Final Report

<u>Project Title:</u>

Submerged Aquatic Vegetation Mapping in the Barnegat Bay National Estuary Update To Year 2003

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Acknowledgements

Funding for this study was provided by the U.S. Environmental Protection Agency through the Barnegat Bay National Estuary Program and the New Jersey Agricultural Experiment Station. We are deeply indebted to Pete McClain who played a critical role in the field reference data collection. In addition, we would like to thank Gregg Sakowicz for his help in the field work. Chris Smith of the New Jersey Natural Resources Conservation Service graciously provided us with the additional field reference data used for validation purposes. We gratefully acknowledge Mike Kennish, Mike DeLuca and Bob Scro for their support in this effort. We would also like to thank Charles Costello of Massachusetts Department of Environmental Protection, Mark Finkbeiner of the NOAA Coastal Services Center, Matthew Herring of GeoVantage Corporation for useful advice in flight planning.

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Table of Contents

Executive Summary

The purpose of this study was to map the areal extent and density of submerged aquatic vegetation within the Barnegat Bay and Little Egg Harbor, New Jersey as part of ongoing monitoring for the Barnegat Bay National Estuary Program. We examined the utility of multi-scale image segmentation/object-oriented image classification approaches to seagrass mapping. Our remotely sensed approach allowed for determination of seagrass at 4 levels of density (including shallow sand/mud flats with < 10% seagrass cover), rather than a simple presence/absence, with a comparatively high degree of consistency and accuracy (68% overall accuracy for 4 categories and 83% accuracy for a simpler presence/absence map). While the aerial digital camera imagery employed in this study had the advantage of flexible acquisition, suitable image scale, fast processing return times and comparatively low cost, it had inconsistent radiometric response across the individual images. While we were not successful in using the eCognition software to develop a rule-based classification that was universally applicable across the 14 individual image mosaics that comprised our 73,000 ha study area, the manual classification approach that we developed provided a flexible and time effective approach to mapping seagrass. This multi-scale image segmentation approach coupled with field transect/point surveys has the potential to be more replicable than strictly boat-based surveys and/or visual image interpretation and allow for more robust conclusions regarding change in areal extent, location and spatial pattern of seagrass beds through time. In the present study based on imagery collected in May 2003, we mapped 5,184 ha of seagrass beds. This area is less than the 6,083 ha of seagrass documented from boat-based surveys conducted between 1996-1999. We do not believe that the difference of 899 ha represents a significant change in seagrass extent between the dates of the two studies, but most likely is an artifact of the difference in mapping techniques.

Introduction and Problem Statement

Submerged aquatic vegetation (SAV) is a term used to describe a variety of estuarine and marine plants including seagrasses. Due to their important ecological role in many coastal ecosystems as well as their sensitivity to degraded water quality, seagrass has been widely adopted as an indicator of estuarine ecosystem health (Orth and Moore 1983; Dennison et al. 1993; Short and Wyllie-Echevarria, 1996; Duarte 1999). Submerged aquatic vegetation (SAV) has been adopted by the Barnegat Bay National Estuary Program as one of the key indicators of the environmental health of the Barnegat Bay system (BBEP, 2003). Of special concern are the bay's two principal species of seagrass, Eelgrass (*Zostera marina)* and Widgeon Grass (*Ruppia maritima*). The bay's seagrasses are an important element of the bay ecosystem, because they harness energy and nutrients that are consumed by other organisms. The seagrass beds also provide a critical structural component in an otherwise barren sandy bottom, serving as essential habitat for a host of organisms from shellfish and crabs to fish and waterfowl. However, in recent years the bay's seagrasses have suffered due to the host of problems including declining water quality, dredging, brown tides, algal infestation, boat scarring and disease.

Due to the important role that seagrasses play in estuaries, there has been a considerable effort at developing sampling and mapping techniques to quanitfy the spatial distribution, biomass and health of seagrass communities and monitor changes over time (Caloz and Collet, 1997; Lehmann and Lachavanne, 1997). Remote sensing approaches have seen increasing application to the mapping of seagrass beds due to their synoptic perspective and cost-effective mapping over large areas. The most widely adopted approach has been the visual interpretation and mapping from aerial photography (Zieman et al., 1989; Ferguson et al. 1993; Robbins 1997; Kendrick et al., 2000; Moore et al. 2000). More recently, this has transitioned to a direct capture through digital photogrammetric techniques or heads-up digitizing of digital rectified photography (Dobson et al., 1995). Satellite based remote sensing of seagrass distribution and abundance has also been investigated (Ackleson and Klemas, 1987; Ferguson and Korfmacher 1997; Mumby et al. 1997; Ward et al. 1997).

In general, airborne imagery acquisition, rather than satellite imagery finds wider application in seagrass mapping as airborne image acquisition as it provides high spatial resolution imagery and the flexibility to more readily meet often rigid temporal constraints for the optimal acquisition of imagery (i.e., sun angle, tide, wind, water clarity) (Dobson et al., 1995). More recently, there has been a move towards direct digital acquisition with digital framing cameras or scanning systems rather than analog film cameras. An advantage of airborne digital camera technology is the ability to provide high quality orthorectified imagery in a digital format with a fast turn-around time.

One issue with all small format aerial images, whether analog or digital, is the radiometric consistency of individual frames when pieced together into a larger mosaic. This frame-to-frame inconsistency is further exacerbated by the inconsistency in spectral response for the features of interest (e.g., seagrass beds) with changes in water depth, water clarity, bottom sediment type and seagrass abundance. A trained image analyst using traditional visual interpretation can generally account for these often conflicting variables. However, in long term monitoring studies there can be problems due to inconsistency between interpreters and even within interpreters across large study areas or between years. More computer automated techniques such a traditional per-pixel based multi-spectral classification approaches have been investigated but are difficult to apply under these varying image and background conditions.

In this study, we examine the utility of object-oriented image segmentation/classification approaches (Burnett and Blaschke, 2003; Benz et al., 2004) to seagrass mapping from airborne digital camera imagery. Our goal was to develop a methodology that was comparatively objective in delineating bed boundaries and characterizing seagrass density, was cost-effective and easily repeatable for future monitoring purposes. We apply this conceptual framework to the mapping and spatial analysis of seagrass beds and the broader benthic environment in Barnegat Bay-Little Egg Harbor estuary in New Jersey, USA.

Project Design and Methods

Study Site

Barnegat Bay-Little Egg Harbor (BB-LEH) is a shallow back-bay lagoonal type of estuary on New Jersey's Atlantic coast (Figure 1) and was designated by the U.S. Environmental Protection Agency in July 1995 as the 28th National Estuary Program site (Kennish, 2001). The impact of increased development within the BB-LEH watershed and its eutrophying impact on estuarine waters coupled with the periodic recurrence of wasting disease, epiphytic algae and brown tide have sparked concern about the status of eelgrass, *Zostera marina*, and widgeongrass, *Ruppia maritima*, in the BB-LEH system (Lathrop et al. 2001). As the BB-LEH estuary contains approximately 75% of the New Jersey's estuarine submerged aquatic vegetation habitat, this seagrass resource is of statewide importance (Lathrop et al., 2001). One goal of this project was to map the the spatial distribution and abundance of seagrass as part of an ongoing effort to assess the status of seagrass in the BB-LEH estuary (Lathrop et al., 2001). As part of the Barnegat Bay Estuary Program overall monitoring plan (BBEP, 2003), the spatial distribution, abundance and health of seagrasses has been adopted as a key environmental indicator.

Image Acquisition

To the greatest extent possible, this project followed the general guidelines established by NOAA's Coastal Services Center for remotely sensed image acquisition for benthic habitat mapping (http://www.csc.noaa.gov/benthic/). A digital camera with four bands centered on blue (450nm), green (550nm), red (650nm) and near-infrared (850nm) was employed. Two GeoTiff image products were created, a true color imagery set and an infrared imagery set at a 1 meter ground cell resolution and 8 bit radiometric resolution. The images were orthorectified, terrain corrected (using 7.5m USGS DEM's), georegistered and mosaicked by flight mission with a spatial accuracy of +/- 3 meters (90% of pixels). While some effort was made to histogram match individual images when adjacent images were mosaicked, a tiling effect due to varying spectral response was still evident. Fourteen mosaicked flight lines were acquired to cover the approximately 73,000 ha Barnegat Bay-Little Egg Harbor-Great Bay, New Jersey study area (Figure 1). The aerial ortho-imagery was flown under contract by GeoVantage Corporation of Massachusetts.

Aerial imagery collection was scheduled for the mid spring time period due to a sufficiently advanced growth state of the seagrass beds and generally low turbidity water conditions. The majority of the imagery was acquired during the early to mid-morning hours of May 4 and 5 to correspond with a low tidal stage. Winds were generally below 10 knots and skies clear to a consistent high overcast. Several of the flight lines were taken later in the afternoon on May 4 (i.e., Boxes 1, 8 and 9) under less than optimal wind conditions (approximately 8 knots and greater) limiting visibility into the deeper portions of the bay. Overall image quality of the resulting digital orthophoto mosaics was assessed and areas of poor quality that inhibited subsequent image interpretation were delineated (Figure 1). Approximately 18% of the bay study area was deemed as exhibiting poor image quality.

In addition to the aerial imagery, a GIS was created that included a 30-meter interpolated bathymetry map of the Barnegat Bay and Little Egg Harbor study area. Past seagrass bed maps were also used as a reference (Lathrop et al., 2001).

Field Surveys

To support the image interpretation and mapping, extensive field reference data were collected in the weeks before and after the image acquisition. Existing maps of seagrass distribution derived from boat based surveys from the mid 1990's were used to plan the reference data collection. A series of transects were established to sample full range of conditions in the Barnegat Bay-Little Egg Harbor study area. Eighteen transects were visited, and data points were recorded at intervals of approximately 250 meters. The transects, perpendicular to the eastern (barrier island) shoreline, extended from shallow inshore areas, across the seagrass beds and into deeper mid-bay water. These intervals were not strict, and often data points were recorded in between the intervals at areas where there appeared to be a noticeable change in seagrass coverage. Additional reference points were also collected to spot check areas of uncertainty. In general, field reference points were collected in areas (i.e., approximately 5 x 5 meters area) where the seagrass bed was reasonably consistent in coverage and distribution. ESRI's ArcMap and Trimble's GPS Pathfinder were used to support the field reference data collection.

All transect endpoints and individual check points were first mapped on the GPS, endpoints were then loaded onto a GPS for navigation on the water. Real time data collection (approximately ± 1-3 meter accuracy) was a sufficient level of accuracy for our purposes. A total of 245 transect and individual points were collected (Figure 2). The objective was to understand how bed characteristics changed from shallow to deep water, and to be able to understand the difference in visual signal on the imagery between beds in shallow (less than or equal to 1.5 m) and deep water (greater than 1.5 m). All 245 points were used to support the interpretation and mapping, none were reserved as independent validation. For each field reference point, the following data were collected:

- GPS location (UTM)
- Time
- Date
- SAV species presence/dominance: *Zostera marina* or *Ruppia maritima* or Algae
- Depth (meters)
- % cover (10 % intervals) determined by visual estimation
- Blade Height of 5 tallest seagrass blades
- Shoot density (# of shoots per 1/9 m^2 quadrat that was extracted and counted on the boat)
- Distribution (patchy/uniform)
- Substrate (mud/sand)
- Additional Comments

Classification

From a landscape ecology perspective as well as from our object-oriented classification approach, the spatial structure of the seagrass habitats was conceptualized at 3 different levels: 1) **bed**, a spatially contiguous area of seagrass of varying % cover composition; 2) **density class**, a spatially contiguous area of overall similar % cover composition; and 3) **patch,** small discrete clumps of seagrass or areas of open bay bottom. This conceptual spatial framework was then broadened to develop a hierarchical classification scheme to encompass the larger bay system for mapping purposes. The bay was categorized into 4 levels of attribute detail (Figure 3). Level 1 differentiated land and emergent wetlands from open water. Level 2 differentiated deep water/channels (> 1.5-2 m depth) and shallow water (<1.5-2m depth) bottom habitats. At Level 3, the shallow bottom habitats were then differentiated into: 1) shallow sand/mud flats (<1.5m depth); macro algae beds (i.e. *Ulva lactuca* and assorted macro algae dominated; scattered seagrass may be present) and seagrass beds (i.e., *Zostera marina* and *Ruppia maritima*). At Level 4, the seagrass beds were partitioned into 3 categories based on the % cover: dense (80-100 % coverage), moderate (40-80% coverage), sparse (10-40% coverage). At Level 5, were the individual patches of seagrass or bare bottom. The very detailed Level 5 delineations were not included in the final output maps.

While this seagrass classification does not represent equal % cover intervals, the class breaks were based on thresholds that appeared to be consistently discernable in both the image interpretation and corresponding field data. These seagrass density class ranges are similar to the scheme used by Moore *et. al.*, 2000. The relative dominance of *Zostera* vs. *Ruppia* was not distinguished. The shallow sand/mud flats can in some ways be considered as potential seagrass habitat as our field surveys showed that seagrass was often present at low levels (i.e., < 10% cover). In these cases, the seagrass generally did not form cohesive clumps but rather a sparse and/or discontinuous covering of individual seagrass plants. Previous experience has shown that some of these areas develop denser cover of seagrass later in the growing season. This may especially be true in the more mesohaline areas of the bay where *Ruppia* is the dominant seagrass.

An object-oriented classification approach was performed using eCognition software (Standard Version 3.0) to segment the image into image objects. Image objects are delineated to minimize within object variance and maximize between object variances. A multi-resolution segmentation can be used to create a hierarchical framework of decomposable image objects (Benz et al., 2004). In other words, a super-object is composed of objects which in turn can be composed of sub-objects. As sub-objects are aggregated to form an object, interior boundaries disappear but exterior boundaries remain stable. This multi-resolution approach was adopted to segment the water portion of the image into 3 general levels of spatial detail using what is termed a classification-based multi-resolution segmentation (CBMS). The first step was to segment the image at a fine level of detail, which corresponded with our conceptual Level 5, i.e., the individual patches of seagrass. The size of a minimum mapping unit for the individual seagrass beds was on the order of 1 ha in size. Next, the segmentation was coarsened to the next higher level of aggregation (determined by the scale parameter), corresponding to conceptual Level 4 where individual sub-object (patches) are combined to create image objects (macro-patches) of similar density class. Finally, the objects (macro-patches) were combined into super-objects to correspond with the conceptual model Level 3 seagrass beds.

Within the eCognition software environment, segmentation parameters can be weighted to take into account object scale, color and shape factors; resulting in drastically different image objects. Optimizing these parameters for the study at hand was an iterative trial and error process. While there was no clear correct set of parameters, certain parameter combinations (affected heavily by the scale parameter) made for more useful image object arrangements than others. These parameters differed from one image mosaic to the next because each image mosaic's radiometry and geographic extent were unique. Once the objects are delineated, they can then be classified using a rules-based approach. While initially we proposed to develop a "universal" set of rules to classify the seagrass and bottom types in a comparatively automated classification approach across the entire study area, we realized that a more manual, analyst assisted approach was necessary. As in determining the segmentation parameters, due to the variability in spectral response between the individual digital photos and the image mosaics as well as the spectral variation of seagrass across varying % cover, water clarity, depth and substrate, it was difficult to determine a set of universally applicable rules.

The following approach was adopted to map bottom types:

1) the entire image was segmented at a fine (i.e, Level 5);

2) using the clear distinction between land and water in the near infrared waveband image, a simple NIR membership rule was established to mask out land;

3) the image segmentation was then coarsened to merge areas of like classes (i.e., Level 4);

4) the Level 4 image objects were visually interpreted and manual encoded as to the appropriate bottom type (Figure 2) with the help of field reference data;

5) the class coding was "forced down" to the level 5 sub-objects;

6) the Level 5 sub-objects were then visually evaluated atop the original imagery to ensure that a proper identification was made and the classification revised where necessary; and

7) the revised Level 5 sub-objects were then transmitted back up the hierarchy and the Level 4 image objects revised accordingly (this was done by specifying "existence based on sub-objects" as a rule for each class).

This approach expedited the process by undertaking the manual classification at a coarser scale with fewer objects to code but without losing the boundary detail afforded by the more detailed segmentation. Using the above approach, each of the 14 image mosaics were classified independently and merged to create a complete bay-wide classification. In addition, to the difficulty in developing consistent classification rules across mosaics, a super-mosaic of all 14 sub-areas would have required enormous computational power and time for a multi-resolution segmentation.

Quality Assurance

The resulting maps were compared with the 245 field reference points. All 245 reference points were used to support the interpretation and mapping in some fashion and so can not be truly considered as completely independent validation. The resulting maps were also compared with an independent set of 41 bottom sampling points collected as part of a seagrass-sediment study conducted during the summer of 2003 (Smith and Friedman, 2004). These additional 41 bottom sample points were collected in an area along the eastern shore of central Barnegat Bay in an area deemed of high image quality. At each sampling point, a sediment grab sample was taken and the presence/absence of seagrass determined for an approximately $5m^2$ area. The spatial locations of the 41 sampling points were recorded using a non-differentially collected GPS receiver (Garmin Map 12) with an approximate positional error of $\pm$ 15m. The presence/absence data for the 245 and 41 sampling points were compared with the same location from the digital seagrass map and summarized in a contingency table and producer's/user's accuracy and Kappa statistic (a measure of agreement corrected for chance agreement) computed.

Spatial Pattern Analysis

Using the resulting study area-wide classified GIS map, we examined the spatial structure of the seagrass beds by analyzing the spatial pattern of seagrass density classes and their shared edge lengths. The health and productivity of seagrass is highly dependent on an adequate amount of solar illumination which in turn is heavily influenced by the water clarity (Dennison et al., 1993). Seagrass beds in deeper water or seagrass at the deep water edge of the bed are therefore more vulnerable to turbid water conditions and a limited light environment. The classified map was used to analyze seagrass adjacency to deep water to highlight areas of greatest vulnerability as well as to examine within bed spatial structure. The amount of border to each contiguous seagrass patch was calculated, and expressed as a percentage of the total border. The Level 3 seagrass beds (i.e., 3 classes of seagrass density grouped together) were coarsened to 5m grid cell resolution and analyzed using the ArcINFO Version 8.3.

Results

Figure 4 displays the spatial distribution of the seagrass and other assorted bottom types based on the classification described above. Table 1 shows the areal extent of each class in hectares. The 3 seagrass classes accounted for 5,184 ha or approximately 14 % of the study area with the sparse and dense cover classes occurring in comparatively equal proportion (38 and 40% respectively) and moderate cover class slightly less at 22% of the seagrass area (Table 1). Shallow sand and mud flat and macro algae beds covered approximately 11,555 ha of bay bottom and represent potential seagrass habitat.

In areas of high image quality (i.e. where the bottom reflectance signal was clear) the seagrass coverage density was much more apparent, and could be mapped with more detail and precision. Approximately 18 % (6,485 ha.) of the bay was categorized as having poor image quality (Figure 1). Of this area, 10 % (647 ha.) was classified as some density of seagrass, and thus 12% of seagrass was classified under poor image quality conditions. The areas where seagrass was mapped with high confidence still had some image banding problems that obscured small areas, but usually these areas were small enough to allow the contextual setting to provide for an accurate classification.

The seagrass density data for the 245 field reference points were categorized into 4 seagrass density classes (absent, sparse, moderate and dense), compared with the same location from the digital seagrass map and summarized in a contingency table (Table 2a). The overall accuracy was 68.2% and Kappa statistic was 56.5%, which can be considered as a moderate degree of agreement between the two data sets. Aggregating the data into a simple presence vs. absence comparison (Table 2b) shows a higher level of agreement with an overall accuracy of 82.8% and a Kappa statistic of 63.1%. Examination of Table 2b reveals that most of the disagreement was due to a high error of omission, i.e., a number of points confirmed as seagrass in the field sampling data were not mapped as seagrass (32 out of 245 points or 13.1%). 20 out of these 32 points (62.5 %) were categorized as Sparse Seagrass (i.e., 10-39%) in the field.

The presence/absence data for the 41 independent sampling points were compared with the same location from the digital seagrass map and summarized in a contingency table (Table 3). The overall accuracy was 70.7% and Kappa statistic was 43%, which can be considered as a moderate degree of agreement between the two data sets. Examination of the Table 3 reveals that most of the disagreement was due to a high error of commission, i.e., a number of points mapped as seagrass were not confirmed as seagrass in the field sampling data (9 out of 41 points or 22.0%). These 9 points were relatively equally spaced across the 3 categories of seagrass density (3 in 10-39%, 2 in 40-79%, and 4 in 80-100%).

We examined the spatial structure of the seagrass beds by analyzing the spatial pattern of seagrass density classes and their shared edge lengths (Table 4). Both Dense and Moderate seagrass were approximately 3 to 4 times more likely to be adjacent to another seagrass class than to shallow sand/mud flats and suggests that these denser beds are generally found in a vegetated matrix. The Sparse seagrass was only 1.6 times more likely to be adjacent to other seagrass classes than to shallow sand/mud flats. Similarly shallow/sand/mud flats were nearly 3 times more likely to be adjacent to sparse sea grass than to either moderate or dense seagrass. These results suggest that sparse seagrass exists more frequently in a non-vegetated matrix. We observed that seagrass patches that exist separately from larger seagrass beds were more likely to have a sparse percent cover.

Approximately 25% of the seagrass bed boundaries border deep water (Table 4). It is these deep water edges that we expect to be the most vulnerable to water turbidity induced light limitation and potentially temporally dynamic, dieing back under poor water quality conditions and regrowing under clearer conditions. It is these deep water edges that are the most difficult to interpret and the mapped location of the deep water edge could change from one remotely sensed survey date to the next depending on water clarity and image quality. To assess those beds potentially most vulnerable to change, we calculated the percent boundary length for each bed that constituted a deep water edge. As displayed in Figure 5, there were a large number of beds, that however only accounted for a comparatively minor percent of the overall seagrass area, that had no border with deep water. Approximately 70% of the seagrass area has between 10 and 40% of their borders shared with deep water, with the mode occurring between 20 and 30% (Figure 5) Only 24% of the seagrass patches have over 40% of their border with deep water. These deep water edges, as well the shallow sand/mud flat edges also serve as the entry and exit points for fauna moving into and out of the beds for feeding or refuge.

Discussion

The mapped seagrass density class thresholds employed in this study were quite similar to those used in the ongoing monitoring work in the Chesapeake Bay (Moore et al., 2000). The agreement between the mapped results and the original field reference as well as independent reference data were only moderate (i.e., 68% for the 4 category map and 83% for the presence/absence map based on the original field reference data and 71% for the simple presence/absence map as compared to independent reference data). The comparison with the original reference data suggests that most of the error is due to the omission of Sparse Seagrass beds. These results are similar to Moore et al. (2000) who found that their aerial photo-interpretation tended to underestimate percent cover at low SAV densities. It should also be noted that while the imagery was collected in early May, the field reference points were not sampled until after the imagery collection, in some cases up to several weeks later. Thus reference points that may not have had distinctly visible seagrass at the time of data collection only to have sparse seagrass densities later in the growing season. A majority of the disagreement in the independent data comparison was due to a comparatively high error of commission and may not be a true measure of the map accuracy but rather be due to: 1) the mismatch between the footprint area of the reference sample in relation to the size of the minimum mapping unit for the seagrass maps; and 2) high positional error (± 15m) of the reference samples. Due to the natural fine scale patchiness within even dense beds, the comparatively small footprint of the reference data (approximately 5m^2) could sample bare patches (i.e., below the minimum mapping unit size of 1 ha) within an otherwise extent bed. Likewise, the high positional error (± 15m) of the reference samples coupled with the fine scale patchiness could also result in a disagreement between the reference data and the mapping.

In the present study based on imagery collected in May 2003, we mapped 5,184 ha. of seagrass beds (Table 1). The 2003 mapped area is less than the 6,083 ha of seagrass documented from boat-based surveys conducted between 1996-1999 (Lathrop et al., 2001). We do not believe that the difference of 899 ha. represents a significant change in seagrass extent between the dates of the two studies, but most likely is an artifact of the difference in mapping techniques. The 1990's boat-based survey mapped SAV by following the exterior perimeter of seagrass beds and recording waypoints using a GPS. Seagrass beds often do not have clearly defined borders making it difficult to trace that border in the field by boat. This technique tends to homogenize characteristics within a bed, creating a continuous SAV coverage where it may actually be discontinuous. Aerial photographic imagery and the multi-resolution image segmentation technique adopted in this study permits a much finer delineation of exterior boundaries, outlying patches and internal bed discontinuities. In addition, our remotely sensed approach allowed for determination of seagrass at 4 levels of density (including shallow sand/mud flats with < 10% seagrass cover), rather than a simple presence/absence, with a comparatively high degree of consistency and accuracy.

In addition to the change in mapping techniques, the difference in the time of year that 2003 imagery was acquired as compared to the 1990's boat based surveys, may also account for some of the differences in mapped seagrass area. The 2003 imagery was collected May 4 and 5, comparatively early in the growing season. While *Zostera* growth was reasonably well advanced, *Ruppia* does not reach peak biomass until much later in the summer growing season. Thus we suspect that we slightly underestimated the amount of *Zostera* cover and significantly underestimated the amount of *Ruppia* cover as it is likely that some of the areas mapped as shallow sand/mud flats based on the May 2003 imagery, would potentially contain mappable seagrass (either *Zostera* or *Ruppia*) beds later in the growing season. This early May acquisition period was selected because the Barnegat Bay-Little Egg harbor study area during the prior two years experienced heavy brown tide blooms reducing water clarity (as measured by secchi depth) by as much as 50% as early as the middle of May (Downes Gastrich et al., 2004). As it happens, the Barnegat Bay-Little Egg Harbor did not experience significant brown tide blooms in 2003.

The object-oriented image segmentation process coupled with visual interpretation provided a robust means of extracting meaningful landscape objects from the imagery and classifying SAV coverage. This image segmentation technique differed from a traditional heads-up digitizing technique commonly performed with standard GIS software. Heads-up digitizing requires the analyst to determine the boundary and the shape entirely according to the polygons drawn by hand on the screen. With eCognition's image segmentation process, image objects are determined based on the inherent spatial patterns captured in the imagery. However, the image segmentation within the eCognition software environment is not truly "automated" but in reality guided by the image analyst. Through the differential weighting of the color, shape and scale parameters, the image analyst controls the image segmentation process. The parameters dictate the type of objects produced, and are often established with the characteristics of certain landscape features in mind. Determining appropriate parameter weights is a heuristic process and there is no single optimal result. Adjusting the segmentation parameters to allow "color" parameter the bulk of influence in determining object boundaries appeared to have the greatest effectiveness in created the meaningful image objects. Increasing the weight of object "shape" parameter only seemed to generate a more confusing segmentation, as often object shapes were more influenced by radiometric differences than by actual benthic distinctions. However, designating a greater weight for the "color" parameter created the opportunities for image objects to cross benthic boundaries, especially where dark seagrass beds transitioned to dark deep water. Since the object boundaries are determined by the segmentation parameters, they are repeatable with less user bias as compared to manual digitization by different photo interpreters.

The inconsistent radiometry within each image and among different images was caused by the tiling effect produced when each digital sub-image was merged with adjacent sub-images to form an image mosaic. In addition, variable surface wind conditions, water turbidity and solar illumination caused differences in image quality, which directly affected segmentation results. In bay areas where image quality was poor (i.e., low contrast) the segmentation's image objects did not appear to adequately capture changes in the benthic characteristics as reflected in the field data. Conversely, in areas of high image contrast, image object boundaries clearly defined landscape feature boundaries, regardless of minor parameter differences. For example, areas where seagrass beds were growing in primarily a sandy substrate as along the bay's eastern shore, provided the best conditions for seagrass bed delineation, as the integrity of the image objects was not compromised by signal attenuation. The primarily organic substrate typical of the bay's western shore combined with poor image quality to complicate segmentation results under these conditions. Overall, the best segmentation of SAV boundaries occurred in depths of less than 1 meter where image quality, surface, and water conditions did not interfere with bay bottom reflectance. The image quality GIS map (i.e., Figure 1) provides the end user with an indication of where they might have higher or lower confidence in the final bottom type/SAV map.

From a practical standpoint, the multi-scale segmentation facilitated the use of eCognition as a digitizing tool in the form of eCognition's "manual classification." Due to the hindrances imposed by the inconsistent radiometry of the mosaicked digital orthoimagery, our initial expectations concerning the feasibility of a universally applicable set of classification rules did not pan out. Instead we adopted a "manual classification" approach that relied on the image analyst to interpret and classify each of the Level 4 feature objects (i.e. density classes) and encode a bottom type class. Rather than interpreting each individual fine scale patch (i.e., Level 5) individually, some economy of scale was possible allowing the image analyst to generally work at one level up (i.e. Level 4 or 3) and translate the results downward through, what is termed, super-object classification. The absence of an extensive knowledge base in the form of classification rules meant the field data had significant weight towards interpreting the seagrass density class. Each image segment was classified either directly via a manual classification or indirectly through super-object classification. Class related super- and sub-object classification rules were the few transferable rules used because they acknowledged the analogous nature of image objects on different levels of the image object hierarchy. Other transferable rules were depth information that provided for stratification of deep and shallow water and drew from ancillary 30 meter bathymetric data. Similarly, a basic NIR band rule was able to be used for each image classification to separate water from land, though the membership values had to be adjusted for each of the 14 image mosaics.

We attempted to integrate GIS data on bottom depth to supplement the imagery in differentiating deep from shallow water. The 30 meter bathymetry grid of the Barnegat Bay and Little Egg Harbor study area was interpolated from depths taken off NOAA nautical charts and was included as a raster layer in the image segmentation of all image mosaics. Rather a simple binary threshold, eCognition allows the user to alter the weighting to provide for a fuzzy threshold. Examination of the results showed that the relatively coarse spatial resolution of the bathymetric data limited its utility. Image objects clearly representing shallow regions were often categorized as deep water because of the inaccuracies inherent in the coarse interpolated grid. Bathymetric data on a fine scale would have been extremely beneficial in masking out deep water, particularly in areas where narrow deep water channels are in close proximity to seagrass beds. Furthermore, better bathymetric GIS data would enable a more finely tuned analysis and handling of the subtle changes in seagrass bed characteristics in areas where shallow flats are closely juxtaposed with deeper water.

From a theoretical standpoint, the multi-scale image segmentation/object oriented classification approach closely mirrored our conceptual model of the spatial structure of the seagrass beds and associated bottom features. Rather than visualizing the seagrass beds as simply a collection of like pixels, this object oriented approach successfully the extracts the spatial features of ecological interest and captures them in the form of a GIS polygon. In many respects the final bottom type/SAV map (Figure 4), is not that different from a typical vector-based polygon GIS map of seagrass mapped as patchy or continuous cover (Robbins, 1997) or at multiple levels of percent cover (Moore et al., 2000). However, within the eCognition environment, the hierarchical spatial structure of the seagrass beds was made explicit. The spatial structure of the seagrass habitats was conceptualized at 3 different levels: 1) **bed**, a spatially contiguous area of seagrass of varying % cover composition; 2) **density class**, a spatially contiguous area of overall similar % cover composition; and 3) **patch,** small discrete clumps of seagrass or areas of open bay bottom. The final bottom type map included only the bed and density class levels, as well as two additional coarser scale levels of spatial organization (Figure 3). A seagrass bed can then be hierarchically conceptualized from a top down or bottom up perspective. From the bottom up perspective, at the finest scale, a seagrass bed is composed of individual patches of seagrass interspersed with open patches of bare sand. These individual patches often form a macro-patch of similar density class due to a similar spatial arrangement, size and/or density of seagrass patches. Finally, a contiguous area of different density class macro-patches forms a bed.

We envision that this hierarchical patch perspective will allow a more nuanced view of seagrass as environmental indicators of estuarine health. In addition to the areal extent, quantifying the change in the spatial pattern of seagrass beds may provide important insights into the processes controlling seagrass decline or recovery. For example, physical disturbance such as boat scarring would be expected to fragment the bed, increasing the number of patches within a bed. Robbins (1997) examined the temporal change in areal extent of seagrass beds in Tampa Bay, Florida based on two categories of seagrass: patchy or continuous. Robbins observed an expansion of those areas categorized as having continuous cover, suggesting the coalescence of seagrass patches rather than a fragmentation of the seagrass habitat. In this study, we quantified the spatial adjacencies of density class patches to examine within bed spatial structure as well as the amount of deep water edge of seagrass beds. We expect that the deep water edge of a seagrass bed is particularly sensitive to declining water transparency whether due to anthropogenically induced eutrophication or brown tide blooms. By examining the change in the deep water edge, as well as other changes in the spatial pattern of both within-bed and between bed structure, we may be able to more strongly relate cause and effect in future monitoring efforts. However, temporally intensive field reference data collection is still vital to more conclusively establish the relationships between water quality and other possible disturbance factors and seagrass abundance and health. In the Barnegat Bay-Little Egg harbor study area, the remotely-sensed mapping program is being supplemented by a series of permanent plots where intensive sampling will be undertaken periodically over the growing season.

Conclusions and Recommendations

In conclusion, the aerial digital camera imagery employed in this study had the advantage of flexible acquisition, suitable image scale, orthorectified, fast processing return times and comparatively low cost. However, it also shared the problems typical of small format aerial imagery in the inherent difficulty in matching radiometric response across the individual images. We recommend that future monitoring efforts should also employ digital airborne imagery but that the imagery acquisition technology and/or post-processing should have better radiometric consistency across the study area. One advantage of a remotely sensed approach is the availability of the archived imagery, as well as the interpreted mapped product, for direct comparison in future monitoring efforts. We also recommend that the utility of fall imagery be examined to provide a better mapping of the spatial extent and abundance of widgeon grass.

While we were not successful in using the eCognition software to develop a rule-based classification that was universally applicable across the 14 individual image mosaics that comprised our 73,000 ha study area, the manual classification approach that we developed provided a flexible and time effective approach to mapping seagrass. This eCognition multi-scale image segmentation has the potential to generate seagrass beds features with more consistent boundary shape and complexity than possible using a standard heads-up interpretation and digitizing approach. It is our contention that this multi-scale image segmentation approach coupled with field transect/point surveys will be more replicable than strictly boat-based surveys and/or visual image interpretation and allow for more robust conclusions regarding change in areal extent, location and spatial pattern of seagrass beds through time.

At a minimum, baywide mapping of seagrass areal extent and density monitoring should be conducted on a 5 year time scale. The remotely sensed monitoring work should be supplemented with a series of permanent field plots, where intensive sampling of seagrass beds will be undertaken periodically over the growing season and succeeding years. The two techniques are complementary and should a better handle on seagrass abundance and health and the impact of possible disturbance factors.

To look at the maps or download the GIS data derived from the present and past SAV surveys go to: http://crssa.rutgers.edu/projects/runj/sav/index.htm. These maps and accompanying information are available to the larger Barnegat Bay research and management community and the interested public to help understand how the seagrass beds are changing, the role of seagrass in the larger bay ecosystem and the success of the Barnegat Bay Estuary program's restoration efforts.

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Table 1. Bottom Type Classification Results

Bottom Type	Class Area (Ha.)	% of Seagrass
Sparse Seagrass (10-40%)	1,971	38
Moderate Seagrass (40-80%)	1,139	22
Dense Seagrass (80-100%)	2,074	40
Total Seagrass	5,184	
Shallow Sand/Mud Flat	11,202	
Macro Algae	353	
Deep Water	19,125	
Total Study Area	35,864	

Table 2. Contingency table comparing seagrass density from field reference data and the GIS seagrass maps for 245 points.

2a. 4 categories: Seagrass Absent, Sparse, Moderate vs. Dense

	Reference				
GIS Map	Seagrass Absent	Seagrass sparse	Seagrass moderate	Seagrass dense	User's Accuracy
Seagrass: Absent	67	20	9	3	68%
Seagrass: sparse	4	37	14	3	64%
Seagrass: moderate	0	4	40	6	80%
Seagrass: dense	6	2	7	23	61%
Producer's Accuracy	87%	59%	57%	66%	68%

2b. 2 categories: Seagrass Present vs. Absent

	Reference	Reference	
GIS Map	Seagrass Absent	Seagrass Present	User's Accuracy
Seagrass Absent	67	32	68%
Seagrass Present	10	136	93%
Producer's Accuracy	87%	81%	83%

Table 3. Contingency table comparing seagrass presence/absence from independent field sampling data and the GIS seagrass maps for 41 points.

GIS Map	Reference Seagrass Absent	Reference Seagrass Present	User's Accuracy
Seagrass Absent	14	3	82%
Seagrass Present	9	15	62%
Producer's Accuracy	61%	83%	71%

Table 4. Border length, as measured in 1 m^2 grid cells and on a percent basis, for each seagrass density class and shallow sand/mud flat.

From/To		Dense	Mod.	Sparse	Shallow	Total Border for each class
Dense	# cells	---	**144,544**	**307,819**	**132,033**	**584,396**
	%	---	*24.7*	*52.7*	*22.6*	
Mod.	**# cells**	**145,341**	---	**233,003**	**102,563**	**480,907**
	%	*30.2*	---	*48.5*	*21.3*	
Sparse	**# cells**	**309,828**	**233,191**	---	**340,510**	**883,529**
	%	*35.1*	*26.4*	---	*38.5*	
Shallow	**# cells**	**131,579**	**102,447**	**339,171**	---	**573,197**
	%	*23.0*	*17.9*	*59.2*	---	
		Deep Water	*Shallow sand/mud flat*	*Macro Algae*	Land	
Combined seagrass	**# cells**	*207,158*	*582,273*	*4,385*	26,085	819,901
	%	*25.3*	*71.0*	*0.5*	3.2	

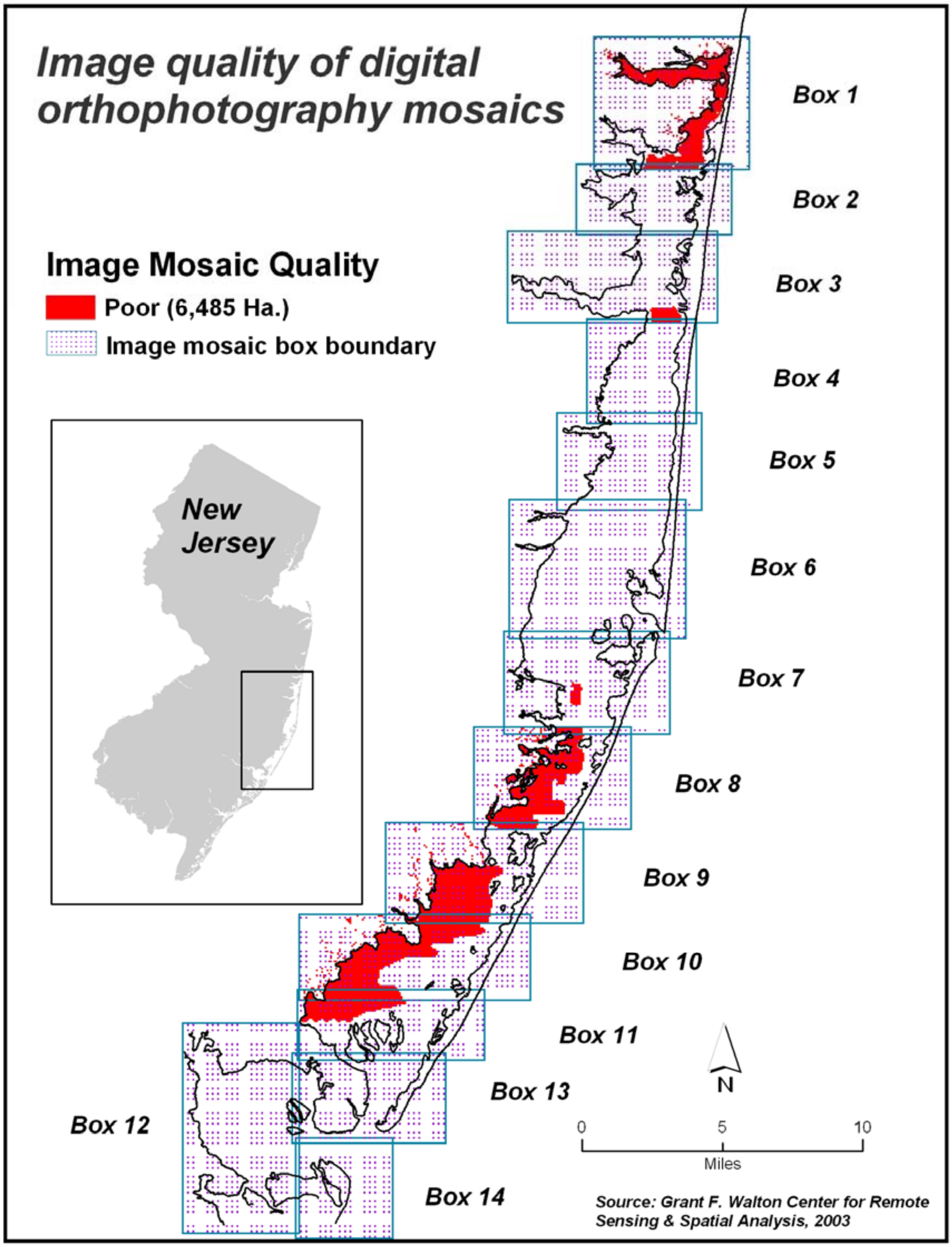

Figure 1: Image quality throughout the study area.

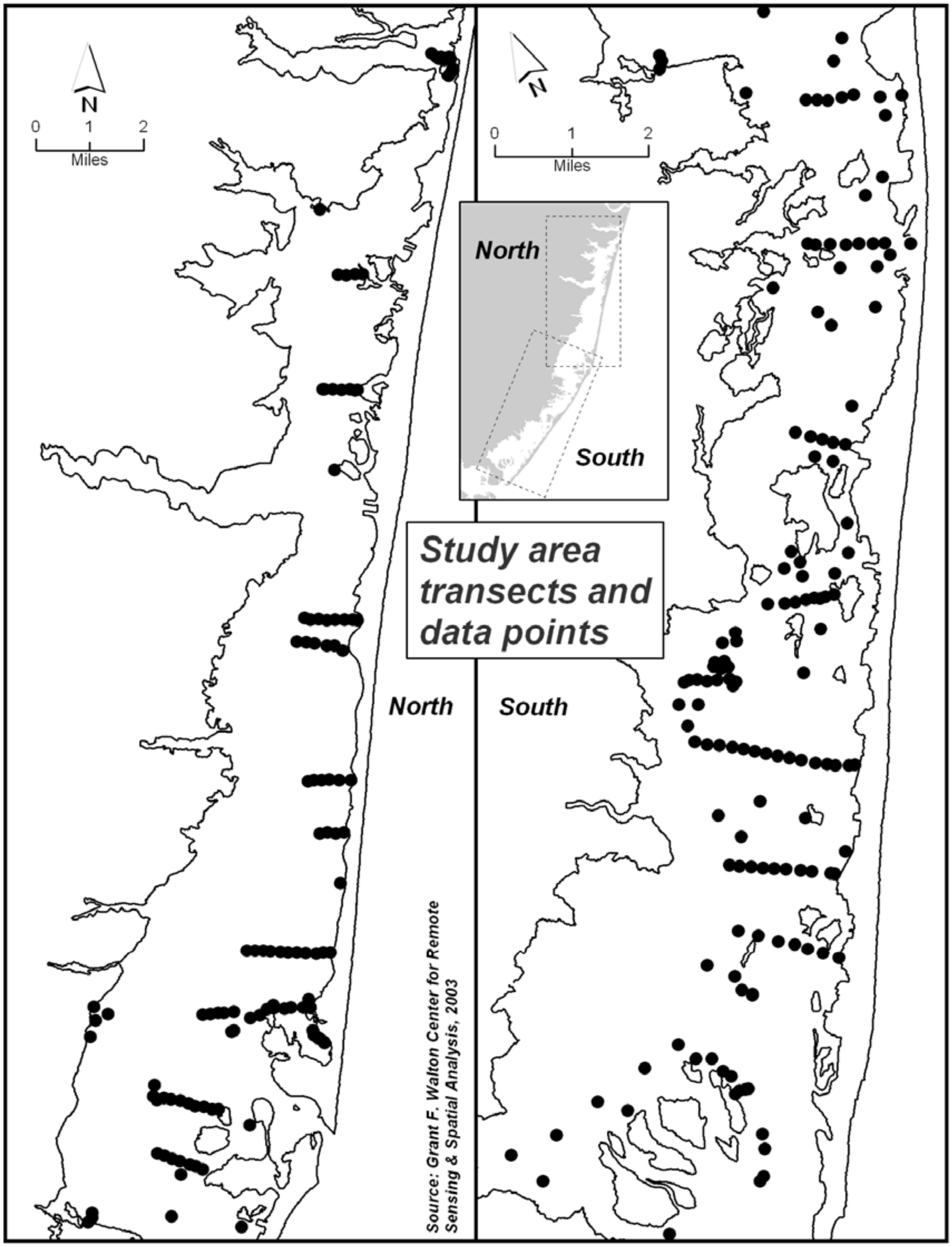

Figure 2. Location of field reference data transects and individual check points.

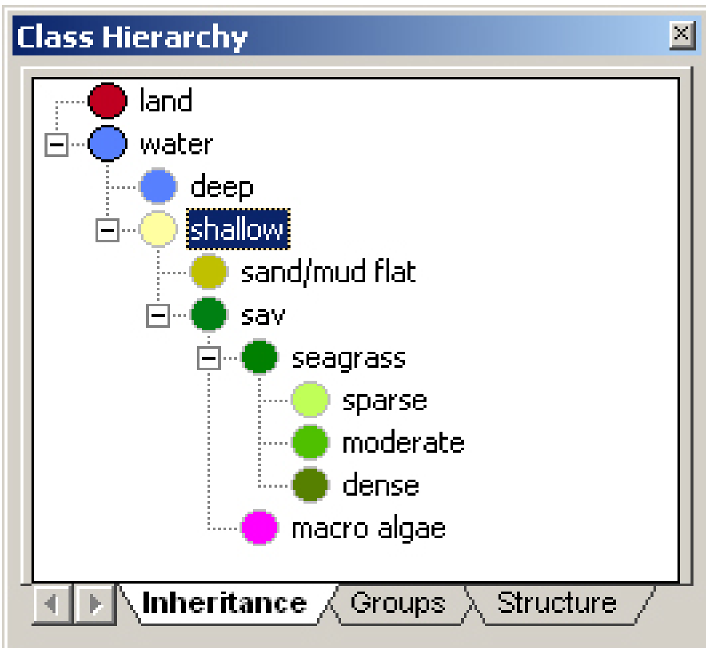

Figure 3. Hierarchical object-oriented classification scheme

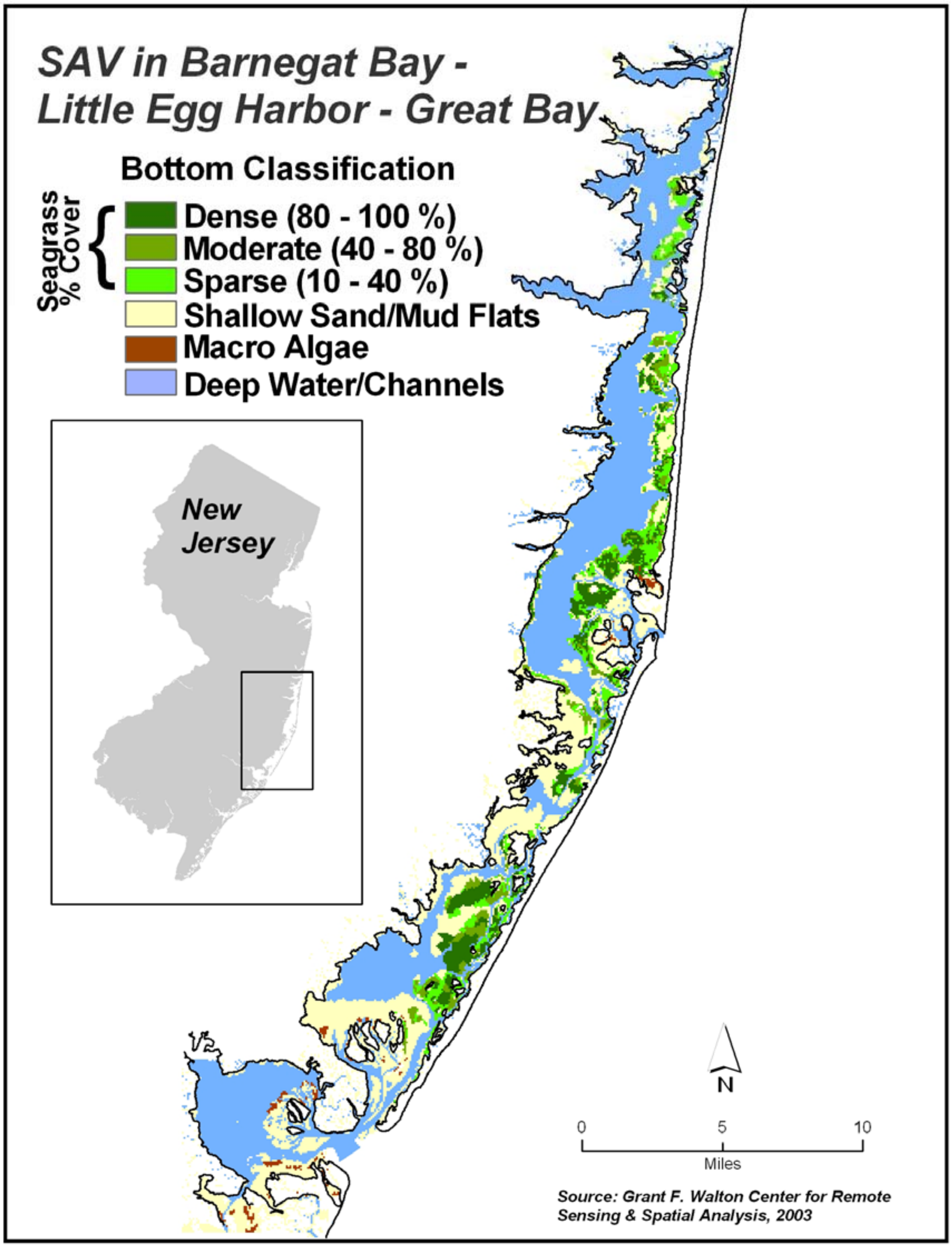

Figure 4: Bottom type classification map.

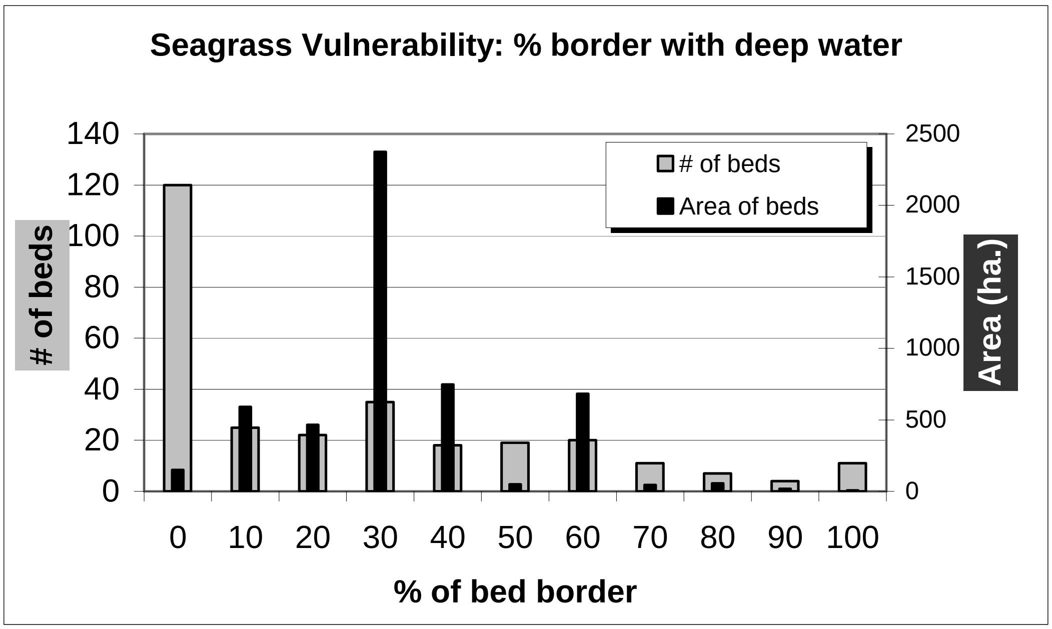

Figure 5: Number of SAV patches and SAV area for each deep water border percentage bin.