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by

Cynthia A. Meyer

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Arts Department of Geography College of Arts and Sciences University of South Florida

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Dedication

This thesis is dedicated to my pack.

"So long, and thanks for all the fish."
   - Hitchhikers Guide to the Galaxy
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Cynthia A. Meyer

ABSTRACT

In the event of a natural or anthropogenic disturbance, environmental resource managers require a reliable tool to quickly assess the spatial extent of potential damage to the seagrass resource. The temporal availability of the Landsat 5 Thematic Mapper (TM) imagery, 16-20 days, provides a suitable option to detect and assess damage to the seagrass resource. In this study, remote sensing Landsat 5 TM imagery is used to map the spatial extent of the seagrass resource. Various classification techniques are applied to delineate the seagrass beds in Clearwater Harbor and St. Joseph Sound, FL. This study aims to determine the most appropriate seagrass habitat mapping technique by evaluating the accuracy and validity of the resultant classification maps. Field survey data and high resolution aerial photography are available to use as ground truth information. Seagrass habitat in the study area consists of seagrass species and rhizophytic algae; thus, the species assemblage is categorized as submerged aquatic vegetation (SAV).

Two supervised classification techniques, Maximum Likelihood and Mahalanobis Distance, are applied to extract the thematic features from the Landsat imagery. The Mahalanobis Distance classification (MDC) method achieves the highest overall accuracy (86%) and validation accuracy (68%) for the delineation of the presence/absence of SAV. The Maximum Likelihood classification (MLC) method achieves the highest overall accuracy (74%) and validation accuracy (70%) for the delineation of the estimated coverage of SAV.
for the classes of continuous and patchy seagrass habitat. The soft classification techniques, linear spectral unmixing (LSU) and artificial neural network (ANN), did not produce reasonable results for this particular study.

The comparison of the MDC and MLC to the current Seagrass Aerial Photointerpretation (AP) project indicates that the classification of SAV from Landsat 5 TM imagery provides a map product with similar accuracy to the AP maps. These results support the application of remote sensing thematic feature extraction methods to analyze the spatial extent of the seagrass resource. While the remote sensing thematic feature extraction methods from Landsat 5 TM imagery are deemed adequate, the use of hyperspectral imagery and better spectral libraries may improve the identification and mapping accuracy of the seagrass resource.
Chapter 1

Introduction

1.1 Background

As essential nearshore aquatic habitat of the Gulf of Mexico, St. Joseph Sound and Clearwater Harbor require the development and implementation of management plans to protect and sustain the ecosystem. The environmental resources include an extensive seagrass resource, macroalgae habitat, mangroves, and tidal flats. Understanding the spatial and temporal scales of the physical substrate is crucial to the assessment of the ecosystem resource status, structures and functions. The application of remote sensing methods may enhance the results from the current field survey monitoring programs and the comprehensive management strategy for the resource. The sustainable management requires an understanding of the seagrass spatial distribution and characterization to create accurate habitat maps. Determining the status of the seagrass resource requires a comprehensive analysis of the geographic extent, composition, health, and abundance of the submerged aquatic vegetation (SAV) in the study area. The current monitoring programs provide data on a limited geographic scale which can not be extrapolated across the entire resource. In turn, the results of the current studies can not provide a comprehensive resource trend analysis or appropriate statistical power.

1.2 Goal

The purpose of this research is to determine the feasibility of using remote sensing image data to delineate the spatial extent of the seagrass resource. Evaluating the accuracy of the classification maps allows the comparison of the study results to the existing aerial photointerpretation SAV maps. The potential
to use Landsat 5 TM imagery as a data source greatly improves the temporal scale for analyzing spatial changes in the seagrass. In turn, the analyses provide more frequent information to the environmental resource managers and aid in the development of resource preservation and protection strategies.

1.3 Objectives

Objective One: To create hard classification maps delineating the presence/absence and estimated coverage of seagrass resource from Landsat TM imagery using Maximum Likelihood classification (MLC) and Mahalanobis Distance classification (MDC) techniques.

Objective Two: To create soft classification maps delineating the presence/absence and estimated coverage of seagrass resource from Landsat TM imagery using a linear spectral unmixing (LSU) and non-linear artificial neural network (ANN) algorithms.

Objective Three: To determine the most appropriate classification mapping technique for the seagrass resource by evaluating the accuracy and validity of the resulting classification maps.

Objective Four: Determine the ability for change detection by each appropriate classification method.
1.4 Description of Study Area

Approximately 30 kilometers north of the mouth of Tampa Bay (Figure 1), the area consists of open water regions bounded east and west by the coastal mainland shoreline and the barrier island chain, respectively. The study area for this project, St. Joseph Sound and Clearwater Harbor, occurs along the northwestern coastline of Pinellas County (Figure 2). Of the 95 km$^2$ in the study area, expansive seagrass beds cover nearly 56 km$^2$ providing essential habitat for the marine flora and fauna (Kaufman, 2007). In comparison, the study area has seagrass acreage equivalent to 60% of the total seagrass acreage found in the entire Tampa Bay estuary. Concluded from the results of the seagrass aerial mapping project (Kaufman, 2007), the seagrass acreage in the study area has increased slightly since the program began in 1998 (Meyer and Levy, 2008; Kaufman, 2007).

Figure 1. Location of the study site.
The ecosystem of the study area provides critical bird nesting areas, sessile algal communities, essential fishery habitats, marine mammal and turtle habitats, and numerous recreational opportunities. The prominent seagrass species consist of *Syringodium filiforme*, *Thalassia testudinum*, and *Halodule wrightii* (Figure 3). In addition to the seagrass species, the SAV includes a variety of rhizophytic algae. Figure 4 shows seven rhizophytic algae and an invertebrate common in Clearwater Harbor and St. Joseph Sound. The habitat also hosts a plethora of invertebrates including the Bay Scallop (*Argopecten irradians*) (Meyer and Levy, 2008).
Figure 3. Seagrass species found in the study area.

Figure 4. Rhizophytic algae and Bay Scallops found in the study area.
The water quality in the study area is relatively good in comparison to the Tampa Bay area (Levy et al., 2008). Transmissivity, measured at 660 nm, is a measurement of the percentage of light that can pass through the water. The mean transmissivity in the study area ranges from 90-95% (Levy et al., 2008). This level of water clarity should be suitable for the use of the satellite imagery.

Anthropogenic and natural stresses impact the health, sustainability, and persistence of the aquatic ecosystem (Short et al., 2001). Correlated with urbanization, anthropogenic factors such as stormwater pollution, hardened shorelines, development, eutrophication, and boat propeller scarring cause direct and indirect damages to the nearshore habitats (Meyer and Levy, 2008). Man-made features in the study area include dredge and fill operations, boat channels, spoil islands, finger canal systems, seawalls, and causeways. In turn, natural factors such as water circulation, beach erosion, climate change, and weather events may also cause changes to occur in the ecosystem. The complexity of the interacting anthropogenic and natural conditions adds to the intricate dynamics of Clearwater Harbor and St. Joseph Sound. These interacting environmental issues present a challenge for resource managers to develop strategies to protect and sustain the quality of the ecosystem (Meyer and Levy, 2008).
Chapter 2

Literature Review

2.1 Seagrass

2.1.1 Seagrass Resource Ecology

Seagrasses are flowering plants, angiosperms, specialized for living in marine nearshore environments (Short et al., 2001). Areas containing dense populations of seagrasses are considered a seagrass resource. Ecological functions provided by seagrass resource include structural and physiological characteristics that support species living in the seagrass communities. Functions such as nutrient cycling, detritus production, sediment formation, and shelter increase the primary productivity of the ecosystem (Dawes et al., 2004). Seagrass beds grow as continuous meadows or a mosaic of various size and shape patches (Brooks and Bell, 2001). Along the central Florida coast of the Gulf of Mexico, the seagrass growing season is May-September (Avery and Johansson, 2001) which coincides with the findings of Robbins and Bell (2000) reporting the greater changes in seagrass spatial extent from the spring to the fall seasons. Other factors such as physiology, growth characteristics, including water depth and salinity gradients may contribute to the spatial distribution of the seagrass beds (Robbins and Bell, 2000).

Seagrass requires available light for photosynthesis (Short et al., 2001), and the depth penetration of the available light is correlated with seagrass growth and survival (Dennison et al., 1993). Thus, good water clarity is crucial to the persistence and growth of the seagrass beds. The health of the seagrass resource may also be an indicator of water clarity and nutrient levels (Dennison et al., 1993). Disturbances in the water quality such as nitrification, sediment suspension, and pollution can negatively affect water quality and light penetration.
Correlated with urbanization, there is an increase of anthropogenic disturbances to seagrass resources (Tomasko et al., 2005). Environmental managers acknowledge the relationship between the anthropogenic factors and the degradation of the seagrass resource and realize the importance of sustaining this valuable ecosystem (Chauvaud et al., 1998). Currently, coastal habitat maps including seagrass areas provide essential information for management and planning decisions (Mumby et al., 1999). The sustainable management requires an understanding of the seagrass spatial distribution and characterization.

2.1.2 Seagrass Assessment Methods

Resource managers and researchers implement various techniques to assess and monitor the spatial and temporal changes of the seagrass habitat. Kirkman (1996) describes some of the methods for seagrass monitoring. The most common field survey technique consists of permanent transect monitoring. Usually monitored annually, transects are revisited by using spatial coordinates from a Global Positioning System. In most cases, the permanent transects start on or near shore and then continue perpendicular to the shoreline (Kirkman, 1996). After arriving on site and locating the transect 0m mark, samplers swim along the transect line with a meter square frame collecting data on seagrass species, condition, abundance, and biomass. Other field survey methods include collecting random point data, stratified random sampling designs (Meyer and Levy, 2008), and seagrass habitat classification mapping (Kaufman, 2007). The latter is the most intensive method which requires researchers to swim the entire seagrass area (Mumby et al., 1999).

In a quest to assess the geographic extent of the seagrass resource, researchers investigate the use of aerial photography for developing habitat maps. Historical aerial photography provides coarse baselines for the seagrass resource extent making it possible to compare the current geographic extent of the seagrass beds to the previous state. Currently, the analysis of aerial
photography supplies seagrass acreage maps to track the spatial and temporal
trends for resource management (Kaufman, 2007). Using digital aerial
photography for seagrass mapping requires the acquisition of large scale
airborne photographs. The resolution of the images typically ranges from 1
meter to 10 meter (Jensen, 2005). Variables such as water clarity and depth can
interfere with the ability of the photo-interpreters to accurately delineate the
seagrass meadows (Kaufman, 2007).

Coastal managers require reliable data to protect and manage ecosystems
(Mumby et al., 1999). Ecological management traditionally relies on small
sample designs and extrapolation of results to larger areas. This practice tends
to ignore the spatial dimension and connectivity of ecosystems (Schmidt and
Skidmore, 2003). Detailed habitat maps aid in the assessment and monitoring of
changes within the seagrass meadows. Seagrass biomass responds quickly to
environmental disturbances and alterations (Short et al., 2001). Usually, these
changes are large enough for detection by remote sensing techniques. In
conjunction with field survey monitoring, remote sensing maps can help provide a
better understanding of the extent of spatial and temporal trends in the seagrass
resource based on their synoptic and frequent characteristics.

2.2 Remote Sensing Applications

Remote sensing refers to a form of measurement where the observer is
not in direct contact with the object of study (Coastal Remote Sensing, 2006).
Two main types of remote sensing data collection include active and passive
systems. Active systems generate a source of illumination such as sound or
light (Jensen, 2005). Passive systems rely on the reflected sunlight and emitted
energy from targets to acquire data (Jensen, 2005). Technologies such as aerial
photography, multispectral satellite imagery, and hyperspectral imagery also
record how the sunlight reflects and refracts and radiance emits from targets
(Jensen, 2005). Multispectral imagery expands the classification abilities and
mapping of aerial photointerpretation. Multispectral imagery is usually satellite
Researchers commonly use multispectral and/or hyperspectral imagery for ecosystem studies. A basic assumption of remote sensing depends on the features of interest uniquely reflecting or emitting light energy; in turn, allowing the delineation and mapping of various features (Fyfe, 2003). As the bandwidths narrow, variation in absorption is detected. In applications to the aquatic environment, the specific wavelengths of light absorb and scatter in the water column and benthic substrate (Coastal Remote Sensing, 2006). Due to the various spectral properties, remote sensing is applicable for characterizing aquatic vegetation and benthic habitats (Schweizer et al., 2005). The spectral signature of seagrass beds in shallow waters differs significantly from the non-vegetated bottom. Considerations for the limitations of passive remote sensing include the water clarity, depth, and wave roughness, and the atmospheric and ionospheric conditions (Phinn et al., 2006). Although the passive remote sensing methods for aquatic benthos are limited to the visible wavelengths, it provides high spectral and spatial resolution for the mapping of features (Fyfe, 2003).

Remote sensing provides an alternative to the traditional boat or land based surveys required to assess an entire seagrass habitat (Dekker et al., 2005). Remote sensing is applicable for characterizing aquatic vegetation and benthic habitats due to the various spectral properties for each bottom type (Schweizer et al., 2005). The multispectral imagery requires several analyses to classify the signatures. In a study classifying the benthic habitat of a shallow estuarine lake, Dekker et al. (2005) addresses five components of the multispectral imagery analysis. The study considers the water and substrate spectral characterization, seagrass and macroalgae spectral characterization, and satellite imagery quality, finally resulting in the benthic substrate classification. Studies by Andrefouet et al. (2003), Schweizer et al. (2005), and
Pasqualini et al. (2005) consider similar components during the analysis and classification of various satellite imagery. Beyond the delineation of the SAV, Fyfe (2005) investigates the spectral reflectance of individual seagrass species and determines that seagrass species are indeed spectrally distinct. The properties of spectral reflectance depend on the chlorophyll and accessory pigment concentrations and the leaf design characteristics (Thorhaug et al., 2007). Fyfe (2005) includes the considerations of epiphytic coverage, and spatial and temporal variability in the reflectance determination of each species and records strong and consistent differences in spectral reflectance between species. The key to mapping species specific seagrass beds is acquiring a reliable spectral library for individual species (Fyfe, 2005). Thorhaug et al. (2007) examines three seagrass species and five marine algae to determine the difference in spectral signatures. The seagrass species, *Thalassia testudinum, Halodule wrightii, and Syringodium filiforme*, share a similar spectral signature for the curve; however, they differ in the height of the curve peak. Thorhaug et al. (2007) also finds significant differences between the seagrasses and marine algae spectral signature. The potential for refining seagrass habitat maps to a species composition level seems possible with the application of remote sensing technologies.

### 2.2.1 Landsat Imagery

The Landsat 5 Thematic Mapper (TM) satellite was launched in March 1984. The TM sensor collects multispectral imagery by recording the energy in the visible, reflective infrared, middle infrared, and thermal infrared regions of the electromagnetic spectrum (Jensen, 2005). The Landsat 5 TM system is described in detail in EOSAT (1992).

Each spectral band of the Landsat TM sensor has specific spectral characteristics (Table 1). For spectral bands 1, 2, 3, 4, 5 and 7, the ground projected resolution is 30m x 30m. Band 6, the thermal band, has a spatial resolution of 120m x 120m (Jensen, 2005). Each band measures the reflectivity
at different wavelengths. Band 1, blue, measures 0.45-0.52 μm in the visible spectrum. Due to the frequency of the wavelength, band 1 penetrates water. Band 2, green, measures 0.52-0.60 μm in the visible spectrum. Studies suggest that band 2 spans the region between the blue and red chlorophyll absorption making it useful for the analysis of vegetation (Jensen, 2005). Band 3, red, measures 0.63-0.69 μm in the visible spectrum and may be used for studies of vegetation for the red chlorophyll absorption. Band 4 measures 0.76-0.90 μm in the near-infrared spectrum. Band 4 is useful for the determination of biomass for terrestrial vegetation, and the contrast of land and water. Band 5 measures 1.55-1.75 μm in the mid-infrared spectrum, and is found useful for determining turgidity and the amount of water in plants. Band 6 measures 10.40-12.50 μm in the thermal spectrum related to the infrared radiant energy emitted from the surface. Band 7 measures 2.08-2.35 μm in the mid-infrared spectrum. Band 7 is mainly used for discriminating rock formations (Jensen, 2005).

Table 1. Landsat 5 TM band descriptions

<table>
<thead>
<tr>
<th>Band</th>
<th>Spectrum</th>
<th>Resolution (m)</th>
<th>Spectral Resolution (μm)</th>
<th>Characteristics/Functions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>blue</td>
<td>30x30</td>
<td>0.45-0.52</td>
<td>Penetration of water and supports vegetation analysis</td>
</tr>
<tr>
<td>2</td>
<td>green</td>
<td>30x30</td>
<td>0.52-0.60</td>
<td>Reacts to the green reflectance of vegetation</td>
</tr>
<tr>
<td>3</td>
<td>red</td>
<td>30x30</td>
<td>0.63-0.69</td>
<td>Reacts to the red chlorophyll absorption and vegetation</td>
</tr>
<tr>
<td>4</td>
<td>near-infrared</td>
<td>30x30</td>
<td>0.76-0.90</td>
<td>Contrast of land and water, and terrestrial vegetation</td>
</tr>
<tr>
<td>5</td>
<td>mid-infrared</td>
<td>30x30</td>
<td>1.55-1.75</td>
<td>Useful for turgidity and hydration in plants</td>
</tr>
<tr>
<td>6</td>
<td>thermal</td>
<td>120x120</td>
<td>10.40-12.50</td>
<td>Radiant thermal energy</td>
</tr>
<tr>
<td>7</td>
<td>mid-infrared</td>
<td>30x30</td>
<td>2.08-2.35</td>
<td>Determining rock formations</td>
</tr>
</tbody>
</table>
2.2.2 Aerial Photography

Aerial photography is usually collected from a plane flying in concentric transects over the study area. Depending on the altitude of the plane and the camera specifications, the swath and resolution vary. Aerial photography also requires preprocessing such as mosaicing the frames together and georeferencing the imagery prior to spatial analysis (Kaufman, 2007).

Agencies use aerial photography to map the land surface characteristics and shallow aquatic habitats including SAV. Aerial photography is collected in analog or digital format. The historic aerial imagery is limited to black and white or color film. The more current aerial photography is collected in a digital format. The digital imagery usually focuses on the three visible spectral bands: red, green, and blue, and may also include the near-infrared band (Kaufman, 2007). True color photography uses the three visible bands only. Features of interest are extracted from the images by a photointerpreter and used to produce maps.

2.3 Remote Sensing Classification

2.3.1 Imagery Classification

The extraction of thematic information from remote sensing data requires a series of processing methods including preprocessing, selecting appropriate logics and algorithms, and assessing the accuracy of the resultant product. The preprocessing steps include radiometric and geometric correction (Jensen, 2005).

The classification of thematic information requires a defined logic and algorithm appropriate for the data. The image classification method includes parametric, nonparametric, or nonmetric logics. Parametric logic assumes that the sample data belongs to a normally distributed population and knowledge of the underlying density function (Jensen, 2005). The nonparametric logic allows for sample data not from a normally distributed population. The nonmetric logic may incorporate both ordinal and nominal scaled data in the classification method. The algorithms may apply supervised or unsupervised methods. The
supervised classifications use known information extracted from training areas concerning the image to label a specific class for every pixel in the image. The unsupervised method allows the algorithm to differentiate between spectrally significant classes automatically. A combination of the supervised and unsupervised methods results in a hybrid approach.

2.3.2 Hard Classification Methods

Two supervised parametric methods, also considered hard classification, include the MLC and MDC algorithms. The MLC algorithm is a parametric supervised method. Based on the statistical probability of a pixel value belonging to a normally distributed population, the algorithm assigns the pixel to the most likely class. The method assumes that the training data for each class in each band are normally distributed (Jensen, 2005). Calculating the probability for the density functions, the MLC algorithm assesses the variance of each training class associated with the pixel brightness values. The MLC method is not recommended for bimodal or n-modal distributions. Variations of the maximum likelihood method without probability information assume that each class occurs equally across the landscape of the image. The MDC algorithm is a direction sensitive distance classification similar to the MLC method. The classification method is based on the analysis of correlation patterns between variables and is a useful way of determining similarity of an unknown pixel to a known one. The MDC assumes that the covariances for all the classes are equal (Richards, 1999). Based on the distance threshold, the algorithm fits pixels to the nearest class.

The unsupervised classification method used in this study is the Iterative Self-Organizing Data Analysis Technique (ISODATA) (Jensen, 2005). The ISODATA requires little input from the analyst. The ISODATA is based on the k-means clustering algorithm. The clustering method uses multiple iterations to determine the data grouping (Jensen, 2005). The cluster means are analyzed and pixels are allocated to the most appropriate cluster. ISODATA is used to for the initial examination of data to investigate the number of significant classes.
2.3.3 Soft Classification Methods

Two supervised nonparametric classification methods, also considered soft classification, include linear spectral unmixing (LSU) and artificial neural network (ANN) algorithms. Theoretically, the pixel-based seagrass abundance is determined by examining the significant spectral signatures of seagrass in individual pixels in the image with a LSU model. The LSU assumes that the spectral signature is the linear sum of the set of pure endmembers which are then weighted by their relative abundance (Hedley and Mumby, 2003). According to Hedley and Mumby (2003) the application of LSU to the aquatic environment is insufficient due to the light attenuation properties of the water causing the divergence from the linear model. However, if a depth correction can be applied to the pixels, then the LSU may produce reasonable results (Hedley and Mumby, 2003).

The ANN is a layered feed-forward classification technique that uses standard back-propagation for supervised learning. Researchers select the number of hidden layers to use and choose between a logistic or hyperbolic activation function. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. One layer between the input and output layers is usually sufficient for most learning purposes (Pu et al., 2008). The learning procedure is controlled by a learning rate, a momentum coefficient, and a number of nodes in the hidden layer that need to be specified empirically based on the results of a limited number of tests. The network training is done by repeatedly presenting training samples (pixels) with known seagrass abundance. Network training is terminated when the network output meets a minimum error criterion or optimal test accuracy is achieved. Finally, the trained network can then be used to unmix each mixed pixel. Therefore, ANN classification performs a non-linear classification and spectral unmixing analysis.
Chapter 3
Methodology

3.1 Methodology Overview
The remote sensing analysis for the study follows the "Remote Sensing Process" as described by Jensen (2005). This substantial process consists of image preprocessing, image enhancement, and thematic information extraction aiming to map the seagrass resources. The methodology for analysis of remote sensing imagery follows an inductive logic approach. A deterministic empirical model is applied to analyze the remote sensing data. This study applies unsupervised and supervised classification methods to extract thematic information from Landsat 5 TM imagery.

3.2 Data Sources
Several types of data are readily available for St. Joseph Sound and Clearwater Harbor. The remote sensing data available consists of aerial photography, aerial photointerpretation maps, and Landsat 5 TM imagery. The field survey data include information from the seagrass monitoring and ambient water quality monitoring programs.

3.2.1 Remote Sensing Data Sources
3.2.1.1 Aerial Photointerpretation SAV Mapping
Available remote sensing data for the study area includes aerial photographs and satellite imagery. The Southwest Florida Water Management District (SWFWMD) collects high resolution natural color aerial photography (SWFWMD, 2006). Collected on a 2-year cycle, the available digital imagery is one-meter resolution.
Beginning in 1999, the aerial seagrass mapping project provides data for the extent and spatial variation of the seagrass resource. The SWFWMD conducts a seagrass mapping program to monitor the changes in seagrass acreages. Using one meter resolution aerial photography, they apply a minimum mapping unit of ½ acre for the photointerpretation. The images are acquired during the dry season (December-January) when water clarity is good (Secchi disk >2m). The project produces an updated seagrass acreage map once every two years. They conduct limited field verification to ensure the accuracy of 90% for the final mapping product (Kaufman, 2007). The map classifies submerged aquatic vegetation (SAV) into patchy and continuous grassbeds. The photointerpretation can not discern information on species composition, condition, or biomass. The SAV is interpreted from 1:24,000 scale natural color aerial photography using Digital Stereo Plotters. The SAV signatures are divided into two estimated coverage categories, patchy and continuous coverage. The patchy areas represent the delimited polygon consisting of 25-75% SAV coverage. The continuous areas represent the delimited polygon consisting of 75-100% SAV coverage. The non-vegetated areas contain less than 25% SAV coverage (Kurz, 2002; Tomasko et al., 2005). The most recent photointerpretation map uses data collected in February 2006 (Figure 5). The geographic extent of the mapped SAV is comparable to the seagrass bed mapped from the Landsat 5 TM imagery.
Figure 5. Aerial Photointerpretation SAV Map based on 2006 aerial imagery (Kaufman, 2007).
3.2.1.2 Satellite Imagery

The Landsat 5 Thematic Mapper (TM) imagery for this study was provided by the Florida Center for Community Design and Research (FCCDR) at the University of South Florida. The image was acquired on 2 May 2006 (Table 2). The image was selected based on the low percentage of cloud cover and the limited budget for the project. The spatial resolution of the Landsat 5 TM imagery is 30m x 30m on the ground. The TM bands used in the study include 1 (blue), 2 (green), 3 (red), and 4 (near infrared). Bands 1, 2, and 3 were used for the spectral signature of the SAV associated with water column. Band 4 was only used for creation of masks.

The preprocessing steps for the image including geometric and radiometric corrections were completed by the FCCDR prior to this study using the ENVI Version 4.3 software program (ITT, 2006). The specifics of the processes were presented by Andreu et al. (2008). The image was georeferenced to the Universal Transverse Mercator map projection as WGS1984 Zone 17N. The radiometric calibration used the Calibration tool to convert the Landsat digital numbers to the at-sensor reflectance values (Andreu et al., 2008). Andreu et al. (2008) performed the atmospheric correction by subtracting the atmospheric path radiance estimated from pseudo-invariant dark water locations.

Table 2. Landsat 5 TM image details.

<table>
<thead>
<tr>
<th>Path/Row</th>
<th>Acquisition Date</th>
<th>Scene Identifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>17/41</td>
<td>May 2, 2006</td>
<td>5017041000612210</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Processing System:</th>
<th>Format:</th>
<th>Product Type:</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPGS</td>
<td>GeoTiff</td>
<td>L5 TM SLC-off L1T Single Segmentation</td>
</tr>
</tbody>
</table>
Figure 6. Landsat 5 TM satellite image from May 2, 2006. The natural color composite was made via TM band 3, 2, 1 vs. Red, Green, and Blue.
3.2.2 Field Survey Data

Available seagrass field survey data consists of information from the Pinellas County Seagrass Monitoring Program (Meyer and Levy, 2008) and the Pinellas County Ambient Water Quality Monitoring Program (Levy et al., 2008).

3.2.2.1 Seagrass Monitoring Data

The Pinellas County Seagrass Monitoring Program collects information on the status of the seagrass resource. Data parameters include SAV species, shoot density, canopy height, epibiont density, sediment type, and depth information. Data points are collected using a 0.5-meter square quadrat. The sampling occurs at the end of the growing season (Oct-Nov). The current seagrass survey sampling design (2006-2008) consists of a combination of stratified-random and permanent transects. The permanent transects intersect the historical permanent transect sites. The random transects are spatially stratified allocating sampling effort to the continuous and patchy grassbeds as delineated from the seagrass aerial mapping project by the Southwest Florida Water Management District (SWFWMD). In the study area, researchers sampled 42 sites in 2006 and 55 sites in 2007 (Figure 7). To account for variation and inaccuracy in the seagrass mapping, 15% of the sampling effort is allocated to areas that are not classified as patchy or continuous seagrass beds. The transects are 30 m in length and placed parallel to the shoreline. Samplers collect seven data points along each transect at 5 meter increments (Meyer and Levy, 2008). The mean abundance and density of seagrass was calculated for each transect from the seven observations. These means were used in the development of the training data for the thematic data extraction from the remote sensing imagery.
Figure 7. Pinellas County seagrass monitoring program results for Clearwater Harbor and St. Joseph Sound (Meyer and Levy, 2008).
3.2.2.2 Water Quality Monitoring Data

The Pinellas County Ambient Water Quality Monitoring Program collects water quality and habitat information. The program samples 72 stratified random sites per year in the study area. Developed in conjunction with Janicki Environmental, Inc, the stratified-random design is based on a probabilistic sampling scheme used by the Environmental Protection Agency (EPA) in their Environmental Monitoring Assessment Program (EMAP) (Levy et al., 2008). The EMAP-based design consists of overlaying a hexagonal grid by strata, and randomly selecting a sample location within each grid cell. The stratified-random design allows for statistical methods to be applied estimating population means and confidence limits for water quality metrics (Janicki, 2003).

Habitat information collected at each site includes the presence/absence of SAV, SAV species, and sediment composition. This study only uses the 2005 - 2007 data to coincide with the satellite imagery and seagrass information (Figure 8).
Figure 8. Observed SAV at the Pinellas County Ambient Water Quality sampling sites for 2005 - 2007 (Meyer and Levy, 2008).
3.3 Landsat 5 TM Imagery Analysis

Remote sensing information extraction techniques are used to estimate the geographic extent and estimated coverage of the seagrass resource in the study area. The goal of the analyses is to determine the feasibility of applying satellite imagery interpretation to delineate the seagrass resource. The following section describes the classification methods applied to the Landsat 5 TM imagery.

3.3.1 Imagery Preprocessing

The remote sensing data for the classification maps are based on a digital Landsat 5 TM image. The study uses data consisting of field survey measurements and ancillary datasets to develop training, testing, and validation data subsets. The field measurements serve as the ground truth data for the model validation as well as biomass and health information for the seagrass. Although this study did not conduct laboratory analyses data, results adapted from the studies of Fyfe (2005), and Thorhaug et al. (2007) provide spectral reflectance information for the Florida seagrass ecosystem. Additional ancillary data for the analysis includes maps from the Aerial Photointerpretation (AP) Seagrass Mapping Project produced by the SWFWMD.

The thematic information extraction from the satellite imagery requires several processing steps. The preprocessing includes radiometric, geometric and topographic corrections, image enhancement, and initial image clustering analysis. The radiometric and geometric corrections were completed for the Landsat 5 TM imagery prior to this study by the FCCDR (Andreu et al., 2008). The image processing is accomplished using the ENVI Version 4.3 software program (ITT, 2006). The first processing step saves the raster files for bands 1, 2, 3, 4, 5, 6, and 7 into a single ENVI image. The image is then clipped to the rectangular boundary of the study area (Figure 9). The clipped image consists of 400 columns and 1050 rows. Due to the strong spectral contrast between the land based features and water, the open water area is masked from the image.
using the near-infrared band 4 (Figure 10). The frequency distribution of the pixels of the image (i.e., histogram technique) allows the segregation of the image based on a threshold for the water versus land spectral properties. This technique does not exclude all of the tidal flat areas in the study area.

Figure 9. Landsat 5 TM imagery clipped to the study area from 2 May 2006
3.3.2 Imagery Classification

To initially investigate the spectral classes of the image the Equalization image enhancement is applied to bands 1, 2, and 3 (Figure 11). An image clustering analysis is conducted using an unsupervised classification (ISODATA) prior to the supervised classification. The ISODATA classification method is applied to bands 1-3 and categorized the data into 10 subclasses. The resultant
classification is visually compared to the field survey information to detect spatial correlations and estimated accuracy. The classes are merged into three categories and an environmentally relevant label was applied. The classes are land, SAV, and No SAV.

Figure 11. Landsat 5 TM image enhancement using Equalization function.
To map the seagrass resource from the TM imagery, two parametric supervised classifications, Maximum Likelihood classification (MLC) and Mahalanobis Distance classification (MDC), are performed on the Landsat 5 TM imagery. The first three bands of the Landsat 5 TM imagery are used for these classification methods. These bands have centered wavelengths of 485 nm, 560 nm, and 660 nm, respectively. The supervised image classifications use field survey seagrass information for the training signature, as well as, testing and validation. The classifications are conducted with two levels of SAV delineation. The first analysis focuses on the presence versus absence of SAV. The training and testing data categories for this classification include absence (<25% SAV) and presence (25-100% SAV). The second analysis uses three classification categories to delineate the estimated coverage of the SAV. The training and testing data categories include No SAV (<25% SAV), Patchy (25-75% SAV), and Continuous (75-100% SAV). Regions of interest (ROIs), delineated from the TM imagery for the training and testing areas, are interpreted from a combination of the Pinellas County Seagrass Monitoring field survey data and 6-inch resolution aerial photography. The selected grid cells are merged and imported into the ENVI 4.3 software as ROIs (ITT, 2006). Each ROI consists of 12 polygons with a minimum of 50 pixels in each polygon. The ROIs are selected from the areas homogeneous with spatial and spectral properties. The ROIs cover a range of water depths, and are spatially distributed throughout the study area. The estimated percent coverage for SAV is based on the mean abundance of seagrass calculated for each field survey sampling location. Using ArcMap 9.2 software, a 30 m x 30 m grid is created to coincide with the seagrass field survey data (ESRI, 2006). The aerial photography is used to compare the grid cells surrounding the field survey transect to ensure a homogeneous area for the ROI polygon.

The spectral properties of the ROIs determine the feasibility of delineating the classes in the classification map. By calculating the radiometric resolution
digital number (DN) for the ROIs in each spectral band, the separability of the classes is determined. Descriptive statistics are calculated for the ROI training data (Table 3). The separability of the ROI categories is examined for the three spectral bands (Figure 12). The ability to accurate separate the categories is relative to the overlap of the histogram curves. As the overlap of the histogram curves increases, the categories become more difficult to separate. The patchy and continuous SAV categories are expected to overlap. In the histograms for band 1 and band 2, there is limited overlap between the No SAV and SAV classes. The separability between the SAV and No SAV categories is greatest for band 2. The categories have the least separability between categories in band 3. This analysis suggests that it is feasible to delineate the SAV and No SAV classes using the visible bands. The overlap between the Patchy and Continuous SAV classes may limit the ability to accurately delineate them during classification.

Table 3. Radiometric Resolution descriptive statistics calculated for the ROI training data.

<table>
<thead>
<tr>
<th>ROI class</th>
<th>Pixels</th>
<th>Band</th>
<th>Minimum DN</th>
<th>Maximum DN</th>
<th>Mean DN</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>No SAV</td>
<td>1401</td>
<td>1</td>
<td>75</td>
<td>99</td>
<td>82.51</td>
<td>3.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>31</td>
<td>49</td>
<td>35.22</td>
<td>2.17</td>
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<tr>
<td></td>
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<td>3</td>
<td>19</td>
<td>37</td>
<td>23.68</td>
<td>2.09</td>
</tr>
<tr>
<td>Patchy SAV</td>
<td>1154</td>
<td>1</td>
<td>65</td>
<td>89</td>
<td>73.85</td>
<td>3.51</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>24</td>
<td>37</td>
<td>29.00</td>
<td>1.89</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>16</td>
<td>27</td>
<td>21.48</td>
<td>2.15</td>
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<tr>
<td>Continuous SAV</td>
<td>1493</td>
<td>1</td>
<td>60</td>
<td>79</td>
<td>68.25</td>
<td>3.65</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>21</td>
<td>33</td>
<td>25.40</td>
<td>2.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>14</td>
<td>27</td>
<td>18.62</td>
<td>2.04</td>
</tr>
</tbody>
</table>
Figure 12. Histograms of the radiometric resolution of the ROI classes: No SAV, Patchy SAV and Continuous SAV for TM 1 (A), TM 2 (B), and TM 3 (C).
The parametric supervised classification methods are calculated with the ENVI 4.3 software program (ITT, 2006). The MLC uses three TM visible bands to map seagrass resource by applying the spectral signatures extracted from the training ROIs. The accuracy assessment of the classification is examined using a confusion matrix based on the testing ROIs. The MDC also uses the three TM visible bands by applying the training ROIs to classify the seagrass resource. The MLC and MDC methods, also considered "hard" classifications, are used to classify the presence/absence of seagrass and the estimated coverage of the SAV. The maps are evaluated using the confusion matrix with the testing subset ROIs. The assessment includes the average accuracy, overall accuracy, producer's accuracy (omission error), user's accuracy (commission error), and Kappa coefficient.

The study also applies two supervised nonparametric classification methods. Considered soft classification methods, LSU and ANN algorithms provide an alternative approach to the hard classification. The LSU is calculated with the ENVI 4.3 software program (ITT, 2006). The training data is derived from the 1-meter resolution aerial photography supplied by the SWFWMD. ESRI ArcMap 9.2 software (ESRI, 2006) is used to examine the MrSID image mosaic and develop ROIs. Due to the small size of the image pixels, a 30m x 30m grid is created using Hawth's Tool (Hawth, 2006) and overlaid on the image. This ensures that the ROIs selected included a minimum of 30-50 (30m x 30m) pixels to coincide with the Landsat TM image. The training ROIs contains a minimum of 30 pixels per polygon and 12 polygons for each ROI category. The LSU can only determine less endmembers than the number of bands used in the analysis. Since three bands are used for the classification, only two categories, No SAV and SAV are delineated. The ANN analysis is attempted using the ENVI 4.3 software program (ITT, 2006).
3.3.3 Classification Accuracy Analysis

Post-processing includes several steps to ensure the accuracy of the classification map. The validation of the classification requires a data source independent from the training and testing data. The validation ROIs for this study are determined from the seagrass data collected by the Pinellas County Ambient Water Quality Monitoring Program. The validation accuracy assessment is calculated using the ESRI ArcMap 9.2 software program (ESRI, 2006). The classification images are exported from the ENVI 4.3 software as ESRI grid files and clipped to the extent of the study area using ESRI Spatial Analyst Extension (ESRI, 2006). The validation data includes spatial and temporal information on the presence/absence and species composition of SAV. Due to the sampling methods, the validation data point location accuracy has a radius of 10 m. Hawth’s Analysis Tool (Hawth, 2006) is used in ESRI ArcMap 9.2 (ESRI, 2006) to analyze the correlation between the validation data and the classification map. Using the Intersect Point function in Hawth’s Tools, the vector validation points and the raster classification map are processed. The correlation matrix is developed to assess the accuracy of the classification.

3.4 Analyses

The comparison of the classification maps is necessary to assess the most appropriate method for SAV delineation. The estimated accuracy from the validation analysis and spatial variation is used to compare the classification maps. The validation estimated accuracies are compared using descriptive statistics calculated with Microsoft Excel. The spatial comparison is described in the following section.

3.4.1 Comparison to existing maps

The AP mapping project conducted by the SWFWMD provides an estimate of the SAV acreage for the study area. Although the project aims for 90% accuracy for the ground-truth points, the geographic extent of the study restricts the validation to approximately 10 sites within Clearwater Harbor and St.
Joseph Sound. To estimate the accuracy of the AP maps, the validation data from the Pinellas County Ambient Water Quality Monitoring Program is used to develop a correlation matrix. The Intersect Point Function in Hawth’s Analysis Tool (Hawth, 2006) is used in ESRI ArcMap 9.2 (ESRI, 2006) to analyze the correlation between the validation data and the AP map.

The Landsat 5 TM classification maps developed in this study are compared to the results from the AP mapping project conducted by the SWFWMD. To investigate the variation between the mapping products, a spatial correlation is completed using the ESRI ArcMap 9.2 software program with the Spatial Analyst Extension. The total area is calculated for the classes of SAV, and No SAV. The areas are compared between the two classification methods. The classification maps are converted into raster grids with 30 m pixel cell dimensions. The grids are overlaid and a comparison analysis is conducted using the Raster Calculator (ESRI, 2006). The difference in SAV acreage is evaluated to determine the effectiveness of the remote sensing supervised classification methods in comparison to the AP mapping project.

3.4.2 Ability to Map SAV variation

The classification methods are analyzed to assess the minimum amount of variation that may be detected by the classification. The ability to assess the variation is based on the accuracy of the classification method as determined by the testing ROI confusion matrix and the validation assessment. The detectable variation in the SAV is related to overall accuracy of the classification. The ESRI ArcMap 9.2 software program is used to calculate the areas for each class (ESRI, 2006).
Chapter 4

Results and Discussion

4.1 Classification Results

The unsupervised and supervised methods produce classification maps with various accuracies. The unsupervised classification method is similar in validation accuracy to the supervised hard classification methods. The supervised soft classification methods did not produce reasonable results. Overall the supervised hard classifications are the most appropriate to map the SAV in the study area.

4.1.1 Unsupervised Classification

The unsupervised ISODATA classification interprets seven categories from the Landsat 5 TM image. The categories are merged into two classes and labeled with environmentally relevant descriptions, SAV and No SAV. The ISODATA classification map (Figure 13) displays the spatial extent of the SAV in the study area. The ISODATA classification reasonably delineates the spectral classes for the SAV features. A validation assessment is conducted using an independent data set from the Pinellas County Ambient Water Quality Monitoring Program (Levy et al, 2008). This point data provides information on the presence/absence and species composition of the SAV. The validation dataset (n=216) is compared to the class of the coinciding pixel. The ISODATA validation estimates 76% accuracy for correctly classifying the SAV and 51% for No SAV with an overall accuracy estimate of 68% (Table 6).
Figure 13. Unsupervised ISODATA classification of Landsat 5 TM image with environmentally relevant labels.
4.1.2 Supervised Classification

4.1.2.1 Hard Classification

The supervised parametric classification methods, Maximum Likelihood (MLC) and Mahalanobis Distance (MDC), uses ROIs developed from the field survey data to delineate the spectral signatures of the SAV. The methods are first used to delineate the presence/absence of SAV. Then, the methods are applied to delineate the estimated coverage of the SAV. Of these applications, the hard classification methods have a higher overall accuracy for separating the presence/absence of SAV.

4.1.2.1.1 Presence/Absence of SAV

Both the MLC and MDC (Figure 14) depict reasonable maps of the presence/absence of SAV. Calculated with a confusion matrix using the testing ROIs, the overall accuracy of the MLC is 85.54 % with a Kappa coefficient of 0.69 (Table 4). The overall accuracy of the MDC is 86.79% with a Kappa coefficient of 0.70. Both classifications produce similar accuracies. The producer’s accuracy is slightly better for the classification of SAV in the MDC (Table 5), and for the classification of the No SAV in the MLC. The user’s accuracy is slightly better for the classification of SAV in the MLC (Table 5), and for the classification of the No SAV in the MDC.

In addition to the accuracy assessment for the classification maps, a validation assessment is conducted using an independent data set from the Pinellas County Ambient Water Quality Monitoring Program (Levy et al, 2008). This point data provides information on the presence/absence and species composition of the SAV. The validation dataset (n=216) is compared to the class of the corresponding pixel. The MLC validation estimates 66% accuracy for correctly classifying the SAV and 69% for No SAV with an overall accuracy estimate of 67% (Table 6). The MDC validation estimates 74% accuracy for correctly classifying the SAV and 58% for No SAV with an overall accuracy estimate of 68% (Table 6).
Figure 14. Supervised classification of Landsat 5 TM image using the Mahalanobis Distance and Maximum Likelihood methods.
Table 4. Accuracy estimates for the supervised classification methods.

<table>
<thead>
<tr>
<th></th>
<th>Overall Accuracy (%)</th>
<th>Kappa Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Likelihood</td>
<td>85.54</td>
<td>0.69</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td>86.79</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Table 5. Supervised classification commission and omission errors, and producer and user’s accuracy.

<table>
<thead>
<tr>
<th></th>
<th>Commission (%)</th>
<th>Omission (%)</th>
<th>Commission (Pixels)</th>
<th>Omission (Pixels)</th>
<th>Producer Accuracy</th>
<th>User Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Likelihood</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAV</td>
<td>7.77</td>
<td>14.85</td>
<td>214/2754</td>
<td>443/2983</td>
<td>85.15</td>
<td>92.23</td>
</tr>
<tr>
<td>No SAV</td>
<td>24.73</td>
<td>13.70</td>
<td>443/1791</td>
<td>214/1562</td>
<td>86.15</td>
<td>75.27</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAV</td>
<td>9.26</td>
<td>11.03</td>
<td>271/2925</td>
<td>329/2983</td>
<td>88.97</td>
<td>90.74</td>
</tr>
<tr>
<td>No SAV</td>
<td>20.31</td>
<td>17.35</td>
<td>329/1620</td>
<td>271/1562</td>
<td>82.65</td>
<td>79.69</td>
</tr>
</tbody>
</table>

Table 6. Validation for classification methods SAV presence/absence

<table>
<thead>
<tr>
<th></th>
<th>SAV Accuracy %</th>
<th>No SAV Accuracy %</th>
<th>Overall Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISODATA</td>
<td>76.6</td>
<td>51.8</td>
<td>68.4</td>
</tr>
<tr>
<td>Maximum Likelihood</td>
<td>66.2</td>
<td>69.4</td>
<td>67.3</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td>74.2</td>
<td>58.5</td>
<td>68.9</td>
</tr>
</tbody>
</table>

A comparison of the MLC and MDC maps presents discrepancies in the classification of SAV in the intertidal areas. Figure 15 illustrates a shallow seagrass bed that is often exposed at low tide. The MDC correctly classifies the area as SAV; whereas, the MLC classifies the majority of the seagrass bed as No SAV. Overall, the MLC and MDC produce very similar classification maps.
Figure 15. Differences (red circle) between the supervised classification of Landsat 5 TM image using the Mahalanobis Distance and Maximum Likelihood methods.
4.1.2.1.2 Estimated Coverage of SAV

Both the MLC and MDC (Figure 16) depict reasonable maps of the estimated coverage of SAV. Calculated with a confusion matrix using the testing ROIs, the overall accuracy of the MLC is 74% with a Kappa coefficient of 0.61 (Table 7). The overall accuracy of the MDC is 65% with a Kappa coefficient of 0.47. The MLC produces better accuracies than MDC in the classification of the estimated coverage of SAV for this case. The producer’s accuracy is better for the classification of No SAV and the continuous and patchy SAV in the MLC (Table 8). The user’s accuracy is better for the classification of continuous and patchy SAV in the MLC (Table 8), and similar in both methods for the classification of No SAV.

In addition to the accuracy assessment for the classification maps, a validation assessment is conducted using an independent data set from the Pinellas County Ambient Water Quality Monitoring Program (Levy et al, 2008). This point data provides information on the presence/absence and species composition of the SAV. Since the data only supports the comparison of SAV and No SAV classes, the patchy and continuous classes of the MLC and MDC are combined for the validation. The validation dataset (n=216) is compared to the class of the corresponding pixel. The MLC validation estimates 86% accuracy for correctly classifying the SAV and 37% for No SAV with an overall accuracy estimate of 70% (Table 9). The MDC validation estimates 85% accuracy for correctly classifying the SAV and 36% for No SAV with an overall accuracy estimate of 69% (Table 9).
Figure 16. Supervised classification of Landsat 5 TM image using the Mahalanobis Distance and Maximum Likelihood methods.
Table 7. Accuracy estimates for the supervised classification methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall Accuracy (%)</th>
<th>Kappa Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Likelihood</td>
<td>74</td>
<td>0.61</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td>65</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Table 8. Supervised classification commission and omission errors, and producer and user’s accuracy.

<table>
<thead>
<tr>
<th>Method</th>
<th>Commission (%)</th>
<th>Omission (%)</th>
<th>Commission (Pixels)</th>
<th>Omission (Pixels)</th>
<th>Producer Accuracy</th>
<th>User Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Likelihood</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Continuous</td>
<td>25.93</td>
<td>18.85</td>
<td>202/779</td>
<td>134/711</td>
<td>81.15</td>
<td>74.07</td>
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<tr>
<td>Patchy</td>
<td>44.99</td>
<td>37.10</td>
<td>337/749</td>
<td>243/655</td>
<td>62.90</td>
<td>55.01</td>
</tr>
<tr>
<td>No SAV</td>
<td>5.53</td>
<td>22.48</td>
<td>41/741</td>
<td>203/903</td>
<td>77.52</td>
<td>94.47</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Continuous</td>
<td>48.91</td>
<td>24.33</td>
<td>515/1053</td>
<td>173/711</td>
<td>75.67</td>
<td>51.09</td>
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<tr>
<td>Patchy</td>
<td>54.63</td>
<td>45.34</td>
<td>431/789</td>
<td>297/655</td>
<td>54.66</td>
<td>45.37</td>
</tr>
<tr>
<td>No SAV</td>
<td>5.89</td>
<td>34.57</td>
<td>64/1086</td>
<td>540/1562</td>
<td>65.43</td>
<td>94.11</td>
</tr>
</tbody>
</table>

Table 9. Validation for classification methods SAV estimated coverage

<table>
<thead>
<tr>
<th>Method</th>
<th>SAV Accuracy %</th>
<th>No SAV Accuracy %</th>
<th>Overall Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Likelihood</td>
<td>86.5</td>
<td>37.8</td>
<td>70.2</td>
</tr>
<tr>
<td>Mahalanobis Distance</td>
<td>85.8</td>
<td>36.5</td>
<td>69.3</td>
</tr>
</tbody>
</table>

A comparison of the MLC and MDC maps presents discrepancies in the classification of patchy versus continuous SAV main areas with deeper water. Figure 17 illustrates a deep (>2m) seagrass bed. The MLC correctly classifies the area as patchy SAV; whereas, the MDC classifies the majority of the seagrass bed as continuous SAV. Figure 18 shows a deeper area classified as mostly continuous SAV by the MDC and patchy SAV by the MLC. Unfortunately, the field survey data does not have enough sampling sites in this area to discern...
which classification is more accurate. Overall, the MLC and MDC produce similar classification maps; however, the MLC is the most accurate and reasonable of the two methods.

Figure 17. Differences (red circle) between the supervised classification of Landsat 5 TM image using the Mahalanobis Distance and Maximum Likelihood methods.
Figure 18. Differences (red rectangle) between the supervised classification of Landsat 5 TM image using the Mahalanobis Distance and Maximum Likelihood methods.
4.1.2.2 Soft Classification

In an attempt to improve the results of the classification technique, the study also applied two supervised nonparametric classification methods. Considered soft classification methods, linear spectral unmixing and neural network algorithms provide an alternative approach to the hard classification. Contrary to the hypothesis the “soft” classification methods, LSU and ANN did not improve the resolution and accuracy of the hard classification map. However, the application of these methods may provide improved classifications for imagery with more than three useful bands in the aquatic environment.

4.1.2.2.1 Artificial Neural Networks

The artificial neural network (ANN) classification does not produce reasonable results (Figure 19). The ANN classifies less than 5% of the study area as SAV. Although this method is not successful in this instance, the use of a different software program or algorithm may provide more reasonable results. In addition, these may be explained by the low spectral difference of between the different classes or the number limitation of the spectral dimension of only three visible bands.
Figure 19. Artificial Neural Network Classification of Landsat 5 TM image.
4.1.2.2.2 Linear Spectral Unmixing

The linear spectral unmixing (LSU) is also applied to the Landsat TM image. The LSU does not produce reasonable results for the classification map (Figure 20). The amount of endmember classes for the LSU must be less than the number of spectral bands used for the classification. Since only three spectral bands (1, 2, and 3) are appropriate for the classification of SAV, only two endmember classes could be delineated.
Figure 20. Linear Spectral Unmixing of Landsat 5 TM image.
4.2 Assessment of Classification Methods

The assessment of the classification methods compares the accuracy and validation estimates, as well as, the spatial distribution of the variation. The aerial photointerpretation (AP) map is used as a baseline for the comparison of the MDC and MLC classifications. The ability of the classification methods to map SAV is estimated from the accuracy and validation results for each technique.

4.2.1 Accuracy Comparison of SAV Maps

Prior to comparing AP map to the MLC classification map, an accuracy assessment is completed for the AP map. Due to the limited ground truth data collected with the AP project, the 90% accuracy can not be compared to the products from this study. The validation method for the classification maps is applied to the AP map. Since the validation dataset only supports the comparison of SAV and No SAV classes, the patchy and continuous classes of the AP map are combined for the validation. The validation dataset (n=216) is compared to the classes of the corresponding pixels (Figure 21). The AP validation estimates 81% accuracy for correctly classifying the SAV and 51% for No SAV with an overall accuracy estimate of 71% (Table 10).
Figure 21. Comparison of validation data to the SAV Aerial Photointerpretation Map, 2006.
The comparison of the classification methods relies on the validation accuracy estimates since it was the only available qualifier for all the methods. Although the overall estimated accuracy varies slightly between classification methods, the estimated accuracy for the classes of SAV and No SAV varies significantly (Figure 22). To examine the variation between the methods the means and standard errors are calculated. For the six methods the SAV estimated accuracy from the validation analysis is 78% for SAV (SE= 3.15), 50% for No SAV (SE= 5.10), and 69% for Overall (SE= 0.58). The AP map has the highest overall accuracy (71.4%). The MDC (69.3%) and MLC (70.2%) maintain a close overall accuracy; however, the accuracy associated with mapping No SAV is below 40%. Although the overall accuracy for the MLC and MDC is lower for the presence/absence than the estimated coverage classifications, the No SAV accuracy is much higher. To consider the best classification method, the researcher needs to determine the focus of the study and the omission and commission statistics related to each method.

Table 10. Comparison of validation for classification methods

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>SAV Accuracy %</th>
<th>No SAV Accuracy %</th>
<th>Overall Accuracy %</th>
</tr>
</thead>
<tbody>
<tr>
<td>ISODATA</td>
<td>76.6</td>
<td>51.8</td>
<td>68.4</td>
</tr>
<tr>
<td>MLC (Presence/Absence)</td>
<td>66.2</td>
<td>69.4</td>
<td>67.3</td>
</tr>
<tr>
<td>MDC (Presence/Absence)</td>
<td>74.2</td>
<td>58.5</td>
<td>68.9</td>
</tr>
<tr>
<td>MLC (Estimated coverage)</td>
<td>86.5</td>
<td>37.8</td>
<td>70.2</td>
</tr>
<tr>
<td>MDC (Estimated coverage)</td>
<td>85.8</td>
<td>36.5</td>
<td>69.3</td>
</tr>
<tr>
<td>AP map</td>
<td>81.1</td>
<td>51.2</td>
<td>71.4</td>
</tr>
</tbody>
</table>
4.2.2 Spatial Comparison to Existing SAV Maps

The classification methods with the highest accuracy, kappa coefficient, and validation accuracy are compared to the existing AP map to determine spatial variation. For the delineation of presence/absence of SAV, the MDC has 86% overall accuracy with a 0.70 Kappa coefficient calculated from the testing ROIs. The overall validation accuracy for the MDL is 68%. For the delineation of SAV estimated coverage, the MLC has 74% overall accuracy with a 0.61 Kappa coefficient calculated from the testing ROIs. The overall validation accuracy for the MLC is 70%. The AP map has an overall validation accuracy of 71% calculated for this study. For each classification method the area per class is
calculated (Table 11). The greatest difference is between the delineation of the SAV (patchy) class in the MLC (48.76 km²) and the AP (11.50 km²).

Table 11. Area calculated for each classification method.

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Number of Pixels</th>
<th>km²</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MDC (Presence/Absence)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No SAV</td>
<td>67277</td>
<td>60.55</td>
</tr>
<tr>
<td>SAV</td>
<td>80623</td>
<td>72.56</td>
</tr>
<tr>
<td>Land</td>
<td>29000</td>
<td>26.10</td>
</tr>
<tr>
<td><strong>MLC (Estimated coverage)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No SAV</td>
<td>46049</td>
<td>41.44</td>
</tr>
<tr>
<td>SAV (patchy)</td>
<td>54183</td>
<td>48.76</td>
</tr>
<tr>
<td>SAV (continuous)</td>
<td>47668</td>
<td>42.90</td>
</tr>
<tr>
<td>Land</td>
<td>29000</td>
<td>26.10</td>
</tr>
<tr>
<td><strong>AP (Estimated coverage)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No SAV</td>
<td>44413</td>
<td>39.97</td>
</tr>
<tr>
<td>SAV (patchy)</td>
<td>12782</td>
<td>11.50</td>
</tr>
<tr>
<td>SAV (continuous)</td>
<td>49250</td>
<td>44.33</td>
</tr>
<tr>
<td>Land</td>
<td>14248</td>
<td>12.82</td>
</tr>
</tbody>
</table>

The spatial comparison of these classifications displays areas of variation between the maps. The comparison of the AP and MDC for the presence/absence of SAV shows most discrepancies in the deep water areas along the edge of the seagrass bed (Figure 23). The classes of Land and No SAV are combined to focus on the similarity for the SAV classification. The AP and MDC both map 43.70 km² of SAV with a discrepancy of 18.74 km² which is 16% of the study area (Table 12). The comparison of the AP and MLC for the SAV estimated coverage displays the most discrepancies in the deep water areas and along the edges of the seagrass beds (Figure 24). The AP and MLC map 32.79 km² of SAV at the same estimated coverage class, and 16.30 km² of SAV with differing estimated coverage classes. The discrepancies cover 21.19 km² which represents 19% of the study area (Table 13).
The spatial variation in the classification may be affected by the water increased water depth along the edges of the seagrass beds. The AP is known to be limited to approximately 2 m water depth due to the refraction and absorption of the penetrating light wavelengths. The areas with dredged boat channels are consistently misclassified by the MDC and MLC. The width of the boat channels in comparison to the pixel size of the Landsat 5 TM imagery may indicate that the feature is too small to be accurately mapped by these classification methods and resolution. Other areas of discrepancy include the intertidal seagrass beds. Depending on the tidal stage at the acquisition time of the Landsat TM imagery, some of the seagrass beds may be exposed with little or no water separating the seagrass blades from the air. This may cause a variation in the spectral signature of the seagrass.
Table 12. Aerial Photointerpretation versus Mahalanobis Distance Classification

<table>
<thead>
<tr>
<th></th>
<th>Number of pixels</th>
<th>km²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discrepancy</td>
<td>20825</td>
<td>18.74</td>
</tr>
<tr>
<td>Land/No SAV</td>
<td>51059</td>
<td>45.95</td>
</tr>
<tr>
<td>SAV</td>
<td>48560</td>
<td>43.70</td>
</tr>
</tbody>
</table>

Figure 23. Discrepancies between the AP and MDC for the presence/absence of SAV.
Table 13. Aerial Photointerpretation versus Maximum Likelihood Classification

<table>
<thead>
<tr>
<th></th>
<th>Number of pixels</th>
<th>km²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discrepancy</td>
<td>23547</td>
<td>21.19</td>
</tr>
<tr>
<td>Land/No SAV</td>
<td>42339</td>
<td>38.10</td>
</tr>
<tr>
<td>SAV (same estimated coverage)</td>
<td>36442</td>
<td>32.79</td>
</tr>
<tr>
<td>SAV (different estimated coverage)</td>
<td>18116</td>
<td>16.30</td>
</tr>
</tbody>
</table>

Figure 24. Discrepancies between the AP and MLC for the estimated coverage of SAV.
4.2.3 Ability to Map SAV Variation

The ability to map the seagrass resource is essential to the management and protection of the resource. The remote sensing methods used to map and estimate the coverage of seagrass must provide reliable information. The detectable amount of the seagrass resource is related to the accuracy of the classification method. To determine the limitations of mapping seagrass, the MDC (presence/absence of SAV) and the MLC (estimated coverage of SAV) classifications were analyzed. Additionally, the AP classification was examined for the ability and confidence of mapping seagrass resource.

Based on the calculated accuracies from the confusion matrix analysis, the potential variation for misclassification ranges from 10.86 km² - 41.39 km² (Table 14). Based on the calculated accuracies from the validation analysis, the potential variation for the misclassification ranges from 31.06 km² - 49.51 km². These potential variation estimates are based on the entire study area and not solely on the seagrass resource.

Table 14. Potential variation associated with the estimated accuracies for the classification methods.

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Overall Accuracy</th>
<th>Potential Variation (Number of Pixels)</th>
<th>Potential Variation (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDC (Presence/Absence)</td>
<td>86.79</td>
<td>23368</td>
<td>21.03</td>
</tr>
<tr>
<td></td>
<td>68.9</td>
<td>55016</td>
<td>49.51</td>
</tr>
<tr>
<td>MLC (Estimated coverage)</td>
<td>74</td>
<td>45991</td>
<td>41.39</td>
</tr>
<tr>
<td></td>
<td>70.2</td>
<td>52713</td>
<td>47.44</td>
</tr>
<tr>
<td>AP (Estimated coverage)</td>
<td>90</td>
<td>12069</td>
<td>10.86</td>
</tr>
<tr>
<td></td>
<td>71.4</td>
<td>34517</td>
<td>31.06</td>
</tr>
</tbody>
</table>
The potential to map and assess the variation in the seagrass is important to the development of resource management plans. The AP mapping project currently assesses the change in the resource. The estimated change in the seagrass resource between 2004 and 2006 was 2.92% increase (Kaufman, 2007). According to the analysis in this study, the 1.63 km² increase in seagrass is below the detectable change threshold. Therefore, the resource is most likely within the variance of the classification method rather than truly increasing. Caution should be used when formulating conclusions on the fine scale trends associated with the classification maps.
Chapter 5

Conclusions

The application of remote sensing techniques to map the seagrass resource has been examined in many studies in the past two decades with varying success. The challenges of delineating habitat classes in the aquatic environment affect the accuracy and reliability of the produced maps. The prominent method of seagrass mapping in Florida, U.S.A. is the AP mapping method. According to the results from this study, the accuracy of the ranges from the estimated validation accuracy of 71.4% to the project’s assessed accuracy of 90%. The AP study provides a consistent baseline for the detection of spatial change in the seagrass resource. However, due to the temporal scale of the AP project, a 2-year cycle, the produced maps may not detect shorter temporal variation in the seagrass resource. The occurrence of natural and anthropogenic events may cause damage to the seagrass resource that would not be detected for up to 2 years. To quickly assess the damage to the resource following the occurrence of a natural or anthropogenic disturbance, such as hurricanes or oil spills, the environmental resource managers require a reliable tool to assess the spatial extent of the seagrass resource on a finer temporal scale. The temporal availability of the Landsat 5 TM imagery, 16-20 days, provides a suitable option to detect and assess damage to the seagrass resource.

This study provides an overview of thematic information extraction methods applied to the classification of the seagrass resource. The results suggest that the ISODATA and MDC methods provide the most reliable maps delineating the presence/absence of SAV. For the delineation of SAV estimated coverage maps, the MLC method is the most appropriate technique according to
this study. While these remote sensing methods provide classification maps with similar accuracies to the AP method, additional research is necessary to improve and evaluate the classification techniques.

To improve the accuracy for these remote sensing techniques, additional studies may focus on the refinement of the spectral signatures of the seagrass habitats. Future studies using the Landsat 5 TM imagery may apply a spectral library for the SAV species in the study area. The time series of the Landsat 5 TM imagery beginning in 1984 may provide an opportunity to apply the classification methods from this study to the historical Landsat Imagery in an attempt to assess the temporal change over the past two decades. Information regarding the spatial and temporal change dynamics assists environmental resource managers in the development of successful management and protection plans for the seagrass resource.

In conclusion, the results of this study suggest that the application of remote sensing methods is appropriate to assess the spatial extent of the seagrass resource in Clearwater Harbor and St. Joseph Sound, Florida. The supervised classification methods applied to the Landsat 5 TM imagery provide reasonable results that were comparable to the existing AP classification methods. While there is always opportunity for improvement, this study offers the option of using satellite imagery as a reliable data source for the mapping of the seagrass resource.
References Cited


