Abstract

The Utility of Digital Globe's WorldView-2 Satellite Data

in Mapping Seagrass in North Carolina Estuaries

by Richard W. Curran

June, 2011

Director: Yong Wang

DEPARTMENT OF GEOGRAPHY

Submerged aquatic vegetation (SAV) is a valuable natural resource in North Carolina estuaries. The State's Coastal Habitat Protection Plan (CHPP) has stated a need to monitor SAV coverage over time. Thus, the Albemarle-Pamlico National Estuarine Program (APNEP) SAV Partners has a project underway developing a mapping methodology combining remote sensing and boat-based methods to map SAV. As a partner in the APNEP mapping program, this research investigated the utility of satellite remote sensing in the mapping of SAV in NC estuaries. In particular, the data of DigitalGlobe's WorldView-2 (WV-2) satellite launched October 2009 were studied. The WV-2 data are of high spatial resolution (~2x2 m) and 5 visible multi-spectral bands, including a "coastal" band (400-450 nm).

One WV-2 image per site was acquired. Three sites were, Jarrett Bay, Blounts Bay, and Sandy Point. Land and deep water (>2 m) pixels were eliminated from each image and subjected to a principal component analysis (PCA), where the first two components were input into the Iterative Self-Organizing Data Analysis Techniques (ISODATA) unsupervised classification. Ground reference points were used to perform an accuracy assessment. At Jarrett Bay, where a continuous SAV bed covered 40%-70% of the study site, results showed an 86.4% classification

accuracy in water depths < 0.8 m and 40.9% accuracy in water depths > 0.8m. At Blounts Bay, where SAV coverage was sparse (0%-10%), classification accuracy was 50% in water depths < 0.8 m and remained at 50% in depths > 0.8m. The Sandy Point image was deemed unusable due to extensive sun glint. Most misclassifications were due to dark sediment and the sensor's difficulty in detecting small SAV patches (< 1x1 m). Additionally, according to the environmental conditions present in the images, a water depth threshold where WV-2 can accurately detect SAV was determined at 0.8 m in NC estuaries. With improved water clarity, this 0.8 m threshold would increase. Finally, the unique coastal band was highly susceptible to scattering and absorption due to suspended sediment and colored dissolved organic matter (CDOM) present in the water column of the study area.

The Utility of Digital Globe's WorldView-2 Satellite Data

in Mapping Seagrass in North Carolina Estuaries

A Thesis

Presented To

The Faculty of the Department of Geography

East Carolina University

In Partial Fulfillment

of the Requirements for the Degree

Master's of Arts in Geography

by

Richard W. Curran

June, 2011

The Utility of Digital Globe's WorldView-2 Satellite Data

in Mapping Seagrass in North Carolina Estuaries

by

Richard W. Curran

APPROVED BY:

DIRECTOR OF THESIS:______________________________________

Yong Wang, PhD

COMMITTEE MEMBER:____

Joseph Luczkovich, PhD

COMMITTEE MEMBER:____

Thomas Allen, PhD

COMMITTEE MEMBER:____

Don Field, PhD

CHAIR OF THE DEPARTMENT OF GEOGRAPHY:

____

Burrell Montz, PhD

DEAN OF THE GRADUATE SCHOOL:

____

Paul J. Gemperline, PhD

This thesis is dedicated to my wife Eileen
who has endured my stress and always given me her unequivocal and sustaining love.

ACKNOWLEDGMENTS

I am indebted to my thesis advisor, Dr. Yong Wang, for the guidance, council, and immense amount of time he has devoted to me during the course of the last two years, I cannot thank him enough. I also want to thank Dr. Joseph Luczkovich for giving me the opportunity to join his seagrass research team and spend countless hours in the field. Additionally, I want thank my other committee members Dr. Thomas Allen and Don Field for their valued input and advise.

The imagery used in this thesis research was purchased from funding provided by the United States Geological Survey (USGS) administered through North CarolinaView (NCView) a consortium member of AmericaView under grant #211654 to t e East Carolina University.

The acquisition of the ground reference data used in this study was funded by the Coastal Recreational Fishing License (CRFL) administered through the Albemarle-Pamlico National Estuarine Program (APNEP) under APNEP Task Order 2428.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SECTION 1.0: INTRODUCTION

1.1 Introduction to the Problem

Seagrasses are typically considered to be submerged aquatic vegetation (SAV) because they are vascular plants that can live in complete submersion in shallow water. However, SAV requires a high level of light in order to survive, which limits their habitat to near-shore shallow waters (Duarte 2002; Kenworthy and Fonseca 1996). Individual seagrass plants or SAV growing in a large, semi-continuous area is considered an SAV bed (Fonseca and Bell 1998). SAV beds have proven to be very valuable to the marine ecosystem. Near-shore fisheries rely on SAV as nurseries for juvenile fish that will eventually migrate into deeper waters (Beck et al. 2003). Industrial and recreational fishing are dependent upon sustainable fish populations, which SAV beds help to provide. Many predators may also acquire prey such as clams that bury in SAV beds, tearing up the seagrass to get at their molluscan prey (Blaylock 1993). Additionally, the root system of the beds stabilizes bottom sediment and the SAV leaves help to attenuate wave energy, which slows coastal erosion. The level of SAV health, as indicated by growth behavior and biomass, can be used to assess estuarine water quality, as was done in the Chesapeake Bay, Virginia (Dennison et al. 1993).

SAV can be impacted by human activity and development, and its living environment can be greatly influenced by eutrophication, dredging, docks, marinas, heavy boat traffic, and propeller scaring; all contribute to the destruction of SAV beds. SAV loss has become a recognized worldwide issue because there is to be a long term decline in SAV worldwide because of coastal development and decrease in water quality due to pollution (Duarte 2002 and Waycott et al. 2009). On a more local scale, SAV loss in North Carolina has become an interest of the State because of its environmental value to estuaries (Street et al. 2005). Coastal North

Carolina is a major summer destination as well as the location of development within the State. Sometimes coastal development requires the removal of SAV to make way for such things as new marinas or coastal housing developments. North Carolina has enacted a law that protects SAV in an effort to look after this important component of the near-shore ecosystem and included it in its Coastal Habitat Protection Plan (CHPP) (Street et al. 2005). However, to protect SAV the State must inventory the SAV resource on a regular basis and determine current baselines for the spatial extent and status of SAV.

There have been studies in the past that have mapped SAV coverage for portions of the North Carolina coastal areas (Davis and Brinson 1990; Ferguson et al. 1993; Ferguson and Korfmacher 1997; Steel 1991). Recently the Albemarle-Pamlico National Estuary Program (APNEP) began a research project lead by the APNEP SAV Partners (http://portal.ncdenr.org/web/apnep/sav-partnership) that is aiming to develop SAV mapping methods to be used to map SAV coverage for the entire estuarine coast (Carpenter et al. 2009). The “Partners” referred to here are researchers from East Carolina University (ECU), National Oceanic and Atmospheric Administration (NOAA), and North Carolina State University (NC State). In order to detect change in coast wide SAV coverage, the APNEP SAV Partners were originally going to use aerial or satellite imagery alone to map SAV coverage, but the remote sensing approach had its deficiencies. Cloud cover, water turbidity, and water depth could result in SAV beds going undetected, which could potentially result in an inaccurate detection of any change in SAV coverage. A protocol is being proposed that a method that incorporates remote sensing along with the boat-based methods of underwater video and sonar to assess change state-wide over time (Dr. Joseph Luczkovich, personal communication).

Both boat-based methods allow for SAV growing in water too deep or too turbid to be detected by remote sensing platforms. Each method involves running transects perpendicular to the shoreline, but each have their own advantages and limitations. The high resolution underwater video takes 1x1 m georeferenced snapshots of the water bottom while the boat travels along each transect. This approach allows the presence or absence of SAV to be identified as well as the seagrass species to be identified. Additionally, the underwater video does not require ground reference data to verify its findings. Its main limitation is the amount of time required to acquire the data as a result of the slow speed the boat needs to be traveling to acquire usable images, which limits the size of an area that can be surveyed in a reasonable amount of time. The images must also manually be interpreted by a trained staff, which requires a significant amount of time to accomplish.

Sonar provides another reliable method to detect SAV in deep, turbid waters. The algorithmic interpretation of an acoustic signal received from the water bottom is able to identify the presence or absence of SAV. The boat is able to travel at a moderate speed, which increases the area it can survey. Since the acoustic method is a form of remote sensing, it requires ground reference data to be acquired to verify its findings. Species identification is not detectable by the acoustic signal. Finally, both boat-based methods are limited to waters that are deep enough to operate a boat, which means any SAV growing in very shallow water cannot be accounted for by either of these methods. In summary, each boat-based method has the capability to detect SAV where remote sensing cannot, deep and turbid water. The APNEP SAV Partners mapping project has not yet identified the water depth threshold at which remote sensing can no longer reliably and accurately detect seagrass.

Digital aerial orthophotographs were acquired for most of the coast for the APNEP SAV Partners mapping project from 2006 - 2008. This imagery was interpreted 2010 – 2011, but the interpretations have not been released to the public. The sensor used to acquire the imagery was the Intergraph Z/I Imaging Digital Mapping Camera (DMC). The imagery was acquired at a 1 m spatial resolution, a radiometric resolution of 12-bits per pixel, and 4 band multispectral bands, 3 visible BGR bands and one near-infrared band (http://www.dewberry.com/uploadedFiles/IntergraphDMC_Presentation_082907.pdf; last accessed 4/30/2010). These spectral specifications have capability for use in benthic mapping (Wolter et al. 2005). Aerial imagery is a useful tool in mapping SAV because of its high spatial resolution and the fact that it is in a digital format that can be analyzed with remote sensing and geographic information system (GIS) software. Also, aerial sensors are able to acquire imagery on demand, which is not possible with satellite sensors. DigitalGlobe launched a new satellite, WorldView-2 (WV-2), in October 2009 which has 9 spectral bands that include one panchromatic band at .46 m spatial resolution and 8 multispectral bands at 1.84 m spatial resolution. It has a radiometric resolution of 11-bits per pixel and with its 20 degree off-nadir capabilities has a temporal resolution from 1.1 to 3.7 days. Of the 8 multispectral bands, 5 are visible bands which include a “coastal” band in the blue light range from 400 to 450 nm (http://www.digitalglobe.com/index.php/88/WorldView-2; last accessed 6/15/2011). This new spectral band could improve benthic mapping capabilities and serve to better fulill APNEP's SAV mapping needs because the narrow coastal band may get deeper water penetration.

Therefore, the purpose of this research is to develop new, improved techniques for mapping SAV via remote sensing imagery by using the new narrow visible band data from the recently launched WV-2 satellite to classify SAV. Such an improvement would contribute to APNEP's SAV mapping project and future resources monitoring capability.

1.2 Research Questions

The study will contribute to the APNEP SAV mapping project by investigating the following research questions:

1. Can the narrow visible bands of the WorldView-2 satellite improve SAV classification accuracy?
2. Does inputting the two PCA derived components into the Iterative Self-Organizing Data Analysis Techniques (ISODATA) classification over the raw 5 visible bands improve classification accuracy?
3. At what water depths can remote sensing techniques accurately classify SAV?

It is important to investigate the latest technology to see if current capabilities can be improved. The WV-2 sensor with its 5 visible bands and its high radiometric, spatial, and temporal resolutions has the potential to improve the current mapping capabilities employed by the APNEP SAV Partners to map SAV in North Carolina. This study will test those capabilities by classifying SAV in images acquired at three different study sites that have three different levels of SAV coverage.

The classification scheme used in this study was an unsupervised classification. Classification accuracy is very important Different variations of the data were input into the ISODATA unsupervised classification algorithm to find the data variation that produced the most accurate classification. To help increase the interoperability of the data by the ISODATA algorithm, the data was compressed using a PCA to derive two components.

Being able to identify a water depth threshold where remote sensing can accurately classify SAV will mean that water depths where the two boat-based methods should be used to map SAV can be identified as well. This type of information will help the APNEP SAV Partners to identify areas that need to be mapped using the boat-based methods instead of remote sensing.

SECTION 2.0: REVIEW OF LITERATURE

2.1 What is SAV?

According to the North Carolina Division of Marine Fisheries, SAV is fish habitat that is made up of one or more species of vascular plants that are rooted in sediment (Street et al. 2005) and are also known as 'seagrass' for the grass like resemblance of the species (Hartog and Kuo 2006). SAV isss angiosperm vegetation that grows in complete submersion in marine and freshwater environments (Duarte 2002). SAV habitat is mainly confined to areas that must have three characteristics; protection from strong waves and currents, adequate amount of sunlight where seagrass can perform photosynthesis (Duarte 1991; Kenworthy and Fonseca 1996), and nutrient rich sediment bottom type (Street et al. 2005). Of the three factors, light is the main factor that controls SAV growth (Street et al. 2005). The factors that determine the penetration depth of light are the amount of particles suspended in the water column (turbidity) and water depth (Duarte 1991; Zimmerman and Dekker 2006).

The value of SAV habitat to the coastal environment has been recognized at the local scale. The State of North Carolina has regulations place through the Coastal Area Management Act (CAMA) to help control human induced impacts on SAV beds (15A NCAC 07H .0209 (d)(4)). Currently, the State is interested in identifying the location and extent of SAV beds within the State's estuaries. The North Carolina Department of Environment and Natural Resources (NCDENR) developed the 2005 CHPP (Street et al. 2005). The CHPP has a section devoted strictly to outlining the role of SAV beds in the underwater ecosystem, the natural and human impacts that face SAV beds, and measures to manage and protect SAV beds. It is important to protect SAV habitats because of the freshwater and marine life that relies on the beds to survive. Coastal fisheries thrive in and around SAV beds, which has implications not only for the fish, but also for the fishing industry (Street et al. 2005). SAV beds provide many juvenile fish protection while they develop to adulthood and subsequently migrate into other habitats where they are fished by recreational and industrial fishermen (Beck et al. 2003; Street et al. 2005).

SAV beds play a vital role in the underwater ecosystem. They serve as near shore nurseries for juvenile marine life as they provide protection from predators during early life development (Beck 2003). Additionally, they are essential in providing oxygen for the water column, lowering water turbidity by knocking down or filtering out suspended particles, trapping, cycling, and consuming excess nutrients, as well as providing a source of food for SAV grazers, such as sea turtles (Duarte 2002; Thayer et al. 1984; SAFMC 1998). As a result of the afore mentioned services and functions, SAV beds have been determined to be one of the most valuable ecosystems in the world (Costanza et al. 1997).

There are numerous species of low salinity and high salinity SAV, in North Carolina estuaries; Three are high salinity species including eelgrass (*Zostra marina*), shoalgrass (*Halodule wrightii*), and widgeon grass (*Ruppia maritima*), which should be noted is found in a wide range of salinity levels (Ferguson and Wood 1994) as well as five fresh water species which include wild celery (*Vallisneria americana*), sago pondweed (*Potamogeton pectinatus*), non-native Eurasian milfoil (*Myriophyllum spicatum*), bushy pondweed (*Najas guadalupensis*), rnd redhead grass (*Potamogeton perfoliatus*) (Deaton et al. 2010). The majority of SAV bed coverage in North Carolina estuaries are dominated by the high salinity species, eelgrass and shoalgrass (Ferguson and Korfmacher 1997). Additionally, it has been determined that SAV in North Carolina does not normally occur in depths deeper than 2.0 m (Ferguson and Wood 1994).

The spatial extent of SAV habitat bottom coverage is highly variable and dynamic, which makes delineating a hard boundary of SAV habitat very difficult. The 2010 CHPP defines SAV habit to be areas that “have been vegetated by one or more [SAV] species . . . within the past 10 annual growing seasons and that meet the average physical requirements of water depth (six feet or less), average light availability (secchi depth of one foot or more), and limited wave exposure that characterize the environment suitable for growth of SAV.” (Deaton et al. 2010). This means that current unvegetated areas between adjacent SAV beds that had been vegetated at one point in the last 10 years are considered SAV habitat just as much as the SAV bed itself because of the potential for SAV to regrow there. The rate at which an unvegetated area between SAV beds can become vegetated could be anywhere from several days to several years depending on the physical conditions and species of SAV (Fonseca and Bell 1998). One factor that contributes to the spatial extent of SAV habitat is the yearly phenological cycle SAV experiences (Moore 2000). Similar to the cycle that a deciduous tree goes through, of growing and then losing its leaves, SAV blades grow from the rhizome system and then later die off. This yearly cycle is determined by the seasonal changes of environmental conditions such as sun radiation, temperature, and weather. For example, if a survey was taken of SAV coverage in a particular estuary during the month of August, then again in January, the area coverage would be substantially lower. This is because August is during the summer months where conditions are conducive to SAV growth, mainly as a result of heightened solar radiation striking the northern hemisphere.

2.2 Human and Natural Impacts to SAV

There are areas outside of North Carolina that have experienced heavy losses of SAV coverage. The Chesapeake Bay has been the site of substantial SAV loss. For example, Fleets Bay, which is a part of the Chesapeake Bay, went from over 500 ha of SAV coverage in 1960 to nearly nothing in 1980. There were similar declines in many other parts of the Chesapeake Bay due to water quality issues (Orth and Moore 1983). Tampa Bay, Florida, has seen losses as high as 50% (Smith 1998). In these examples much of the cause of SAV coverage decline was due in part to nearby urban development and industry affecting water quality, particularly in the Chesapeake Bay.

Since SAV habitat is near the shore, the biggest impact to SAV beds is human activity (Duarte 2002). The North Carolina Outer Banks permanent population rose an estimated 32% from 40,800 to 54,000 from 1990 to 2000 (Street et al. 2005). Since the year 2000, the rate of permanent population increase in coastal communities has slowed, which is due to the fact that the thin barrier islands were built out during the 1990’s not allowing room for more homes and other structures to be built. This lead to a boom of new housing developments built along the mainland waterfront or the “Inner Banks” from 2002 to 2006. The expansion of development and the increase in infrastructure needed to support such development has put further stress on SAV (Deaton et al. 2010). Additionally, during the summer months tourism increases, this attracts people from other states as well and from mainland North Carolina counties to the coastal region. At beach towns, the latest estimates show a seasonal population that is 3 to 59 times larger than the permanent population (Deaton et al. 2010). The heightened human activity in the North Carolina coastal region during the summer months occurs at the time of the SAV growing season, which inevitably results in heightened stress on SAV. The impacts from human activities include coastal development, dredging, eutrophication from non-point source pollution, siltation, frequent industrial ship traffic, and frequent recreational boating (Beck et al. 2003; Duarte 2002). Dredging commonly occurs in areas where there is high traffic of industrial and recreational boats and is a direct threat to SAV beds because it not only can remove SAV habitat, but it can cause an increase in turbidity and wave action from further increases in vessel traffic as well as produce dredge spoils that are sometimes deposited on top of SAV beds as was the case in the Core Sound in North Carolina outlined in Ferguson and Wood (1994).

Hardened shorelines, a development reaction to erosion, sea-level rise, and storm damage protection have also impacted SAV. As the sea-level rises, SAV will have to adapt by spreading to newly submerged sandy bottom area. Structures such as bulkheads, rip rap, and marinas/docking facilities stand literally as barriers to SAV adaptation because SAV cannot spread past the structures, resulting in a net "placement loss" of habitat. Bulkheads are a common structure built on coastal residence properties as well as the use of rip rap to prevent erosion and are quite readily permitted in estuarine environments of NC under current policy. Also, bulkheads are standard at marinas in addition to concrete boat ramps coupled with a high frequency of boat traffic prevent SAV from growing or adapting. (Street et al. 2005).

Though many anthropogenic influences impact SAV growth, nature too has impacts that can adjust SAV growth. Nature has a role that effects SAV growth, but nature's way helps to sustain a sense of equilibrium in the natural environment by keeping SAV bed growth at a sustainable level. Large storms such as hurricanes and tropical storms produce strong waves that can rip SAV out from the water bottom resulting in a large scale blow to SAV beds. These large storms also create high levels of turbidity from resuspended particles and flood waters flowing into the system. The heightened turbidity can obstruct light from penetrating the water column down to the water bottom, which can kill off SAV, particularly the SAV growing in deeper water where adequate light might be limited under standard conditions. Events such as hurricanes or tropical storms that produce high levels of turbidity are called pulsed turbidity events (Orth et al. 2006 and Preen et al. 1995). As an example, in Hervey Bay, Australia there was a documented loss of nearly 1000 km^2 of SAV resulting from tropical storms causing pulsed turbidity events (Preen et al. 1995). Additionally, grazers and foragers impact SAV coverage. Grazers such as sea turtles will graze on SAV and foragers such as Atlantic stingrays will rip up SAV searching for prey (Thayer et al. 1984).

Other natural impacts on SAV beds include infectious diseases, called seagrass wasting disease, that are sometimes introduced to SAV beds, by migrating foragers (Jackson et al. 2001). Low salinity SAV species are less susceptible to pathogens because they are in low saline water (Short et al. 1987). The South Atlantic Fisheries Management Council (SAFMC) stated in their 1998 final report that Zostera SAV in Core Sound, Back Sound, and Bogue Sound displayed signs of wasting disease (1998). These three sounds are high salinity sounds because of the high saline seawater brought up from the Gulf Stream Current.

In North Carolina, historical observations of SAV coverage have shown SAV coverage trends from the early 1900's to 2002. Most of the losses occurred as a result of circumstances such as increases in water turbidity, diseased seagrass, increases in salinity in freshwater environments, and hurricanes. The overview of SAV coverage history based on the qualitative analyses of Davis and Brinson (1990) and Steel (1991) were outline by the 2005 North CHPP (Table 1). These historical trends highlight the fact that SAV coverage has been highly variable over time due to its susceptibility to human and natural impacts, which why it is important to regularly monitor SAV coverage, so current coverage trends and their causes can be understood.

To do this contemporary coverage statistics are needed for analysis of the current state of SAV and to create a baseline for future SAV coverage change analysis.

Year	Changes in SAV Coverage in North Carolina
1918 – 1919	Currituck Sound experienced a significant decline attributed to opening of Albemarle and Chesapeake Canal.
1930	Eelgrass decline in Pamlico, Core, and Bogue sounds resulting from seagrass wasting disease
1952	Full recovery of SAV in Currituck Sound from better management practices of canal locks
1955	Major SAV loss in Currituck Sound due to four hurricanes, but within two years SAV recovered
1960	Eelgrass in Pamlico, Core, and Bogue sounds near full recovery from wasting disease
1962	Freshwater species in Currituck Sound decline because influx of salt water and being displaced by non-native Eurasian watermilfoil
1975	SAV is common in upper Pamlico River estuary
1985	Major loss of SAV in upper Pamlico River estuary (1% of pre-1970 levels), western Pamlico Sound, and Neuse River estuary resulting from extreme sediment loading
1990	Minor recovery of SAV in Neuse and Pamlico estuaries due to improved erosion control methods and/or weather patterns
2002	Increase of SAV reported in Albemarle Sound possibly from improved water clarity caused by drought conditions

Table 1: Major temporal trends in coverage of SAV in North Carolina (Davis and Brinson 1990; Steel 1991)

2.3 SAV Mapping

SAV coverage loss can be severely extensive as a result of anthropogenic stresses to the near shore ecosystem. There have only been historical reports based on observations of SAV loss in North Carolina, SAV loss has yet to be quantified (Street et al. 2005; Davis and Brinson 1990). Since coverage variation (loss or gain) of SAV for coastal North Carolina has never been quantified temporally, the CHPP 2010 stated there is a need in North Carolina to begin quantifying SAV coverage in order to develop a baseline map that can be used for regular SAV coverage monitoring in the future (Deaton et al. 2010). Also, in addition to the published studies in the past that have mapped SAV beds off North Carolina's coast (Carroway and Priddy 1983; Davis and Brinson 1990; Ferguson and Korfmacher 1997; Ferguson and Wood 1993) there have been unpublished mapping projects done between 1997 and 2008 by the Division of Water Quality (DWQ), DWQ Rapid Response Team, Division of Marine Fisheries (DMF), Department of Transportation (DOT), Elizabeth City State University Mapping Program, and North Carolina State University (Unpublished SAV Mapping Inventory, http://www.ncfisheries.net/habitat/miscdownloads/SAV_mapping_inventory_2008.pdf, last accessed 6/15/2011). None of these studies or projects were aimed at investigating statewide SAV coverage as the current APNEP mapping project is aimed at trying to accomplish using the new approach of combining acoustic, video, and remote sensing mapping techniques.

Sonar has the ability to detect the presence or absence of SAV. In the instance when SAV is present, the first return from the ping is the SAV and the last return is the bottom. Thus, a sonar acoustic sensor can provide three types of data, presence or absence of SAV, water depth, and plant height. Water depth data can be used to improve unsupervised classification of SAV

(Ferguson and Korfmacher 1997). The limitations of a sonar sensor are that it cannot detect SAV species and there is minimum threshold of object height that is set at 2 acoustic bins (approximately 3.5 cm) above the substratum in the software associated with the sonar sensor which processes the raw sonar data. Therefore, any SAV shorter than ~3.5 cm threshold goes undetected, which from the preliminary finding of the ANEP project has shown would tend to underestimate SAV coverage. Additionally, the acoustics are limited to water that is deep enough to support boat navigation, so that seagrass located in water too shallow cannot be surveyed.

Remote sensing imagery has been used for mapping large areas of SAV bed coverage (Mumby and Edwards 2002; Ferguson and Korfmacher 1997; Luczkovich et al. 1993; Andrefouet et al. 2003; Chauvaud et al. 1998; Wabnitz et al. 2008). With remote sensing techniques, one can classify imagery for large areas to be mapped, with less resources, and less expenses that are required to employ ground based surveying techniques (Mumby et al. 1999).

Ferguson and Korfmacher (1997) completed a study in the Core Sound in North Carolina where they mapped SAV coverage using Landsat data to map SAV in North Carolina. Based on the results of principle component analysis, bands 1 (450-520 nm, blue) and 5 (1,550-1,750 nm, middle IR) were used to classify the SAV. A bathymetric layer was also included in the classification. It is interesting that band 5 in the middle infrared wavelength was used, since infrared light is absorbed by water, which can be problematic when mapping benthic habitats (Wolter et al. 2005). SAV habitat was found at shallow water depths down to 2 m with most SAV coverage being most prominent at depths shallower than .5 m. The use of a bathymetric data layer as another “band” for classification was determined to improve SAV classification. Ferguson and Korfmacher (1997) used a bathymetric layer created from data collected in the 1800’s and suggested that contemporary bathymetric data should be used to further improve classification accuracy. Additionally, the Landsat spatial resolution is 30 x 30 m, which is course when compared to the higher spatial resolution satellite sensors available in 2011 (such as WV-2) that did not exist previous to 1997 when the Ferguson and Korfmacher published their work. Using higher spatial resolution would likely increase the ability to accurately detect the extent of SAV coverage.

Using high spatial resolution Quickbird imagery (2.44x2.44m), a study was done in the Great Lakes (Wolter et al. 2005). Three visible bands of the sensor (485, 560, and 660 nm) were used in the analysis to classify SAV using unsupervised ISODATA classification method. Visible bands are the optimal bands to use when classifying marine habitats because they have a lower wavelength enabling them to penetrate the water column, unlike the infrared bands which are absorbed by water (Wolter et al. 2005). Wolter et al. (2005) were able to quantify SAV coverage for each study site.

A change detection analysis of SAV coverage using aerial photography was done on the Texas Gulf Coast (Fletcher et al. 2009). They used aerial photos from three consecutive years then changed the RGB values to intensity, hue, and saturation values. The histograms were then used to define bare bottom and vegetated bottom. They had classification accuracies ranging from 75 to 100% and used GIS techniques to quantify the change throughout the three years. This study showed that aerial remote sensing can also be used to map SAV.

DigitalGlobe launched WV-2 in October 2009. The new satellite has five bands in the visible light spectrum and three in the near infrared (NIR) (Table 2). The radiometric resolution is 11-bits per pixel (http://www.digitalglobe.com/index.php/88/WorldView-2 accessed 6/15/2011). DigitalGlobe advertises and shows examples of the coastal band being used in clear tropical water on their website. The price for new acquisition of an 8 band bundle dataset is

\$30.40 per km^2 with a minimum image size of 47 km^2, which brings the minimum purchase to approximately \$1,430. DigitalGlobe does have archived imagery that can be purchased at a cheaper rate though in order for an image to be archived it must have previously been a new acquisition order. Also, sample datasets are not provided before data are purchased.

Band	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Name	Coastal	Blue	Green	Yellow	Red	Red Edge	NIR 1	NIR 2
Spectrum Width (nm)	400 - 450	450 - 510	510 – 580	585 - 625	630 - 690	705 - 745	770 - 895	860 - 1040

Table 2: Multi-Spectral bands of the WorldVeiw-2 satellite sensor (http://www.digitalglobe.com/index.php/88/WorldView-2, last accessed 6/15/2011).

The wavelength of the Coastal band (400-450 nm) is shorter than the blue band (400-550 nm) of the DMC used in the APNEP SAV Partners project. Though the aerial sensor (12-bit) has a higher dynamic range than the satellite sensor (11-bit), the improvement with the shorter wavelength band should theoretically allow for a more accurate classification of SAV coverage as well as an increase in the area that can be mapped using remote sensing imagery.

Even with the improved spectral and radiometric resolutions of the Worldview-2 imagery, it still has limitations. One limitation is of course, water turbidity. It does not matter how fine the spectral and radiometric resolutions may be, if the water is highly turbid then the sensor still cannot detect benthic habitat. Another limitation is the temporal resolution. WV-2 has off-nadir capabilities, but still it is unable to go over the same spot every day and at times off-nadir look angles may provide difficulties when mapping underwater habitats because the reflectance must travel through a larger portion of the water column, attenuating the signal.

Furthermore, the cost of the imagery can be a limitation as it may be too costly for some to use WV-2 imagery.

Geolocation accuracy is also a limitation, as is true with all remote sensing sensors. The stated geolocation accuracy for WV-2 is 4.6 to 10.7 meters (http://www.digitalglobe.com/index.php/88/WorldView-2, last accessed 6/15/11). This means that the actual location of a mapped SAV bed could be up to almost 11 m off of the actual real world location, which could present potential issues. For example, if a homeowner wanted to build a dock out from his/her property and a permit request was denied because the SAV map shows there is an SAV bed where the dock is proposed to be built. However, in reality the map location of that SAV bed is off 10 m and the location of the proposed dock is over an unvegetated bottom. A scenario such as this could go the other way as well, where a dock is approved because the SAV map shows that there is no SAV at risk, but in reality there is SAV and a portion of an SAV bed is subsequently destroyed. With remote sensing georeferencing techniques there is the potential that the geolocation accuracy of the imagery can be improved. Georeferening imagery is a common remote sensing technique (Jensen, 2005). But georeferencing images where a majority of the image is water can be problematic because there are virtually no reliable ground control points (GCP) on the water.

In this study, remote sensing classification techniques will be used to investigate the capabilities of the WV-2 satellite to map SAV in North Carolina estuaries and its potential to be used as part of the APNEP Mapping Partners SAV mapping project currently underway for the North Carolina DMF.

2.4 Study Sites

Three study sites were used: Sandy Point, Blounts Bay, and Jarrett Bay (Figure 1). Three was the chosen number of sites largely because there was only enough funding to purchase three images. The study sites at Blounts bay and Jarrett Bay extended out from the shoreline approximately 300 m and was 300 m wide. The Sandy Point study site extended out from the shoreline approximately 500 m and was 300 m wide. The site extended out to 500 m because the SAV coverage was so extensive that the SAV bed edge extended beyond 300 m from the shoreline. Sandy Point is located in the Albemarle Sound near Edenton, NC. This was a low salinity site that is mainly fed by the Roanoke River. This site was selected because there was a previous seagrass survey completed at the same location for a proposed coastal community and because it was located in the north portion of the North Carolina estuarine system (Dr. Joseph Luczkovich, personal communication). SAV species present at the site were Myriophyllum spicatum, Najas guadalupensis, Potamogeton, and Vallisneria. The shoreline was relatively pristine with a line of trees near the shore and a large farm field behind the trees. An exception of the pristine setting was a canal that had been dredged through the SAV bed in preparation for the building of the housing development.

Blounts Bay is located off the Pamlico River across from Goose Creek State Park, east of Washington, NC. This too is a low salinity site that is mainly fed by the Tar/Pamlico River as well as the small tributary Blounts Creek, hence the name of the bay. Blounts Bay was selected as a site after a probing survey identified SAV at this location and because it is located in the mid portion of the estuarine system. SAV species found at the site were Najas guadalupensis, Potamogeton, Ruppia, and Vallisneria. SAV cover of the site was very sparse. The shoreline is mostly lined by private property where many homeowners have hardened shorelines and docks.

Jarrett Bay is located off of the southern portion of the Core Sound, which is north of Harkers Island, NC. This is the only high salinity study site used in this study. Beaufort Inlet, located south of Core Sound, and Drum Inlet, located in the northern portion of Core Sound, are the two inlets located closest to Jarrett Bay and which provide the high salinity water found at the site. Ocean water is forced in and out of both inlets during flood and ebb tides respectively. Additionally, there are frequent Nor'easter winds that push water from the Pamlico Sound into Jarrett Bay, which at times can minimize the difference of high and low tide water levels. Jarrett Bay was selected as a site using aerial imagery flown in 2007 for the APNEP SAV Partners project and was selected because it represented high salinity seagrass species and was located in the southern portion of estuarine system. SAV in Jarrett Bay is predominantly made of the high salinity species of Halodule, Ruppia, and Zostera (Ferguson and Korfmacher 1997). SAV coverage of this site was moderate.

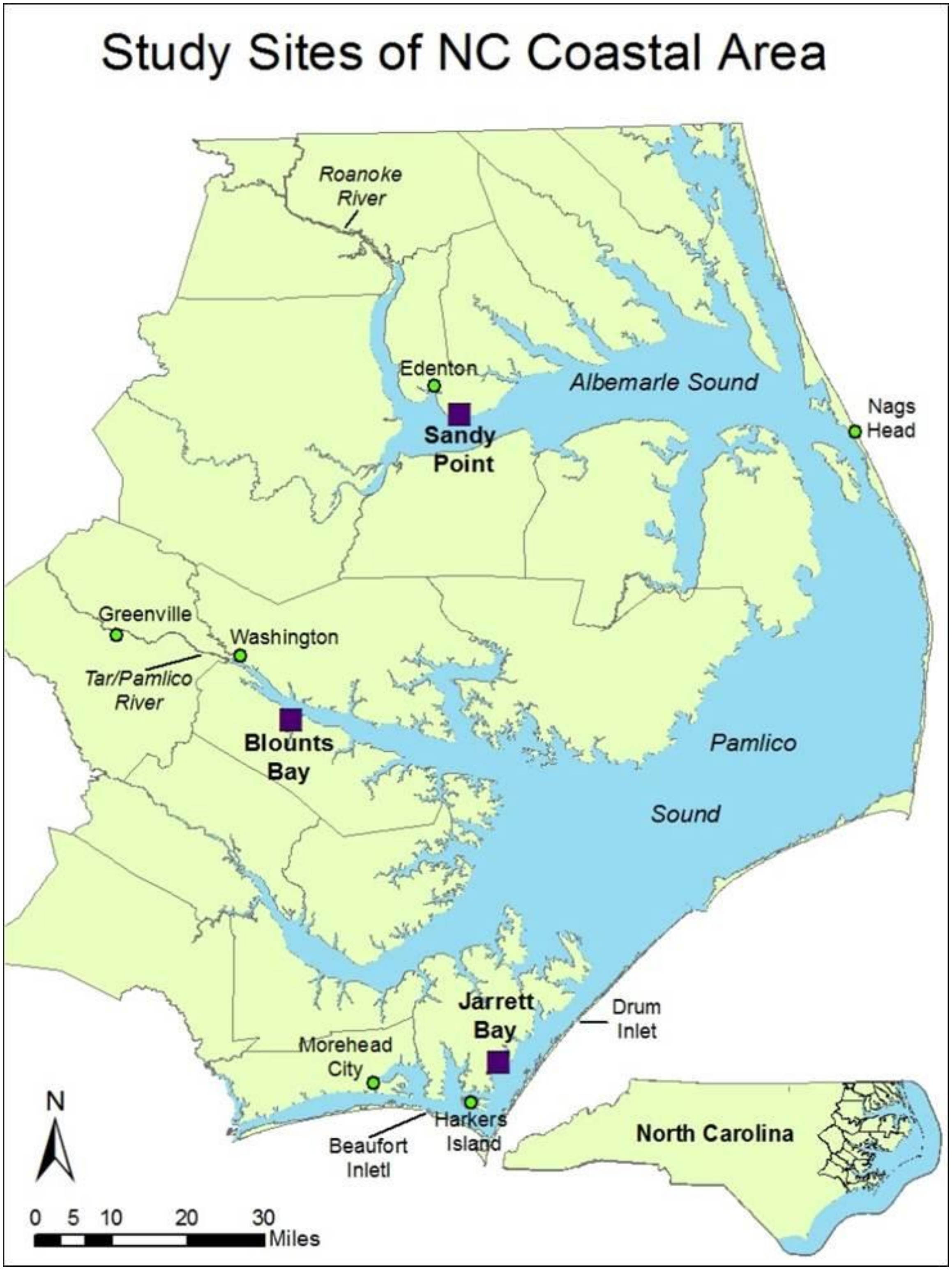


Figure 1: Location map for three sites.

SECTION 3.0: METHODOLOGY

3.1 Mapping North Carolina SAV

There were a total of three images that were analyzed in this study, one image for each site. The images were purchased from the DigitalGlobe as a new acquisition order. The first of the three images was acquired September 18, 2010 and the last image was acquired a month later on October 18, 2010 (Table 3). The imagery was analyzed and classified using ERDAS Imagine.

Study Site	**Date of Image Acquisition**	**Date of Ground Ref. Acquisition**
Blounts Bay	October 18, 2010	September 24, 2010
Jarrett Bay	September 18, 2010	September 17 & 18, 2010
Sandy Point	October 15, 2010	September 25, 2010

Table 3: Dates of WV-2 image acquisition and ground reference data acquisition for each site.

The WV-2 imagery went through an analytic process aimed at determining the best classification methodology, which would yield the most accurate classification. From initial inspection of the imagery, it was determined that the Jarrett Bay image, which had a dense, continuous SAV bed that covered a moderate portion of the site, was the best image available and was subsequently used as the center of the remote sensing analysis to develop the classification methodology. Using this image a methodology was created to classify the coverage of SAV at the other two sites. From field observations and ground reference data, Blounts Bay was identified as having very sparse coverage and Sandy Point had extensive coverage. Each of the three sites were put identified by one of the four classes of percent coverage (0-10%, 10-40%, 40-70%, and 70-100%) used by Lyons (2011). From the classification methodology developed, four analyses were performed:

- Testing what classification had the highest classification accuracy between using all 5 visible bands, using components derived from a PCA, or using a combination of the 5 visible band and the PCA components.
- Apply the same methodology to the Sandy Point image, where SAV coverage predominantly fell into the 70%-100% coverage class, to test the upper end of the coverage classification methodology.
- Apply the coverage classification methodology to the Blounts Bay image, where SAV coverage predominantly fell into the 0%-10% coverage class to investigate the lower end of the coverage classification methodology.
- Perform and accuracy assessment at incremental water depths in order to identify the depth threshold where remote sensing classification can reliably map SAV.

As a general outline of the classification methodology, it started with eliminating pixels that had the potential of confusing the unsupervised classification algorithm by masking out land using WV-2 NIR 2 band (band 8) (Table 2) and masking out deep water pixels using the acoustic sensor derived water depth data. A covariance matrix PCA was then run to compress the WV-2 five visible bands down to two components (Chauvaud et al. 1998; Ferguson and Korfmacher 1997; Khan et al. 1992). With the PCA components as input data, the ISODATA clustering, an unsupervised classification method, was used to identify natural groupings that existed within the imagery (Chauvaud et al. 1998; Ferguson and Korfmacher 1997; Su et al. 2006; Wolter et al. 2005) as well as using cluster busting (Jensen 2005b) in problem areas where it was difficult to differentiate pixels associated with SAV from other dark pixels such as dark sediment bottom type, turbid water, or deeper water. From the unsupervised classification there were two output classification categories: SAV and Bare Bottom. There were only two classification categories because the APNEP mapping project was concerned with defining either presence or absence of SAV (Dr. Joseph Luczkovich, personal communication). The classifications were each subject to an accuracy assessment.

3.1.1 ISODATA unsupervised classification

There were two segments involved in the classification of each WV-2 image, the ISODATA classification algorithm and the remote sensing analyst. The unsupervised classification process used in this study primarily entailed accounting for each pixel's spatial and spectral properties. For a pixel to be classified as SAV it must have met certain spatial and spectral standards. The spatial standard was accounted for by the analyst, while the spectral standard was accounted for by the analyst and the ISODATA algorithm. In order for the analyst to maximize classification accuracy, pixels that potentially may have had similar spectral properties of the SAV pixels, but were not located in the nearshore were masked out. Nearshore here, is being defined as the area were water depths were shallower than 2.0 m. The nearshore threshold was set at 2.0 m because it has been shown that SAV in North Carolina does not typically grow in water depths deeper than 2.0 m (Furguson and Korfmacher 1997). Field work done in conjunction with this study confirmed the 2.0 m threshold, with the exception of the Sandy Point study site where SAV presence was observed deeper than 2.0 m. When classifying SAV, which is a near shore benthic habitat, all pixels not located in the near shore nor in the water were eliminated from the image because many of these pixels had the potential of meeting the spectral standard, but did not meet the spatial standard as a result of their location. When a pixel is wrongly classified, meaning the pixel is classified as something it is not, this is called pixel confusion (Ferguson et al. 1993; Su et al 2006; Wabnitz et al. 2008; Wolter et al. 2005).

Bathymetric data available from NOAA was a possible data source to be used to identify and mask out deep water pixels, but the spatial resolution of the NOAA bathymetric maps were too course for the purposes of this study. The finest horizontal and vertical resolution available from NOAA was their 1x1 arcsecond map, which has a cell size of ~30x30 m horizontally and 1 m vertical resolution. For the relatively small study areas, these resolutions were too course. Also, as stated before, much of the NOAA bathymetric maps that exist for North Carolina estuaries were derived from data that dates back from the late 1800's to mid 1900's, which presented water depth accuracy issues as results of the course resolution and potentially out-of-date of the maps. This same issue was encountered by Ferguson and Korfmacher (1997). They pointed out that the historical depth data created some error in their SAV classification and went on to suggest that contemporary bathymetric data should be used for SAV classification. Contemporary bathymetric data used in this study was derived from the boat-based active acoustics mapping method used in the APNEP SAV Partners mapping project.

Contemporary bathymetric data used in this study were derived from the boat-based BioSonic DT-X echosounder acoustic sensor used in the APNEP SAV Partners mapping project. The acoustic method uses a BioSonics single-beam sonar 420-kHz transducer attached to the side of a flat bottom boat to collect data. The transducer sends out pings that travel through the water column and strike the water bottom or whatever structure, object, or even living plants (seagrass) or animals (such as fish) that may be between the DT-X and the water bottom. Then the ping bounces off the water bottom or object and travels back through the water column and is received by the DT-X. The raw acoustic data collected was then processed via BioSonics ECOSAV2 software, which aggregated the data into individual goereferenced acoustic reports. An acoustic report consisted of 10 pings and holds information such as percent SAV cover and water depth. The ECOSAV2 output data were in a GIS compatible CSV format. This file was converted into georefernced point data into ArcMap 9.3 where SAV coverage and bathymetry layers were created. A bathymetric layer was created through the kriging interpolation algorithm available in ArcMap. From the active acoustic derived bathymetry, water pixels within each study site that did not meet the spatial standard of being located in water depths shallower than 2.0 m were identified and subsequently masked out of the imagery (Figure 2). According to Ferguson and Korfmacher, this contemporary bathymetry increased the classification accuracy of SAV coverage (1997).

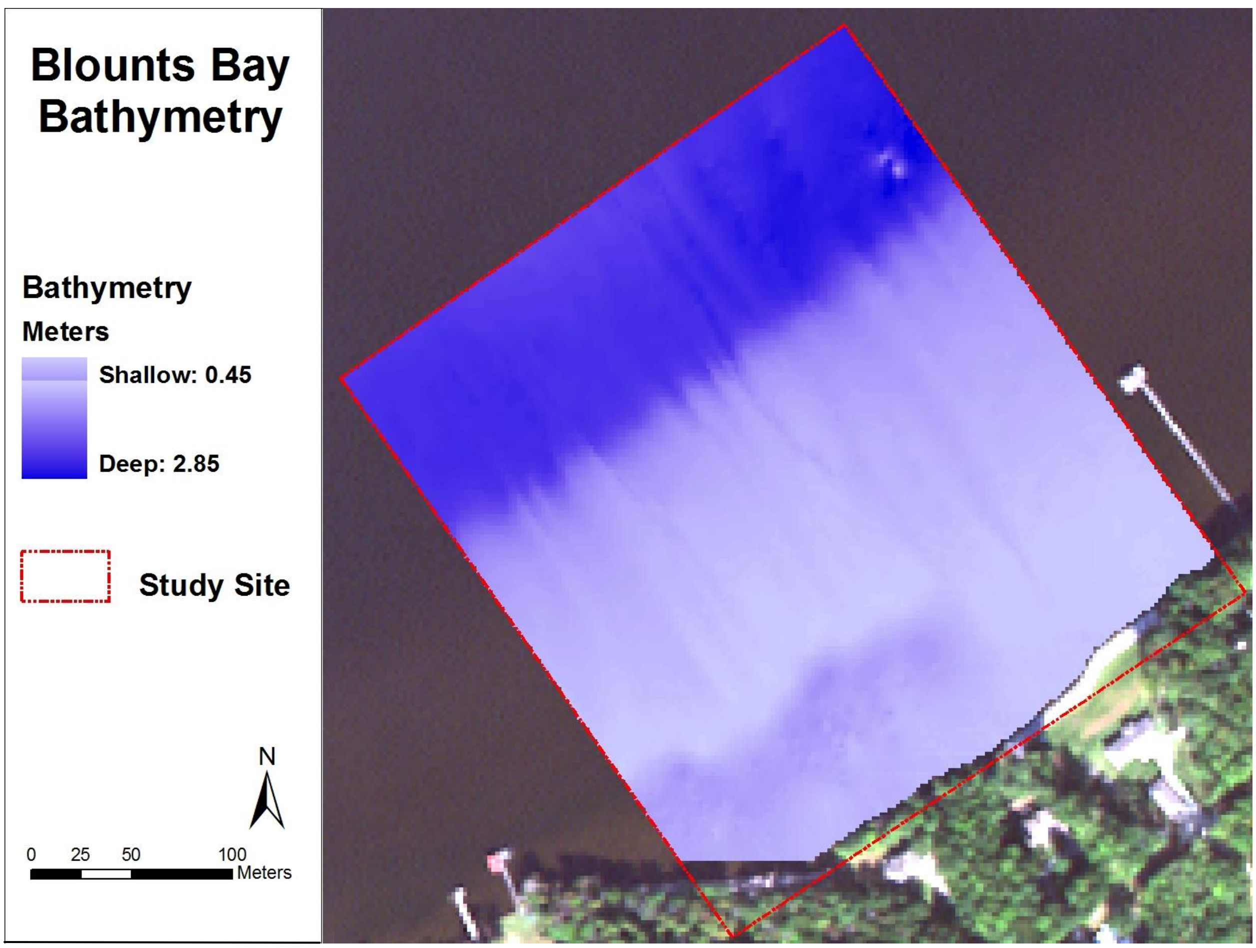


Figure 2: Map of the bathymetry for Blounts Bay derived from the acoustic survey.

As stated previously, the coverage of the acoustic derived data was limited to water depths that were deep enough for the boat to navigate. From the unpublished results of the Summer 2010 acoustic surveys done by the ECU membership of the APNEP SAV Partners, it was determined that anything shallower than 0.5 m was too shallow to survey. In addition to navigation difficulties in shallow water, this 0.5 m threshold was also due to detection limitations of the transducer. The transducer sat nearly 0.2 m in the water column and was unable to detect SAV or bottom within the "acoustic near-field," which is approximately 0.3 m. Therefore, 0.5 m in depth was set as a threshold.

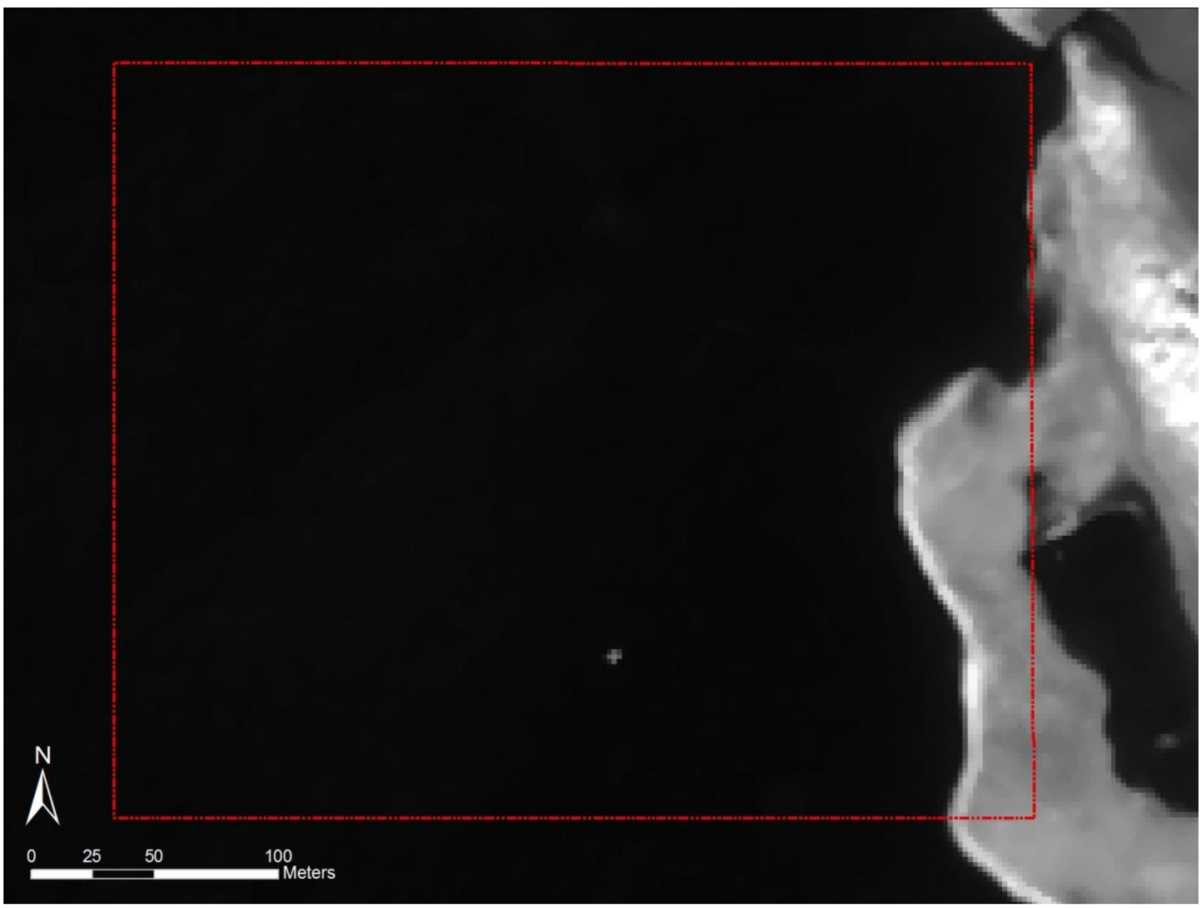


Figure 3: WV-2 image in the near IR2 (band 8) for Jarrett Bay, NC. Water appears black and land in shades of gray. The bright spot in the water was the pixel of our boat when the satellite flew over the site where the fieldwork was being conducted concurrently.

Pixels located on land were also masked out of the imagery. This was done because including land in the unsupervised classification would increase the number of irrelevant clusters in the output classification. Land pixels were easily identified using WV-2 Band 8, which is the NIR 2 band. Reflectance in the IR spectrum is absorbed by water, so in an image displaying an IR band, water appears dark in contrast to land because the IR light only gets reflected back to the sensor from the land (Figure 3). Using this band, water and land were identified and a boolean water mask was created to mask out the land at each study site. What remained in each image were only the pixels in the nearshore environment and were then subsequently submitted into a PCA to further investigate.

The spectral standard of each pixel was investigated by first running the nearshore water pixels through a PCA. Since SAV grows in complete submersion, only WV-2's 5 visible bands were input into the PCA. The PCA was used in order to maximize the interpretability of the data in an effort to improve classification accuracy.

The ISODATA unsupervised classification is a remote sensing classification method that uses an algorithm to group all the pixels into an analyst defined number of clusters. The algorithm uses the pixel values of each pixel in the image, which in this case was derived from the two new bands created from the PCA, to create a feature space. It is in this feature space that the data are grouped into an analyst set number of clusters, by the first iteration of the algorithm. The algorithm calculates the mean of each cluster and subsequently assigns each pixel to the cluster with the closest mean. The algorithm continues to recalculate these statistics and grouping the pixels in the defined number of clusters until the max amount of iterations, which amount is analyst defined, is met or until little change occurs between iterations, this change is called the convergence threshold (Jensen 2005b).

The parameters used for the ISODATA classification of the study images were 10 classes and 15 iterations with a convergence threshold of 95%. 10 classes was determined through process of trial and error to yield the best classification of the SAV. 15 iterations provided enough iterations for the 95% convergence threshold to be reached before the maximum number of iterations was reached.

The clusters from the ISODATA output were identified by the analyst to be one of three classes; vegetated, unvegetated, and confused. Areas where pixel confusion was recognized, were masked out and reclassified using the ISODATA unsupervised classification, which is called “Cluster busting” (Jensen 2005). The final classification was imported from ERDAS Imagine to ArcMap 9.3 for accuracy assessment.

3.3 Accuracy Assessment

An accuracy assessment was performed at each study site. Because of the highly variable growth behavior of SAV throughout its annual phonological cycle, using any other reference data source aside from ground reference data collected on or near the imagery acquisition date would introduce high levels of uncertainly in the accuracy assessment. The ground reference data used were point data gathered from two sources, snorkeling quadrats and GPS recorded walking transects.

3.3.1 Quadrat Data

All quadrats were collected via snorkeling and were located only in water depths where it was deep enough for the acoustic surveying boat to navigate. The quadrat locations were randomly selected from the acoustic reports, which each report had a lat/long location. The acoustic reports came from the boat transects that had start and end points that were derived from a systematic random location selection process. In order for the acoustic survey method to obtain an adequate amount of sample points within a 300x300 m study site to detect at least a 10% change in spatial coverage of SAV it was determined by a statistical power analysis that at least 36 transects should be done. The location of the first transect was randomly located within the first 8.3 m (300 m / 36 transects) of the top of the study site and the remaining 35 transects were spaced 8.3 m apart for the rest of the width of the study site. All transects ran perpendicular in nature to the shoreline starting at the systematic random start locations and ending at the opposite side the of the study site.

Each of the quadrats used were 1x1 m and were divided up into 100 10x10 cm squares by string. A percent cover was derived from each quadrat reading by simply counting the number of squares with the presence or absence of SAV. For example, if 25 squares had SAV present then that quadrat location had a percent cover of 25%. In the accuracy assessment the coverage in percent values were not used, but rather each quadrat point location was designated as SAV or bare bottom.

3.3.2 Walking Transects

Walking transects were used to obtain reference data for the areas too shallow for the boat to navigate. GPS units used were Garmin 76 and 76s with a locational accuracy of up to 15 m. At each data point a vegetated or not vegetated distinction was made and the water depth was also recorded. The walking transects ran near parallel to the shoreline along the entire length of the study site. The starting locations of the walking transects were randomly selected in the field. The location at which a data point was collected was every 10 then 15 steps, alternating between the two step distances. The ground reference data were collected on September 18, 2010 for Jarrett Bay and on September 24, 2010 for Blounts Bay. The Jarrett Bay image was acquired on September 18, 2010 and the Blounts Bay image was on October 10, 2010.

3.3.3 Classification Accuracy Statistics

Standard confusion matrices were generated. The accuracy statistics included: user's accuracy (error of commission), producer's accuracy (error of omission), overall accuracy, and $\hat{\kappa}$ coefficient of agreement. The classification accuracy methodology was done in a way that would identify the water depth threshold where remote sensing could accurately detect SAV. Using the bathymetry layer created from the acoustics, the ground reference points were divided into groups according to water depths at every 10 cm. For each study site there were a total of 6 groups ranging from depths less than 0.5 m up to 1.0 m (< 0.5 m, 0.50 to 0.59 m, 0.60 to 0.69 m, . . . etc.). A confusion matrix as well as user's and producer's statistics and a $\hat{\kappa}$ coefficient were calculated for each group. There were a minimum of 6 points in each group. There were substantially more ground reference points in the shallow water than there were in the deeper water of the study site (Figure 4). This was simply the result of the difficulty of obtaining data in the deeper water.

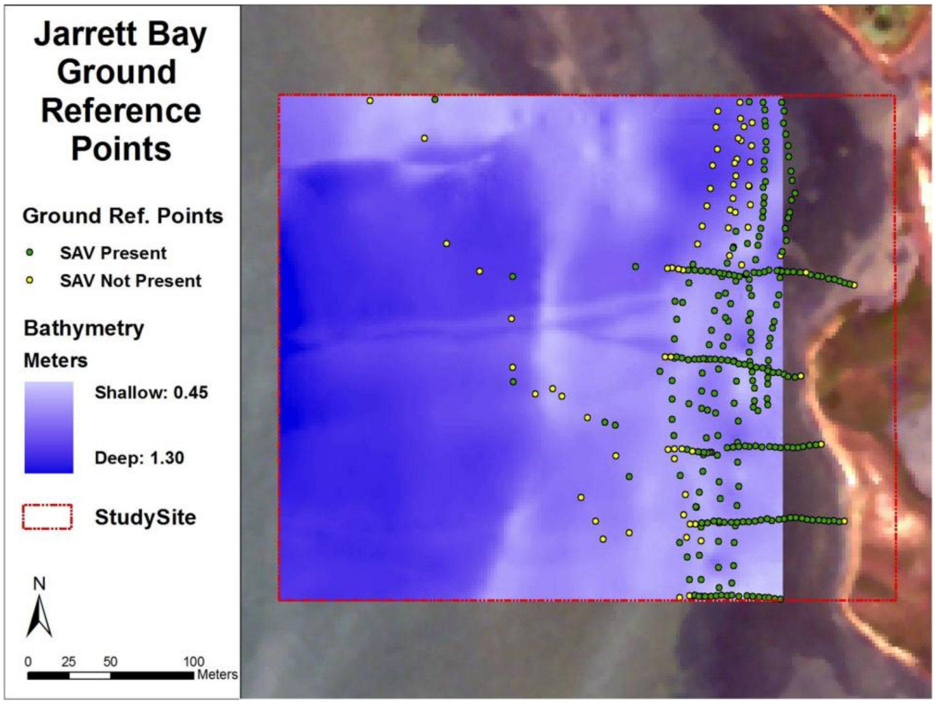
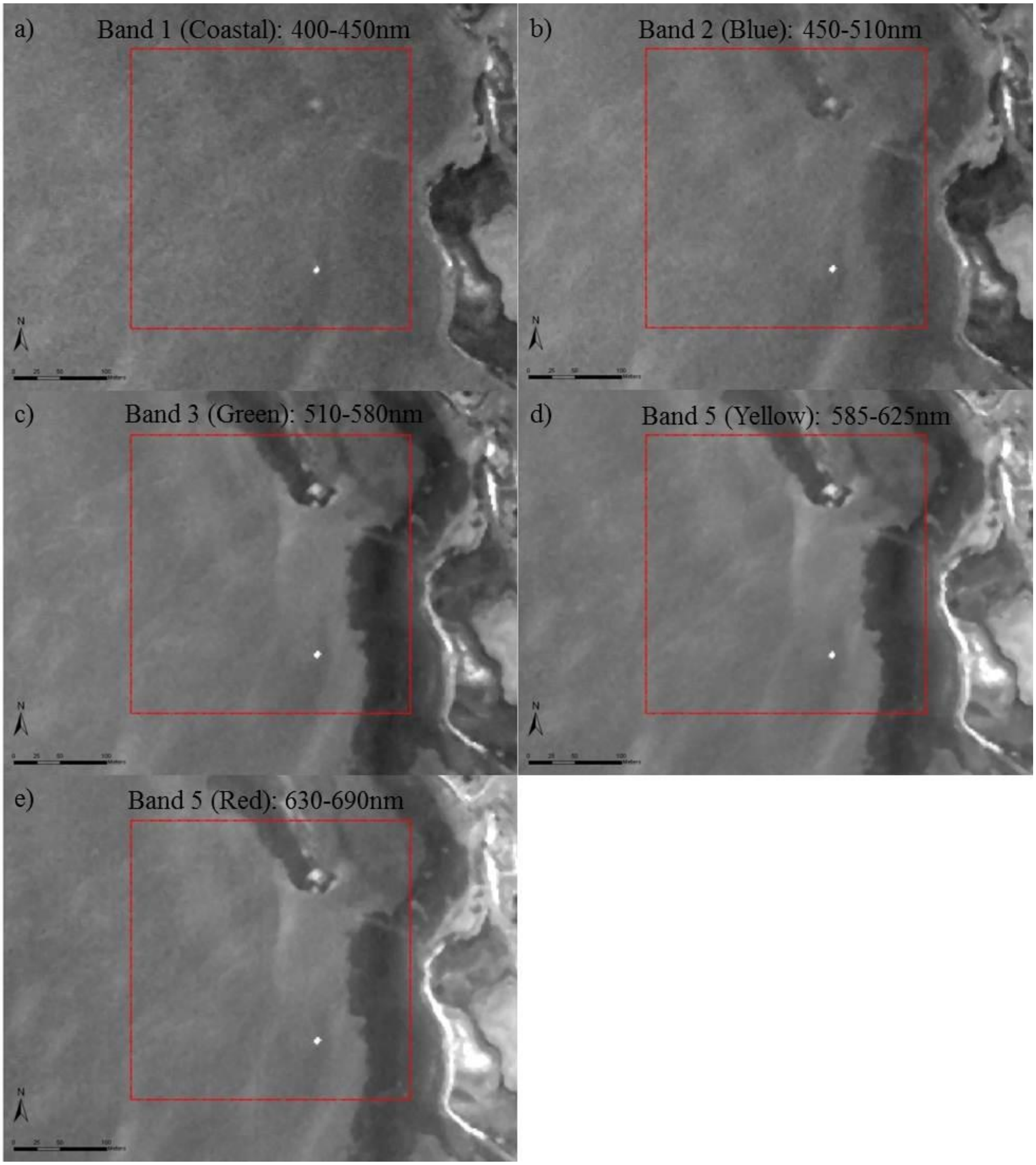


Figure 4: Map showing the depths of the ground reference points at Jarrett Bay.

SECTION 4.0: RESULTS AND DISCUSSION

4.1 Jarrett Bay

After the examining of 5 visible bands, the shorter wavelength bands (coastal and blue) showed the least contrast between SAV and bare bottom. In particular, the coastal band seemed unable to detect the SAV bed at all (Figure 5). This was surprising because the ground reference data indicated that the most shallow portion of the water column covering the SAV bed was only 20 cm and the deepest was 85 cm and yet it was unable to detect any of the benthic cover type. This may be attributed to two factors. The reflectance of short wavelengths is more susceptible to Rayleigh scattering and suspended particles that could contribute to the diffused scattering. Also, colored dissolved organic matter (CDOM) greatly absorbs the energy in the wavelength region of blue light (Biber et al. 2008). The reflectance absorption of the coastal and blue bands may have input noise into the ISODATA classification of the visible bands causing the classification to have difficulty accurately delineating the edge of SAV bed. Bands 3, 4, and 5 seemed to best define the SAV bed in the image as a result of these three bands being less susceptible to scattering from suspended particles and being absorbed by CDOM. Inputting the image through a PCA seemed to remove the noise caused by the scattering and absorption of the two shorter wavelength bands and emphasized the spectral differences of SAV and bare bottom.


a)
Band 1 (Coastal): 400-450nm
b)
Band 2 (Blue): 450-510nm
c)
Band 3 (Green): 510-580nm
d)
Band 5 (Yellow): 585-625nm
e)
Band 5 (Red): 630-690nm
N

The band combination of the WV-2 image (R: band 8, G: band 3, and B: band 1) shown in Figure 6, gives some insight into the imagery. In the water, bare bottom is a light blue color, while the SAV is the dark blue and the red in the image is land vegetation. The vegetation appears red because band 8 (NIR 2) was assigned to be displayed as red in the red, green, and blue (RGB) display composition. Because of chlorophyll, healthy vegetation will always reflect high amounts of green and NIR light and absorb blue and red light. SAV too, has chlorophyll in its biological makeup, but it grows under water, so the NIR light is absorbed by the water. This is why the SAV in the image is a dark blue not a red color.

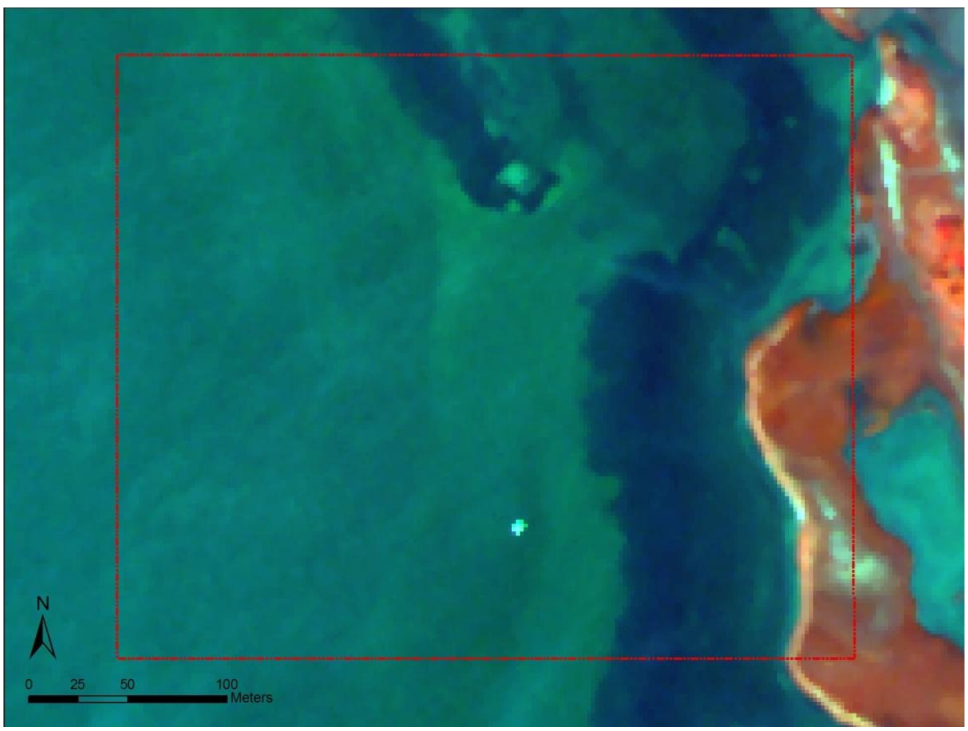


Figure 6: WV-2 image of Jarrett Bay with a RGB combination of bands 8, 3, and 1.

Only the first two (Figure 7a and b) of the five available PCA components were used because a total of 98% of the data variation were explained by components 1 and 2. The remaining three components did not provide much information (Table 4). From the eigenvector matrix, it was clear that band 3 (green) and band 4 (yellow) dominate the first component. The second component was dominated by band 3 (green) and band 5 (red) (Table 5). Through visual interpretation of Components 1 and 2 and consideration that bands 3, 4, and 5 were the leading contributors to the first two components, it was assumed Component 1 was showing variation in bottom type and Component 2 was showing variation in water depth. Further analysis is needed to verify these interpretations. Component 1

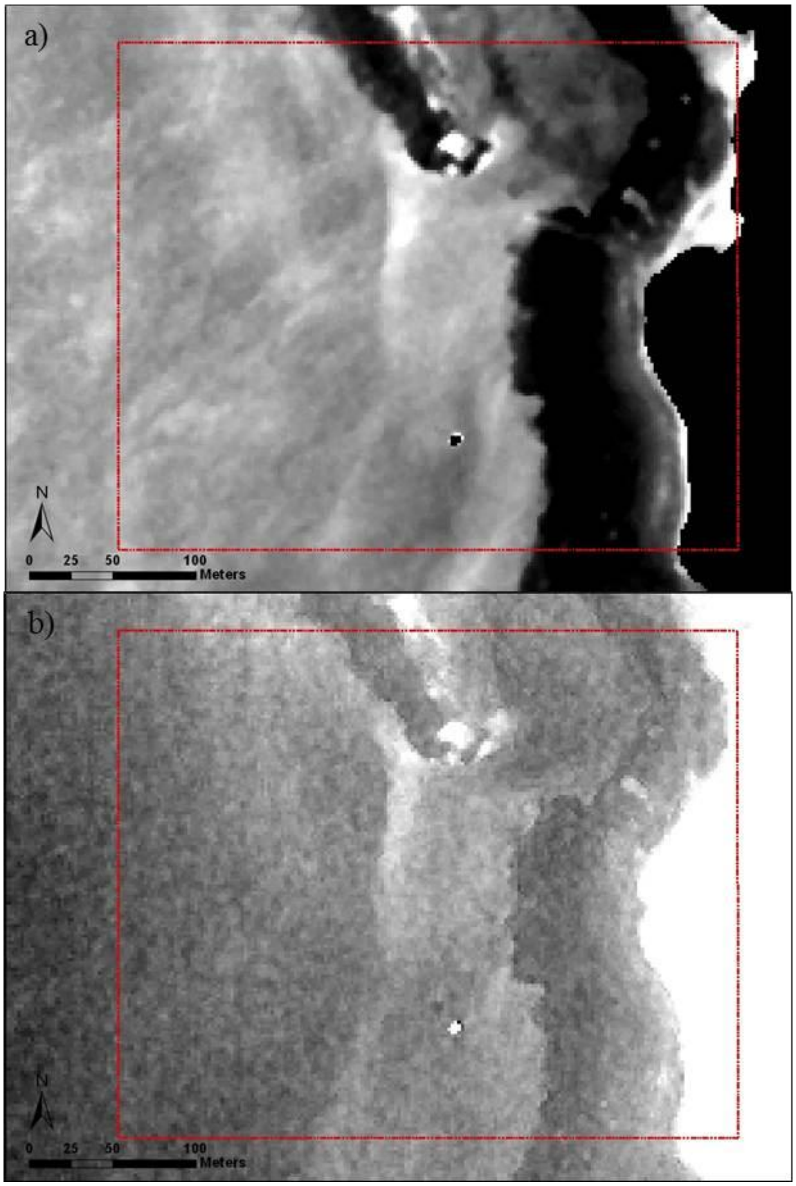


Figure 7: a) The first PCA component at the Jarrett Bay study site explaining 87.7% of the data variation.
b) The second PCA component explaining 10.3% of the variation.

and Component 2 became two "bands," that were then input into the ISODATA unsupervised classification.

PCA Component	Eigen-values	Variation Explained
1	191.12	87.7%
2	22.41	10.3%
3	2.75	1.3%
4	1.02	0.5%
5	0.59	0.3%

Table 4: Eigenvalue table for the Jarrett Bay PCA.

Eigenvector Matrix					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Band 1	0.12	-0.23	**-0.62**	0.25	**0.70**
Band 2	0.26	-0.34	**-0.61**	-0.10	**-0.66**
Band 3	**0.66**	**-0.54**	0.42	-0.25	0.18
Band 4	**0.56**	0.37	0.09	**0.71**	-0.15
Band 5	0.41	**0.63**	-0.24	**-0.59**	0.14

Table 5: Eigenvector matrix for the Jarrett Bay PCA.

Additionally, through process of trial and error with the Jarrett Bay image, it was determined that the most accurate classification resulted from inputting only the two PCA components as a two-band image into the ISODATA algorithm. The other two possible inputs were the 5 visible bands and a combination of the visible bands and 2 PCA components.

The resulting classification of the image was able to detect the SAV bed in the study site (Figure 8). The overall classification accuracy was 71.2% with an SAV producer's accuracy of 80%, a user's accuracy of 74%, and $\hat{\kappa}$ coefficient of agreement of 71.2% (Table 6). These results, at best were moderate. There were three main causes of misclassification. Dark sediment bottom type in the nearshore environment seemed to cause some false positive error by classifying bare bottom as SAV. Also, in the northeast portion of the study site there was an area that had combination of dark sediment as well as deeper water (~0.95 to 1.0 m), which too caused bare bottom to be mistakenly classified as SAV. The third cause of classification error resulted from the fact that the sensor was unable to detect small patches of SAV in the deeper turbid water. As a result of the 2x2 m spatial resolution of WV-2, it would have difficulty detecting any patches that were smaller than 1 m in diameter or a 1x1 square. Additionally, the small SAV patches that were present were in fact just that, small. Quadrat results showed very low percent coverage (<15%) for all of the locations in the deeper water .

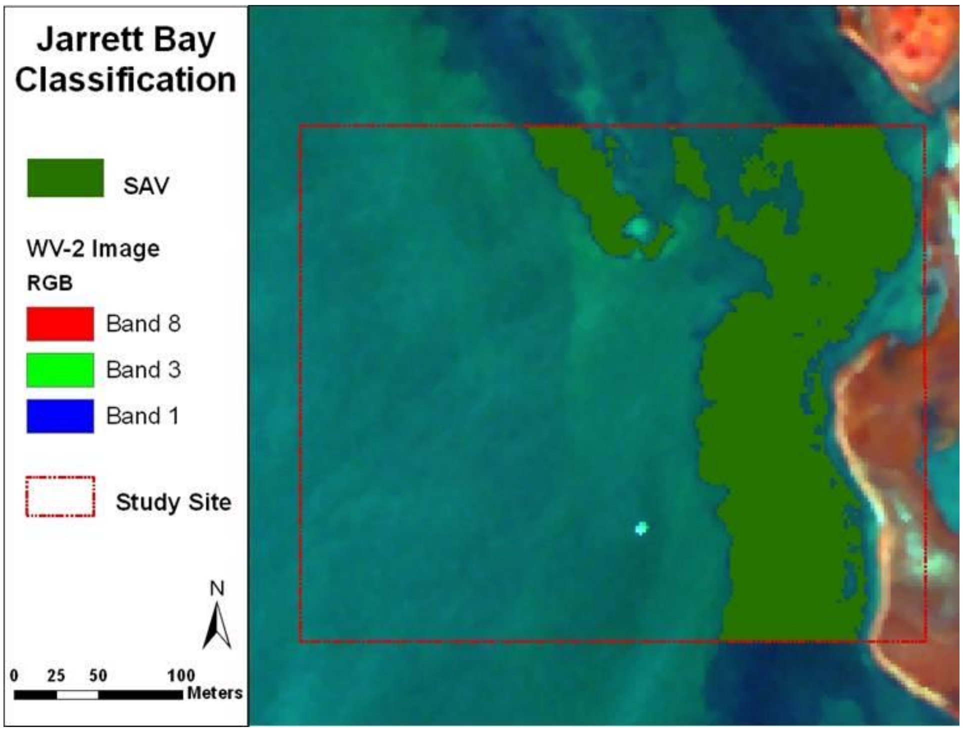


Figure 8: Map showing an overlay of classified SAV at Jarrett Bay over R= Band 8, G= Band, and B=Band 1 of the WV-2 imagery.

However, the classification was able to accurately delineate the deep and shallow edges of the dense SAV bed. It is important for the classification to be able to accurately delineate the boundaries of the bed in order to accurately quantify the spatial coverage of SAV. The SAV producer's error of 80% says that SAV can be classified correctly 80% of the time and a user's accuracy of 74% means that a pixel classified as SAV is correct 74% of the time (Table 6). A $\hat{\kappa}$ of 38.5% shows a satisfactory agreement between the classification and the ground reference data (Landis and Koch, 1977).

Jarrett Bay Overall Classification Accuracy					
		Ground Reference		# of Classified Pixels	User's Accuracy
		SAV	Bare		
Classification	SAV	**32**	11	43	**74%**
	Bare	8	**15**	23	**65%**
# of Ground Ref. Pixels		40	26	**66**	
Producer's Accuracy		**80%**	**58%**	**Overall Accuracy =**	**71.2%**
				$\hat{\kappa}$ Coefficient =	**38.5%**

Table 6: Table showing the confusion matrix and overall classification accuracy as well as the user's and producer's accuracy and $\hat{\kappa}$ Coefficient of Agreement.

4.2 Jarrett Bay Results by Depth

Breaking down classification accuracy by depth allowed for classification accuracy trends related to depth to be investigated. The four depth ranges ranging from < 0.50 m up to 0.70 - 0.79 m, had moderate to high classification accuracy results with the lowest being 73% and highest 100%. The two deepest depth ranges (0.80 - 0.89 m and 0.90 - 0.99 m) had the same classification accuracies at 36.4% and 45.5% respectively, which was considered low (Figure 9). The trend in the classification accuracy by depth shows a steep drop in accuracy from depth range 0.70 - 0.79 m to 0.80 - 0.89 m. This trend shows that in this image the water depth threshold of 0.8 m is the limit that remote sensing can accurately detect SAV if the water depth is shallower than 0.8 m. With the identification of the threshold one can determine where the boat based methods should be utilize to map the SAV. It should be noted that the 0.8 m depth threshold would vary and depend on the turbidity levels. When comparing the classification accuracies of the depth ranges below 0.8 m with the depth ranges above 0.8 m, there is a substantial difference. Within the four shallow depth ranges the classification accuracy jumped up to 86% (Table 7). The SAV producer's and user's accuracies also increased up to 84% and 100% respectively. This producer's accuracy means that with the classification scheme

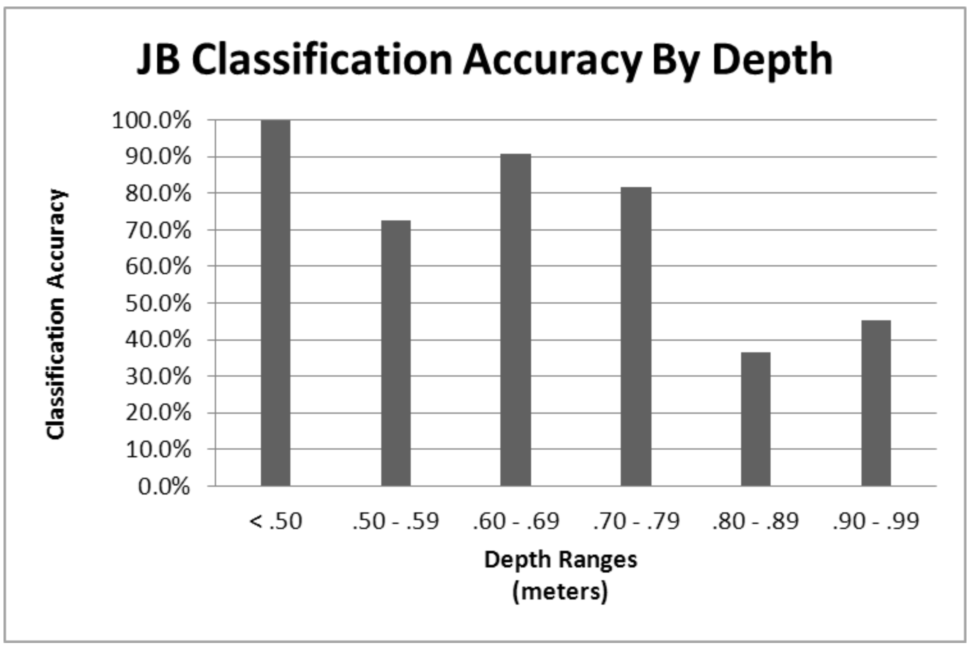


Figure 9: Classification accuracy according to water depth.

presented, SAV can be correctly classified 84% of the time in water depths shallower than 0.8 m. The user's accuracy means that SAV is correctly classified nearly 100% of the time. All values are high and further show that remote sensing can accurately identify SAV in waters shallower than 0.8 m. The user's accuracy of 50% for bare bottom, was probably attributed to the pixel confusion of dark bare bottom sediment being incorrectly classified as SAV.

Jarrett Bay Classification Accuracy SHALLOWER than 0.8 m					
		Ground Reference		# of Classified Pixels	User's Accuracy
		SAV	Bare		
Classification	SAV	**32**	0	32	**100%**
	Bare	6	**6**	12	**50%**
# of Ground Ref. Pixels		38	6	**44**	
Producer's Accuracy		**84%**	**100%**	**Accuracy =**	**86.4%**
				$\hat{\kappa}$ Coefficient =	**59.3%**

Table 7: Table showing the confusion matrix and classification accuracy as well as the user's and producer's accuracy and $\hat{\kappa}$ coefficient.

Jarrett Bay Classification Accuracy DEEPER than 0.8 m					
		Ground Reference		# of Classified Pixels	User's Accuracy
		SAV	Bare		
Classification	SAV	**0**	11	11	**0%**
	Bare	2	**9**	11	**82%**
# of Ground Ref. Pixels		1	21	**22**	
Producer's Accuracy		**0%**	**45%**	**Accuracy =**	**40.9%**
				$\hat{\kappa}$ Coefficient =	**-18.2%**

Table 8: Table showing the confusion matrix and classification accuracy as well as the user's and producer's accuracy and $\hat{\kappa}$ coefficient.

In contrast, at the two deepest depth ranges alone the classification accuracy plummeted from the overall accuracy of 73% down to 40.9% (Table 8). Both the SAV producer's and user's accuracies were 0%, which signifies the fact that as the water depth increased the ability of the sensor to detect SAV, particularly small SAV patches, significantly decreased in water depths deeper than 0.8 m. Interestingly enough, the bare bottom user's accuracy was relatively high at 82%. This shows that when a pixel is classified as bare bottom in water depths ≥ 0.8 m it was is correct 82% of the time. On the other hand, the bare bottom producer's accuracy of 45% shows that there was a high level of omission error when it came to classifying bare bottom in water deeper than 0.8 m. Therefore, the classification scheme could correctly identify bare bottom 45% of the time and 82% of the pixels classified as bare bottom were classified correctly.

4.3 Blounts Bay

Upon first inspection of the Blounts Bay image only a small patch of SAV near the south east shoreline could be visually interpreted. Also, there were shadows, cast by trees immediately adjacent to the shoreline over the water nearest to the shore (Figure 10). It was determined from ground reference data that a significant portion of SAV was present under the tree shadows. The shadows were masked out because they were too dark to distinguish SAV from bare bottom. As a result, all land, deep water, and shadow pixels were excluded. The first two PCA components explained 96.5% of the data variation (Table 9). Component 1 was primarily comprised of band 4 (yellow) and Component 2 bands 1 (coastal) and 2 (blue) (Table 10). These components differ from what was found at Jarrett Bay. The amount of variation explained by the first two components decreased and the make-up of the components changed. Component 2 was interesting because it had the same composition as Component 3 in the Jarrett Bay PCA, which were bands 1 and 2. These bands were susceptible to suspended particles and CDOM, which are elements of turbidity. Therefore, it can be also assumed that Component 2 was showing variation in water turbidity. There was little SAV present in the image, so variation in bottom type would be difficult for the sensor to detect, which more than likely contributed to the reason why the composition of the first two components differed from Jarrett Bay and why the classification had difficulty identifying the SAV in the image (Figure 11). Further analysis is needed to confirm such observations.

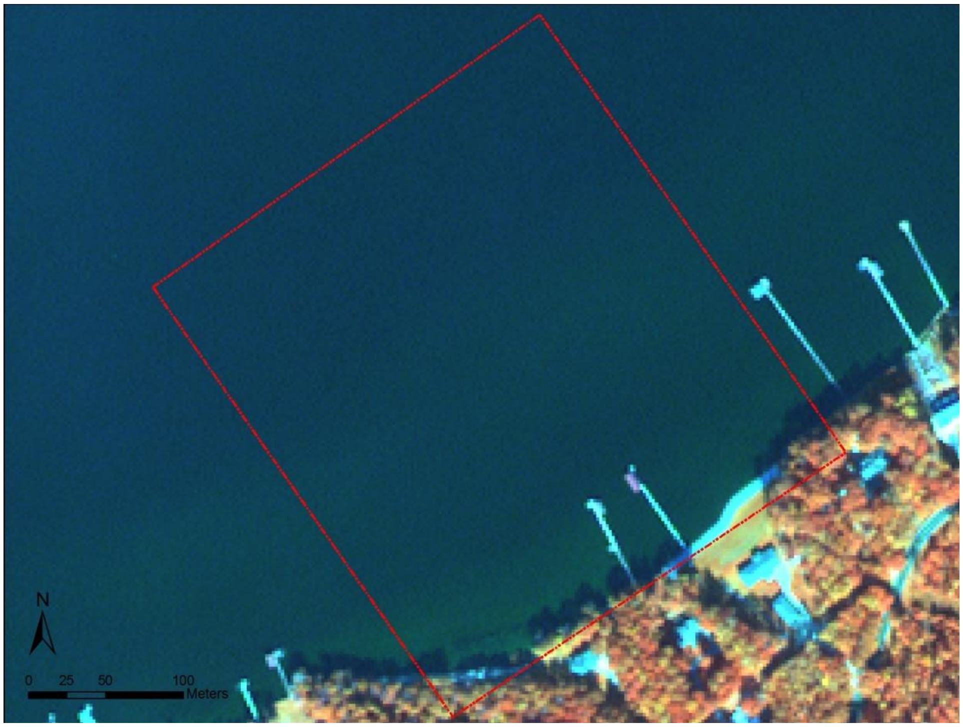


Figure 10: WV-2 image of Blounts Bay with a RGB combination of bands 8, 3, and 1.

PCA Component	Eigen-values	Variation Explained
1	46.37	81.08%
2	8.82	15.42%
3	0.96	1.68%
4	0.59	1.03%
5	0.45	0.79%

Table 9: Eigenvalue table for the Blounts Bay PCA.

Eigenvector Matrix					
	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5
Band 1	0.03	**-0.56**	0.38	0.41	**0.61**
Band 2	0.07	**-0.63**	0.02	0.22	**-0.74**
Band 3	0.42	-0.44	-0.16	**-0.76**	0.18
Band 4	**0.79**	0.31	0.49	0.13	-0.14
Band 5	0.44	0.00	**-0.77**	0.44	0.16

Table 10: Eigenvector matrix for the Blounts Bay PCA.

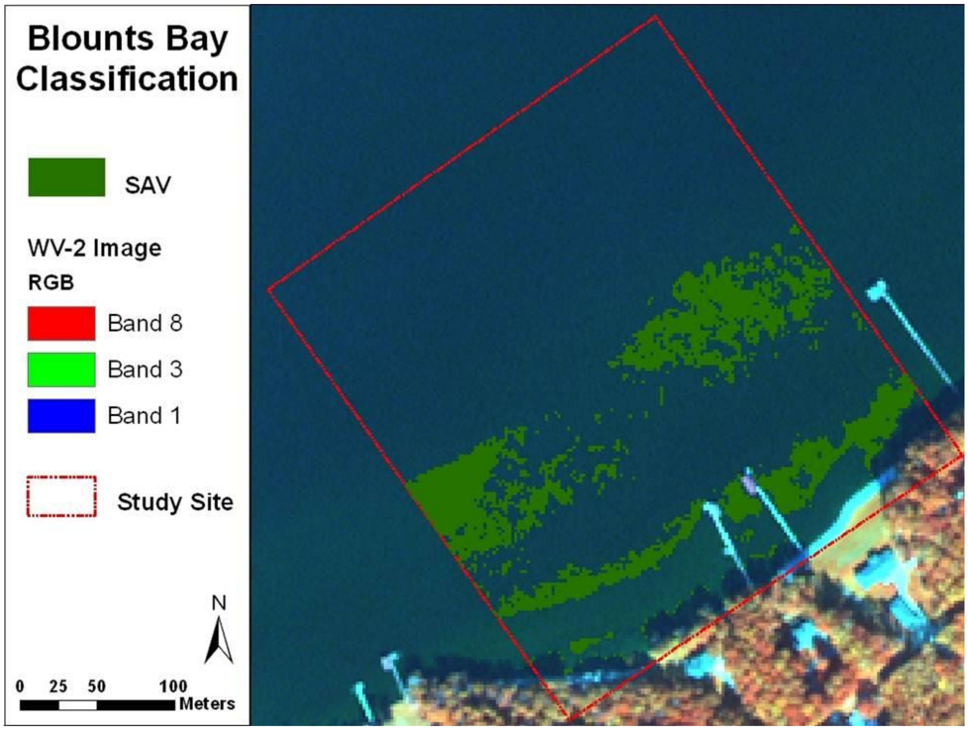


Figure 11: Map of the final classification of SAV at Blounts Bay.

Blounts Bay Overall Classification Accuracy					
		Ground Reference		# of Classified Pixels	User's Accuracy
		SAV	Bare		
Classification	SAV	**6**	1	7	**86%**
	Bare	15	**10**	25	**40%**
# of Ground Ref. Pixels		21	11	**32**	
Producer's Accuracy		**29%**	**91%**	**Overall Accuracy =**	**50.0%**
				$\hat{\kappa}$ **Coefficient =**	**15%**

Table 11: Table showing the confusion matrix and overall classification accuracy as well as the user's and producer's accuracy and $\hat{\kappa}$ coefficient.

The classification was able to detect only a section of the small SAV patch in the southeast portion of the study area (Figure 11). The portion of the SAV that was detected seemed to be the most dense section of the bed. Some water pixels that were deeper than 1 m as well as some dark sediment pixels were incorrectly classified as SAV. Overall classification accuracy was 50% with an SAV producer's accuracy of 29%, an SAV user's accuracy of 86%, and a $\hat{\kappa}$ of 15% (Table 11). These results showed that the WV-2 sensor had significant difficulty in the classification of sparsely growing SAV beds.

It should be noted that the unsatisfactory outcome in Blounts Bay classification could be caused by the time lapse between the dates when the ground reference data was collected and the image was acquired. The ground reference data was collect on September 22 and 24, 2010 and the image was acquired on October 18, 2010. The time span was at least 24 days. According to the unpublished findings of the monthly acoustic surveys there were noticeable declines in SAV coverage at Blounts Bay between monthly surveys that were taken from May to September.

4.4 Blounts Bay Results by Depth

The trend of the classification accuracy levels according to depth range showed a steep decline in accuracy as the water got deeper down to 0.8 m (Figure 12). The lowest accuracy level was in the 0.70 to 0.79 m range, with the highest accuracy level occurring at depths shallower than 0.5 m. The two deepest depth ranges had the same accuracy level of 50%. It was apparent that the classification did not produce accurate results.

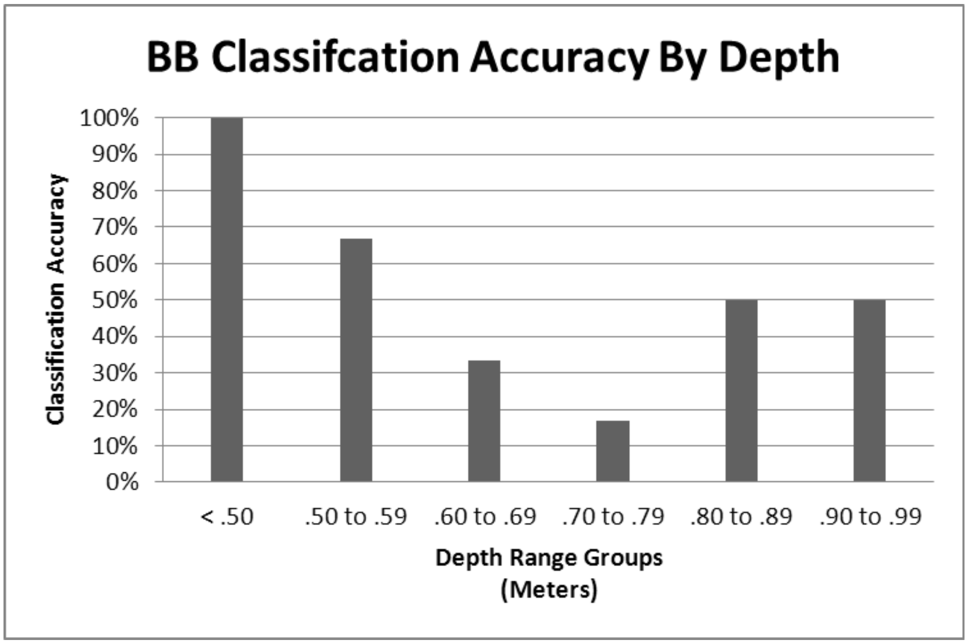


Figure 12: Classification accuracy according to water depth in Blounts Bay.

Looking only at the water depths shallower than 0.8 m, the classification accuracy actually remained at 50%. The SAV producer's and user's accuracy also fell with percentages of 9% and 50% respectively (Table 12). The $\hat{\kappa}$ coefficient dropped down to 0%. These results are

Blounts Bay Classification Accuracy SHALLOWER than 0.8 m					
		Ground Reference		# of Classified Pixels	User's Accuracy
		SAV	Bare		
Classification	SAV	**1**	1	2	**50%**
	Bare	10	**10**	20	**50%**
# of Ground Ref. Pixels		11	11	**22**	
Producer's Accuracy		**9%**	**91%**	**Overall Accuracy =**	**50%**
				$\hat{\kappa}$ Coefficient =	**0%**

Table 12: Table showing the confusion matrix and classification accuracy as well as the user's and producer's accuracy and $\hat{\kappa}$ coefficient for Blounts Bay.

opposite of what would be expected according to the findings at Jarrett Bay. Based on quadrat data, there was a big difference at two bays. At Blounts Bay, the SAV coverage was sparse at levels from 0 to 10%. This indicates that satellite remote sensing had difficulty detecting sparse SAV coverage. The classification was only able to correctly classify 1 of the 10 SAV ground reference points correctly, which resulted in a mere 9% producer's accuracy. Of the 11 bare bottom reference points the classification correctly classified 10, giving a high bare bottom producer's accuracy of 91%. Both user's accuracies were only 50%.

The classification accuracy from water depths deeper than 0.8 m remained at 50% and had a $\hat{\kappa}$ coefficient of 0%, indicating poor agreement between the classification and ground reference data (Table 13). The SAV user's accuracy was surprisingly 100%, but this level was questionable because of the error introduced by the large time lapse between image and ground reference data acquisitions.

Blounts Bay Classification Accuracy DEEPER than 0.8 m					
		Ground Reference		# of Classified Pixels	User's Accuracy
		SAV	Bare		
Classification	SAV	**5**	0	5	**100%**
	Bare	5	**0**	5	**0%**
# of Ground Ref. Pixels		10	0	**10**	
Producer's Accuracy		**50%**	**N/A**	Overall Accuracy =	**50%**
				$\hat{\kappa}$ Coefficient =	**0%**

Table 13: Table showing the confusion matrix and classification accuracy as well as the user's and producer's accuracy and $\hat{\kappa}$ coefficient for depths deeper than 0.8 m.

4.5 Sandy Point

From visual interpretation there was a pattern that could be seen in the nearshore that appeared to be a strip of brown colored water (Figure 13). This could have possibly been SAV or suspended sediment. There were high hopes for this study site because SAV growth was documented by ground reference data gathered in the beginning of the summer to be as deep as 2.5 m. On the day ground reference data was collected, continuous SAV coverage was out to 2 m with small SAV patches seen out to 2.5 m. This study site had the potential to investigate the water depth threshold of SAV detection for the WV-2 data.

Figure 13: Zoomed out Sandy Point image highlighting the brown colored pattern of water present along the nearshore

Unfortunately, this image showed one of the limitations of satellite remote sensing, which is sun glint. There was a possibility to request a reacquisition however, by the time a new image could have been acquired by WV-2, it would have been in the beginning or middle of November, which would have been long past the SAV growing season.

Despite the difficulties presented by the sun glint, the Sandy Point image was classified to see if it had any sort of utility. The classification showed similar results to what the ground reference data had shown, but the patterns of the classification indicated that the classification was questionable. It was apparent from the two PCA components that the sensor was not able to reliably detect any SAV (Figure 14). A classification of the image shows a coverage pattern that may have been consistent with the coverage (70%-100% coverage) shown from the ground reference data, but the classification wasn't the result of detected SAV. As the PCA components showed, the variability in the present in the water was dominantly caused by the sun glint not, the presence or absence of SAV coverage. Using a PCA to derive two components showed that it

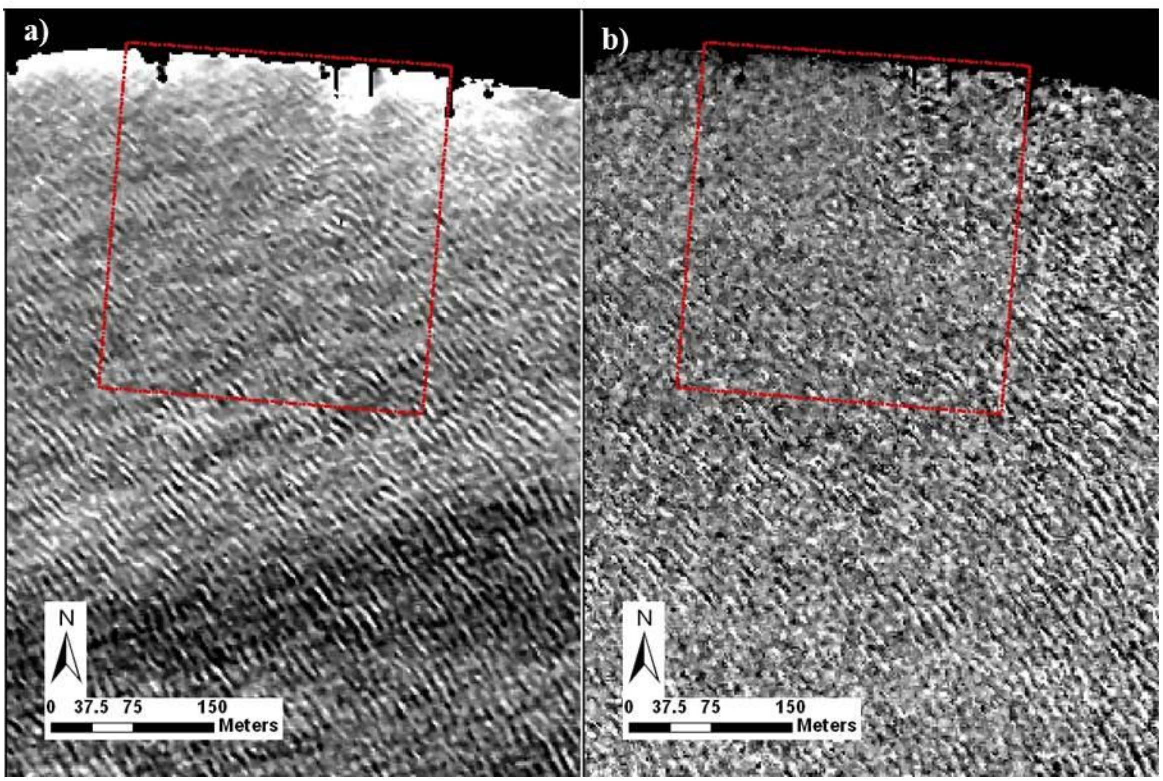


Figure 14: PCA components from the Sand Point image. Ground reference data showed nearly 100% coverage for the majority of the study site, which was undetected by the sensor and is shown by the bottom type component. a) Component 1 and b) Component 2.

has an additional purpose of allowing the remote sensing analyst to determine if an image subject to sun glint is still usable. Because the PCA was unable to detect SAV, it was determined that the brown water along the shoreline was suspended sediment stirred up by the wind generated waves.

4.6 Product Derived from Depth Accuracy Results

With the establishment from the Jarrett Bay results that remote sensing can reliably map continuous SAV in water depths shallower than 0.8 m, areas where the two boat-based methods (active acoustics and underwater video) should be employed along the North Carolina estuarine coast can be identified. Using the bathymetry data available from NOAA, the total area and percentage area of the nearshore habitat (water depths from 0.0 m to 2.0 m) was calculated for three different depth thresholds where remote sensing should be used to map the SAV. These calculations also allowed the same two metrics to be calculated for the boat-based surveying methods (Table 14). Three thresholds were used because it is assumed that with improved water turbidity conditions, WV-2 would be able to accurately detect SAV in waters deeper than 0.8 m. Depths

Area and Percentage of Nearshore Habitat Mapped by Remote Sensing or Boat-based Methods			
Depth Threshold	**0.8 m**	**1.0 m**	**1.5 m**
R.S	1533.5 km²	1761.9 km²	2214.6 km²
	58%	67%	84%
Boat-based	1108.4 km²	880.7 km²	427.9 km²
	42%	33%	16%

Table 14: Table showing the total and percentage area of nearshore habitat that should be mapped using remote sensing or boat-based methods with depth thresholds of 0.8, 1.0, and 1.5 m.

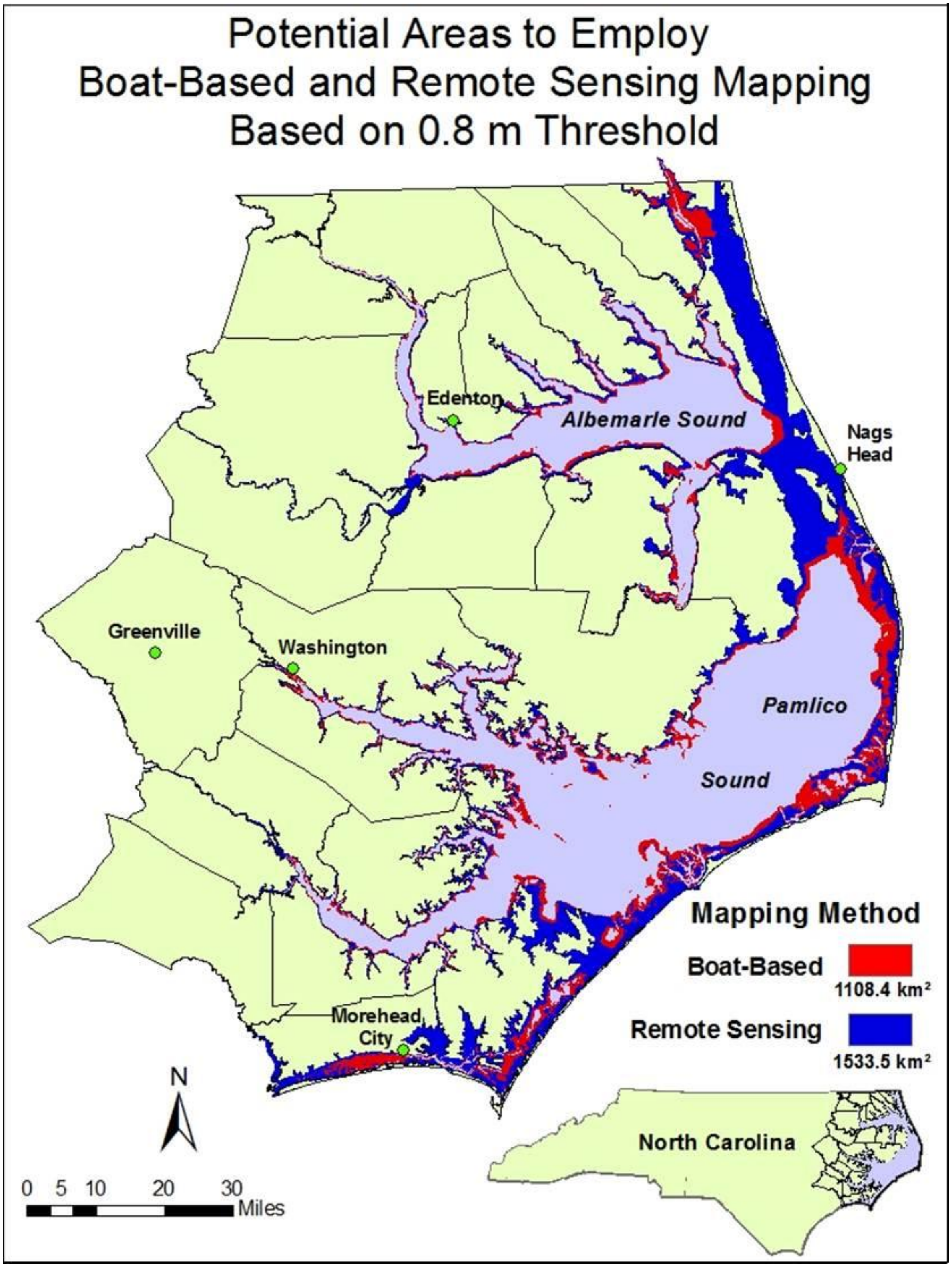


Figure 15: Map showing potential areas, according to bathymetry, where boat-based surveys and remote sensing should be used to map SAV in North Carolina estuaries.

shallower than 0.8 m were identified as areas where remote sensing should be used and depths from 0.8 m to 2.0 m were identified as areas where boat-based methods should be used to map SAV (Figure 15). Though the spatial resolution of the bathymetric data is 30x30 m, product such as this would aid the APNEP SAV Partners to identify areas where they should focus their boat-based and remote sensing efforts.

SECTION 5.0: CONCLUSIONS AND REMARKS

Using WV-2 data, one could map SAV in North Carolina estuaries. The Jarrett Bay image showcased this study. The edges of the SAV bed were accurately delineated with the deep edge being in approximately 0.8 m of water. Dark sediment located in the nearshore habitat at Jarrett Bay caused pixel confusion with the classification or misclassified of SAV, which resulted in an over classification of the spatial coverage of SAV.

Study at the Blounts Bay showed that sparse SAV coverage (0%-10%) was not able to accurately be delineated. Additionally, tree shadows covered the majority of the SAV that was present at the study site. If the SAV bed were uncovered by the shadows, the sparse SAV bed might have been detected because the SAV would have introduced more spectral variability in the image, which could have been highlighted by the PCA.

The upper end of the SAV coverage (up to 100%) was not able to be assessed due to sun glint in the Sand Point image. Sun glint was an example of one of the limitations in the use remotely sensed data since the glint severely affected the light penetrating into the water column.

Patches of SAV smaller than the 1x1 m spatial resolution of WV-2 are not able to be detected by the sensor, which was shown in both the Blounts Bay and Jarrett Bay classifications. This limitation can be off-set by the use of the two other boat based SAV surveying methods of the APNEP Partners in water depths deeper than 0.8 m because the spatial resolutions of the data obtainable by both methods can be much finer than 1x1 m.

According to the environmental conditions present when the WV-2 images were acquired, the threshold of water depth where WV-2 data can accurately detect SAV was determined at 0.8 m. For the purposes of the APNEP SAV Partners mapping project, boat-based methods should be employed in the water depths deeper than 0.8 m. However, one should anticipate that the threshold could increase with an improved water clarity. Further analysis is needed to quantify the depth threshold as a function of remote sensing and water turbidity data in the accurate mapping of SAV.

The coastal band is one of the unique characteristics of WV-2 when compared to other multi-spectral satellite-borne or airborne sensors. Unfortunately, as a result of the coastal band being severely impacted by the scattering from the suspended sediment in the water column and/or CDOM absorption, other multi-spectral sensors with high spatial resolution (but without the coastal band) can be used to map the SAV in North Carolina. This may result in more economical imagery acquisition options.

SECTION 6.0: REFERENCES

Beck, M. W., Heck, K. L., Jr., Able, K. W., Childers, D. L., Eggleston, D. B., Gillanders, B. M., Halpern, B. S., Hays, C. G., Hoshino, K., Minello, T. J., Orth, R. J., Sheridan, P. F., & Weinstein, M. P. (2003). The role of nearshore ecosystems as fish and shellfish nurseries. Washington, D.C: Ecological Society of America, 12 p.

Biber, P. D., C.L. Gallegos, and W.J. Kenworthy. (2008). Calibration of a bio-optical model in the North River, North Carolina (Albemarle-Pamlico Sound): a tool to evaluate water quality impacts on seagrass. Estuaries and Coasts: J CERF 31: 177-191.

Blaylock, R.A. (1993). Distribution and Abundance of the Cownose Ray, Rhinoptera-Bonasus, in Lower Chesapeake Bay. *Estuaries*, 16: 2, 255-263.

Carpenter, D., Kenworthy, W.J., Luczkovich, J.J., Eggleston, D.B., and Plaia, G.R. (2009). Development of a Performance-Based Submerged Aquatic Vegetation Monitoring and Outreach Program for North Carolina. Grant from the North Carolina Coastal Recreational Fisheries License Fund to the Albemarle-Pamlico National Estuary Program, Raleigh, NC.

Carroway, R.J., and L.J. Priddy. (1983). Mapping of submerged grass beds in Core and Bogue Sounds, Cartaret County, North Carolina, by conventional aerial photography. CEIP Report No. 20, 88p.

Chauvaud, S., Bouchon, C., & Manière, R. (1998). Remote sensing techniques adapted to high resolution mapping of tropical coastal marine ecosystems (coral reefs, seagrass beds and mangrove). *International Journal of Remote Sensing*, 19, 3625−3639.

Costanza, R., d'Arge, R., De Groot, R., Fraber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R.V., Paruelo, J., Raskin, R.G., Sutton, P. & Van den Belt, M. (1997) The value of the world's ecosystem services and natural capital. *Nature,* 387, 253–60.

Davis, G.L. and Brinson, (1990). A Survey of Submersed Aquatic Vegetation of the Currituck Sound and the Western Albemarle-Pamlico Estuarine System. Albemarle-Pamlico Estuarine Study Report 89-10. East Carolina University, Greenville, NC., 137 p.

Deaton, A.S., W.S. Chappell, K. Hart, J. O'Neal, B. Boutin. (2010). North Carolina Coastal Habitat Protection Plan. North Carolina Department of Environment and Natural Resources. Division of Marine Fisheries, NC. 639 pp.

Dennison, W.C., Orth, R.J., Moore, K.A., Stevenson, J.C., Carter, V., Kollar, S., Bergstrom, P.W., & Batiuk, R.A. (1993). Assessing water quality with submerged aquatic vegetation. *BioScience,* 43(2), 86-94.

Duarte, C. M. (1991). Seagrass depth limits. *Aquatic Botany*, 40, 363-377.

Duarte, C. M. (2002). The future of seagrass meadows. *Environmental Conservation,* 29, 192−206.

Ferguson, R.L., Korfmacher, K. (1997). Remote sensing and GIS analysis of seagrass meadows in North Carolina, USA. *Aquatic Botany*, 28, 241-258.

Ferguson, R. L., Wood, L.L., & Graham, D.B. (1993). Monitoring spatial change in seagrass habitat with aerial photography. *Photogrammetric Engineering & Remote Sensing,*59(6), 1033-1038.

Ferguson, R. L. and Wood, L.L. (1994). Rooted vascular aquatic beds in the Albemarle-Pamlico estuarine system. NMFS, NOAA, Beaufort, NC, Project No. 94-02, 103 p.

Fletcher, R.S., Pulich, W., & Hardegree, B. (2009). A semiautomated approach for monitoring landscape changes in Texas seagrass beds from aerial photography. *Journal of Coastal Research*, 25(2), 500-506.

Fonseca, M.S. and Bell, S.S. (1998). Influence of physical setting on seagrass landscapes near Beaufort, North Carolina, USA. *Marine Ecology Progress Series*, 171, 109-121.

Hartog, C. den and Kuo, J. (2006). Taxonomy and biogeography of seagrasses. In A.W. D. Larkum, R. J. Orth, & C.M. Duarte (Eds.), Seagrasses: Biology, ecology and conservation (pp. 503−536). Dordrecht (The Netherlands): Springer.

Jackson, J. B. C., M. Kirby, W.H. Berger, K.A. Bjorndal, L.W. Botsford, B.J. Bourque, R.H. Bradbury, R. Cooke, J. Erlandson, J.A. Estes, T.P. Hughes, S. Kidwell, C.B. Lange, H.S. Lenihan, J.M. Pandolfi, C.H. Peterson, R.S. Steneck, M.J. Tegner, and R.R. Warner. (2001). Historical overfishing and the recent collapse of coastal ecosystems. *Science* 293, 629-638.

Jensen, J.R. (2005). Thematic Map Accuracy Assessment. In Introductory Digital Image Processing: A Remote Sensing Perspective (pp. 495-415). Prentice Hall Inc., New Jersey.

Jensen, J.R. (2005b). Thematic Information Extraction: Pattern Recognition. In Introductory Digital Image Processing: A Remote Sensing Perspective (pp. 383-389). Prentice Hall Inc., New Jersey.

Kenworthy, J.W., & Fonseca, M.S. (1996). Light requirements of seagrasses Halodule wrightii and Syringodium filiforme derived from the relationship between diffuse light attenuation and maximum depth distribution. Coastal and Estuarine Research Federation: *Estuaries*, 19: 3, 740-750.

Khan, M.A., Fadlallah, Y.H., & Al-Hinai, K.G. (1992). Thematic mapping of subtidal coastal habitats in the western Arabian Gulf using Landsat TM data - Abu Ali Bay, Saudi Arabia. *International Journal of Remote Sensing*, 13, 605-614.

Landis, J.R. & Koch, G.G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33: 1, 159-174.

Luczkovich, J.,Wagner, T., Michalek, J., & Stoffle, R. (1993). Discrimination of coral reefs, seagrass meadows, and sand bottom types from space: A Dominican Republic case study. *Photogrammetric Engineering and Remote Sensing*, 59, 385−389.

Lyons, M., Phinn, S., & Roelfsema, C. (2011). Intergrating Quickbird multi-spectral satellite and field data: Mapping bathymetry, seagrass cover, seagrass species and change in Moreton Bay, Austrailia in 2004 and 2007. Remote Sensing, 3, 42-64.

Moore, K. (2000). Sediment impacts on submerged aquatic vegetation. In The impacts of Susquehanna sediments on the Chesapeake Bay, Chesapeake Bay Program Scientific and Technical Advisory Committee Workshop Report, March (Elkridge, MD).

Mumby, P. J., & Edwards, A. J. (2002). Mapping marine environments with IKONOS imagery: Enhanced spatial resolution can deliver greater thematic accuracy. *Remote Sensing of Environment*, 82, 248−257.

Mumby, P. J., Green, E. P., Edwards, A. J., & Clark, C. D. (1999). The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. *Journal of Environmental Management*, 55, 157−166.

NCDMF (North Carolina Division of Marine Fisheries) Habitat Protection Section. (2009). Inventory of SAV Maps and Survey Work in Coastal North Carolina (1981-2008). For the Albemarle-Pamlico National Estuary Program Submerged Aquatic Vegetation (SAV) Mapping Partnership. Morehead City, NC

NCMFC (North Carolina Marine Fisheries Commision). (2009). North Carolina Rules for Coastal Fishing Waters. Division of Marine Fisheries, Morehead City, NC., 5 p.

Orth, R. J., Carruthers, T. J. B., Dennison, W. C., Duarte, C.M., Fourqurean, J.W., Heck, K. L. Jr., Hughes, A. R., Kendrick, G. A., Kenworthy, W. J., Olyarnik, S., Short, F. T., Waycott, M., & Williams, S. L. (2006). A global crisis for seagrass ecosystems. *Bioscience*, 56, 987–996.

Orth, R.J. & Moore, K.A. (1983). Chesapeake Bay: An unprecedented decline in submerged aquatic vegetation. *American Association for the Advancement of Science*, 222: 4619, 51-53.

Orth, R.J., Wilcox, D.J., Whiting, J.R., Nagey, L.S., Owens, A.L., Kenne, A.K. (2008). 2008 Distribution of Submerged Aquatic Vegetation in Chesapeake Bay and Coastal Bays. Special Scientific Report #149. Virginia Institute of Marine Science College of William and Mary. Gloucester Point, VA.

Preen, A.R., W.J. Lee, and R.G. Coles. (1995). Flood and cyclone related loss, and partial recovery, of more than 1000 km^2 of seagrass in Hervey Bay, Queensland, Australia. *Aquatic Botany* 52: 3-17.

SAFMC (South Atlantic Fisheries Management Council). (1998). Final habitat plan for the South Atlantic region: Essential Fish Habitat requirements for fishery management plans of the South Atlantic Fishery Management Council. SAFMC, Charleston, SC.

Short, F. T., L.K. Muehlstein, and D. Porter . (1987). Eelgrass wasting disease: cause and recurrence of a marine epidemic. *Biological Bulletin*, 173: 557-562.

Smith, K. (1998). A summary of limited vessel entry zones for managed seagrass protection in Florida. Florida Department of Environmental Protection, St. Petersburg, Fl, 30p.

Steel, J. (1991). Albemarle-Pamlico Estuarine System, Technical Analysis of Status and Trends . DENR, Raleigh, NC, APES Report No. 90-01.

Street, M.W., A.S. Deaton, W.S. Chappell, and P.D. Mooreside. (2005). North Carolina Coastal Habitat Protection Plan. North Carolina Department of Environment and Natural Resources, Division of Marine Fisheries, Morehead City, NC. 656 p.

Su, H., Karna, D., Fraim, E., Fitzgerald, M., Dominguez, R., Myers, J.S., Coffland, B., Handley, L.R., and Mace, T. (2006). Evaluation of Eelgrass beds mapping using a high-resolution airborne multispectral scanner. *Photogrammetric Engineering & Remote Sensing*, 72: 7, 789-797.

Swain, P.H., & Davis,

Thayer, G. W., Kenworthy, J.W., and Fonseca, M.S. (1984). The ecology of eelgrass meadows of the Atlantic coast: a community profile. U.S. Fish and Wildlife Service, FWS/OBS-84/02, 147p.

User Guide, DTX Echosounder and Visual Acquisition 5.0, BioSonics, Inc. 4027 Leary Way, NW Seattle,WA, USA. Biosonicsinc.com

User Guide, EcoSAV1, BioSonics, Inc. 4027 Leary Way, NW Seattle, WA, USA. Biosonicsinc.com

User Guide, GPS 76, GARMIN International Inc. 1200 East 151st Street, Olathe, KA 66062 USA. Garmin.com

Wabnitz, C.C, Andréfouët, S., Torres-Pulliza, D., Müller-Karger, F.E., Kramer, P.A. (2008). Regional-scale seagrass habitat mapping in the Wider Caribbean region using Landsat sensors: Applications to conservation and ecology. *Remote Sensing of Environment*, 112 : 3455-3467.

Waycott, M., C. M. Duarte, T. J. B. Carruthers, R. J. Orth, W. C. Dennison, S. Olyarnik, A. Calladine, J. W. Fourqurean, K. L. Heck, Jr., A. R. Hughes, G. A. Kendrick, W. J. Kenworthy, F. T. Short and S. L. Williams. (2009). Accelerating loss of seagrasses across the globe threatens coastal ecosystems. PNAS, 106, 12377-12381.

Wolter, P.T. , Johnston, C.A. and Niemi, G.J. (2005). Mapping submergent aquatic vegetation in the US Great Lakes using Quickbird satellite data. *International Journal of remote Sensing*, 26: 23, 5255-5274.

Zimmerman, R.C. and Dekker, A.G. (2006). Aquatic Optics: basic concepts for understanding how light affects seagrasses and makes them measurable from space. In A.W. D. Larkum, R. J. Orth, & C.M. Duarte (Eds.), Seagrasses: Biology, ecology and conservation (pp. 503−536). Dordrecht (The Netherlands): Springer.