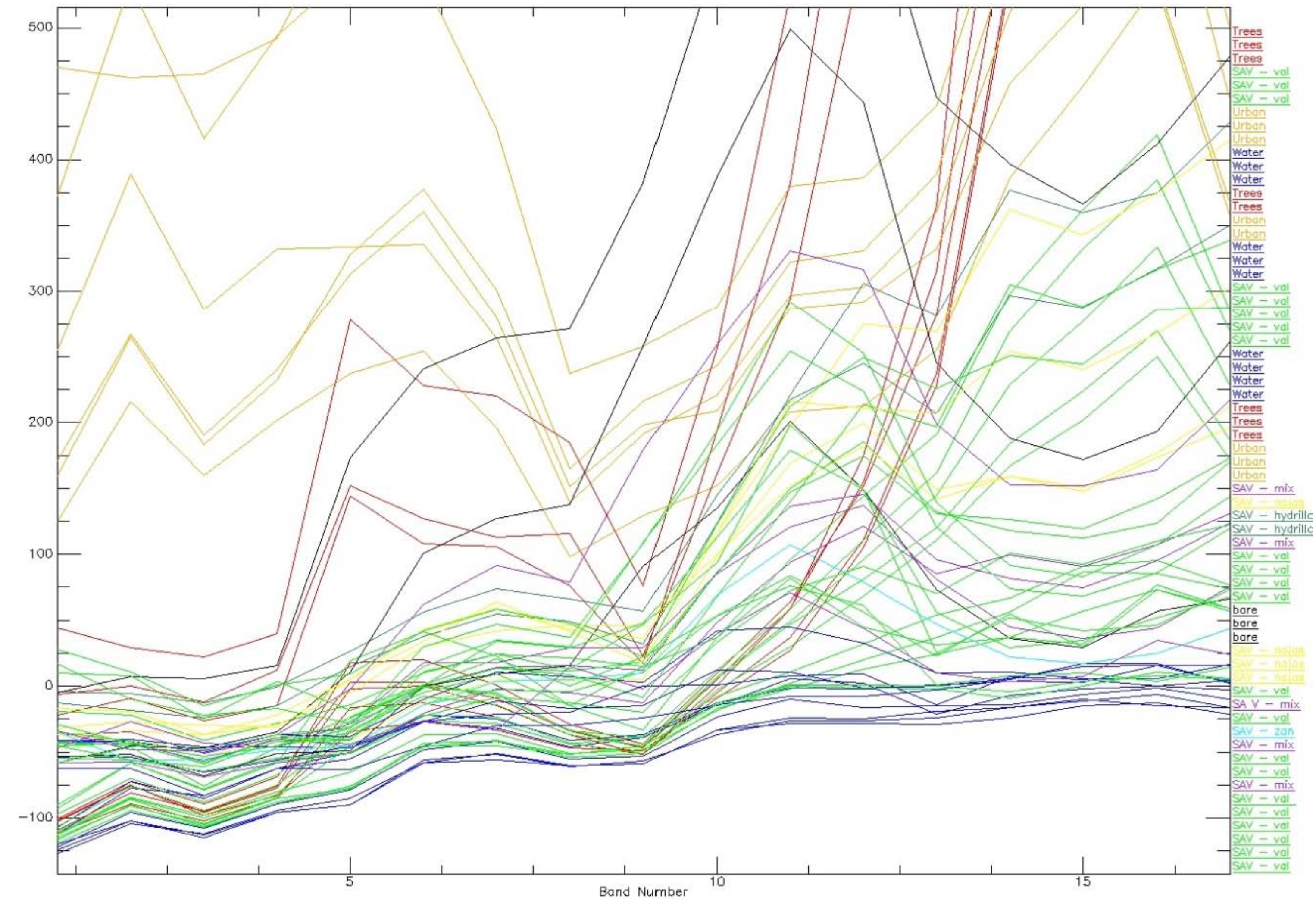

Figure 4. Spectral library with all 63 spectral signatures

The classified hyperspectral imagery identifies 1,202 acres of SAV in the mainstem of the St. Johns River and 71 acres in Doctors Lake for a total of 1,273 acres. This estimate is lower than the 2,140 acres estimated using the 2003 imagery and earlier transect data (Dobberfuhl 2002, Dobberfuhl and Trahan 2003). Several factors are likely responsible for the observed reduction in coverage.

One factor influencing the reduced estimate is the method of grass bed delineation. With traditional photo interpretation, small bare areas within grass beds are not as likely to be identified as in hyperspectral imagery classification. Thus the larger number of bare patches, or "holes," will tend to decrease the aggregate areal coverage estimate.

A second factor is differences in shoreline delineation. A 2003 image analysis used shoreline boundaries derived from SJRWMD DOQ imagery, since spatial accuracy of the HSI imagery was too low to identify the shoreline. In contrast, 2006 HSI imagery had much higher spatial accuracy and the shoreline boundary was generated from the imagery itself. Differences in shoreline boundary between 2003 and 2006 may account for a small proportion of the overall loss in coverage. It should be noted that because of these types of issues using different analytical methods to compare areal coverage, results between years should not be compared in light of analytical errors.

The final factor relating to the reduction in coverage is not imagery-related but water quality-related. Drought conditions persisted from fall 2003 through fall 2004, during the winter/spring of 2005, and again during winter/spring of 2006. The consequence of these repeated drought conditions was unusually high salinity values that reduced or eliminated SAV from many downstream areas in the lower basin. Field measurements of SAV coverage corroborate these reductions. Therefore, a large fraction of the SAV reduction observed in the imagery between 2003 and 2006 is a real and verifiable change.

Hyperspectral imagery continues to be a useful tool in identifying the presence and absence of SAV in the St. Johns River. As technology improves and analysts gain more experience in data collection and analysis, it is expected that hyperspectral imagery analysis will become more accurate and yield more detailed SAV maps in the future. For future hyperspectral analyses, additional questions may be addressed such as determining the maximum depth at which hyperspectral imagery can accurately identify SAV or determining whether or not hyperspectral imagery can accurately differentiate between SAV species. In future monitoring efforts, it may be possible to accurately map individual species' distributions with only a minimum in-water effort.

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