SUBMERGED AQUATIC VEGETATION IN A LOW-VISIBILITY LOW-SALINITY ESTUARY IN NORTH CAROLINA: IDENTIFYING TEMPORAL AND SPATIAL DISTRIBUTIONS BY SONAR AND LOCAL ECOLOGICAL KNOWLEDGE

by

Hilde Speight

May, 2020

Director of Dissertation: David C. Griffith, Ph.D.

Major Department: Department of Coastal Studies

The rapid loss of Submerged Aquatic Vegetation (SAV) across the globe has prompted state and federal agencies to conduct SAV inventories and develop monitoring programs, which are vital to the conservation and management of ecosystems. Due to advances in optical remote sensing technologies, the distribution and status of SAV in higher salinity, less turbid regions have been better documented than in turbid, low-salinity waters. Hence, much less is known about the status and trends of low-salinity SAV. The objectives of this dissertation were to document SAV abundance, distribution, and temporal variation in Albemarle Sound (AS), so scientists and managers can detect SAV changes through time and develop adequate management strategies. In 2014, I sampled the AS, North Carolina shoreline utilizing a single-beam sonar system. The AS rapid assessment survey (RAS), guided me to identify three large SAV beds (>10 km in length) and smaller intermediate size beds (<10 km in length) throughout the Sound, most beds shallower than 2 m. The initial RAS allowed me to establish 10 permanent sentinel sites (SS) in the Sound. The purpose of establishing these sites was to examine SAV's

spatial and temporal variation at regional (sound-wide) and local (site) scales at different depths, and to examine intra-annual variation of SAV to determine the optimal SAV sampling time. I sampled the SS for two consecutive years (2015, 2016), in the spring and fall each year. SAV abundance in AS was highly asynchronous sound-wide and by site.

The biological surveys were complemented by a social science study that utilized Local Ecological Knowledge (LEK) to study SAV stakeholders' perception about SAV and to assess their historical SAV distribution knowledge in western AS. Often, biological surveys do not go far back in time, so historical information (e.g., social surveys, interviews with fishers) can help expand our habitat knowledge beyond data collected during traditional surveys. I carried out open-ended interviews and written surveys with coastal residents, commercial fishers, and fisheries managers. The three groups had unique perspectives about SAV's ecological value and the effect of development on SAV. The LEK historical SAV distribution closely agreed with biological distribution data.

SUBMERGED AQUATIC VEGETATION IN A LOW-VISIBILITY LOW-SALINITY ESTUARY IN NORTH CAROLINA: IDENTIFYING TEMPORAL AND SPATIAL DISTRIBUTIONS BY SONAR AND LOCAL ECOLOGICAL KNOWLEDGE

A Dissertation

Presented to the Faculty of the Department of Coastal Studies

East Carolina University

In Partial Fulfillment of the Requirements for the Degree

Doctor of Philosophy in Coastal Resources Management

by

Hilde Speight

May, 2020

SUBMERGED AQUATIC VEGETATION IN A LOW-VISIBILITY LOW-SALINITY ESTUARY IN NORTH CAROLINA: IDENTIFYING TEMPORAL AND SPATIAL DISTRIBUTIONS BY SONAR AND LOCAL ECOLOGICAL KNOWLEDGE

by

Hilde Speight

APPROVED BY:

DIRECTOR OF
DISSERTATION: ____
David C. Griffith, Ph.D.

COMMITTEE MEMBER: ____
Thomas R. Allen, Ph.D.

COMMITTEE MEMBER: ____
Rachel K. Gittman, Ph.D.

COMMITTEE MEMBER: ____
W. Judson Kenworthy, Ph.D.

COMMITTEE MEMBER: ____
Enrique Reyes, Ph.D.

DIRECTOR OF THE
COASTAL RESOURCES
MANAGEMENT PROGRAM: _____________________________________
Siddhartha Mitra, Ph.D.

DEAN OF THE
GRADUATE SCHOOL: ____
Paul J. Gemperline, Ph.D.

ACKNOWLEDGEMENTS

I would not have been able to complete this paper without the support of the following:

My Lord Jesus Christ, I thank you for making the impossible possible. I also thank you for making me a steward of nature and providing me with the wisdom and strength to accomplish this project. Thanks to Him when I am weak then I am strong (2 Corinthians 12:10).

My husband, your support, love, and patience helped me reach the finish line. I am thankful for your company in many long drives, and for the time you spent with our beloved son, as I worked to complete this project. Thank you for reminding me to put my faith in God.

Family and friends, your prayers and support cannot be forgotten. They were an encouragement, and they brought motivation in the toughest of times. Also, I thank my mom and sisters for helping me in the field and sort through field samples.

My advisor, Dr. David Griffith, I am so grateful for the support and encouragement you gave me through the years. Thank you for opening my eyes to the importance of social science and inter-disciplinary studies. It was a joy to learn from you about social science field work.

Dr. Judson Kenworthy, thank so much for your patience and guidance. It was your commitment to this project that pushed me to the end, without your support this manuscript would not have been possible. You are a mentor to me, and you taught me how to be a better researcher and writer. Your dedication and passion for nature is admirable. Thank you for always reminding me that this manuscript was of impact to the state of North Carolina and other low-visibility coastal systems.

Dr. Rachel Gittman, I am in debt to you for making the completion of this project possible. I am grateful for the time you spent reviewing the manuscript, providing input, and communicating with me. I have learned so much from you. I also want to thank Dr. Tom Allen for his readiness to help and broadening my research horizons; you always inspired me with new ideas. I thank Dr. Enrique Reyes for his advice and feedback. Thank you for sharing your knowledge with me and giving me useful recommendations. I would also like to thank Dr. Luczkovich for getting me started in this adventure and giving me many of the basis for this work.

Albemarle-Pamlico National Estuary Partnership (APNEP) for helping fund this project and providing volunteers to help with the work. Thanks to Dan Crane, we spent many field days in inclement weather, getting stuck, and getting lost. Yet, you were always ready to work and "macgyvered" us out of trouble. Special thanks to the many volunteers that came out to the field and to the lab: Dan Craine, Laura Bishop, Tyler Peacock, Dr. Cecilia Krahforst, Henry Raab, Tommy Davis, Davis Mitchell, Hannah Ferry, Michael Isaak, Marygrace Rowe, and many others. Thank you Dr. Hui Bian for your guidance on statistical analysis.

I would like to thank the Department of Coastal Studies at ECU and Dr. Siddhartha Mitra and Dr. Hans Vogelsong, former and current directors of the Coastal Resources Management Ph.D. Program, for facilitating my research and providing funding to complete this research. Dr. Mitra thank you for making this graduate program a success and for your unwavering support.

Finally, I would like to thank the people of Edenton, Columbia, and other regions of the Albemarle Sound, NC that helped make this project possible. To everyone, sincere thanks and gratitude.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

APES	Albemarle-Pamlico Estuarine System	24
APNEP	Albemarle-Pamlico National Estuary Partnership	3
AS	Albemarle Sound	3
AVP	Absent Verified Percentage	76
CDOM	Colored Dissolved Organic Matter	3
Chl	Chlorophyll	39
CHPP	Coastal Habitat Protection Plan	4
EFH	Essential Fish Habitat	1
GDOP	Geometric Dilution of Precision	31
GEE	Generalized Estimating Equations	78
GLM	Generalized Linear Mixed Models	78
LEK	Local Ecological Knowledge	10
LMEM	Linear Mixed Effects Models	77
MEL	Maximum Extent Layer	33
NCDEQ	North Carolina Department of Environmental Quality	1
NCDMF	North Carolina Division of Marine Fisheries	34
NCDP	Nutrient Criteria Development Plan	42
PVP	Present Verified Percentage	74
RAS	Rapid Assessment Survey	30
SAV	Submerged Aquatic Vegetation	1

SAVEWS	Submersed Aquatic Vegetation Early Warning System	27
SEK	Scientific Ecological Knowledge	10
SS	Sentinel sites	35

INTRODUCTION

Background

Submerged Aquatic Vegetation (SAV) are rooted angiosperms and are considered valuable ecosystems that provide habitat for invertebrates and fish (Rozas and Odum 1988; Hitch et al. 2011; Mormul et al. 2011). SAV can also help reduce shoreline erosion, improve water quality, connect various habitats (Barbier et al. 2011; Orth et al. 2017), and sequester carbon (Fourqurean et al. 2012). Furthermore, SAV are both foundational species and indicator species (Lirman et al. 2008; Orth et al. 2017). Unfortunately, this habitat has been under threat due to increasing human population growth in coastal areas across the world. Human activity has a direct and indirect impact on SAV through upland development, dredging, water quality degradation, propeller scaring, and increased sedimentation (Orth et al. 2006). It is estimated that since 1980, marine SAV have been disappearing globally at a rate of 110 km^2 every year (Waycott et al. 2009). Evidence suggests that SAV in the Chesapeake Bay, likely one of the most studied SAV resources in the world, has declined (Orth et al. 2010a), as well as other areas in the North Atlantic, like in Massachusetts (Costello and Kenworthy 2011). North Carolina (NC) anecdotal reports indicate a 50% SAV loss on the mainland side of the coastal sounds of the Albemarle and Pamlico sounds (Moorman et al. 2014; NCDEQ 2016). The global trend in SAV decline, coupled with a growing understanding of their ecological value, have prompted scientists and managers to be more interested in monitoring and managing this resource. As an effort to protect valuable coastal ecosystems, from the negative impacts of human activity, managers in the United Sates (US) have assigned SAV and other habitats the status of Essential Fish Habitat (EFH). Through the Magnuson–Stevens Fishery Conservation and Management

Act, SAV have become a habitat of high management priority to various federal and state agencies. In NC, SAV are of great interest, as they are not only considered EFH, they are also one of the six critical coastal habitats in the state (NCDEQ 2016).

SAV inventory programs provide management agencies the necessary information to determine the status and trends of this critical resource in order to develop management strategies. The Chesapeake Bay Program is an exemplary case study, where after several large-scale SAV loss events, states instituted an SAV monitoring program in the 1970s (Moore et al. 2009). Through this program, management agencies have been able to identify some of the threats that SAV faced and assessed its status and trends. However, many coastal regions still need to establish routine monitoring programs, particularly in low-salinity estuaries, where estuaries tend to be more turbid and SAV are more ephemeral, making monitoring more challenging.

SAV species composition in coastal areas shifts along a salinity gradient (Orth et al. 2010b; Orth et al. 2017). Estuaries, like the Chesapeake Bay, can be stratified into different salinity regimes, known as the Venice system of classification of marine waters (Oertli 1964), where three zones are classified as: polyhaline (18-25 psu); mesohaline (5-18 psu); and oligohaline (0.5-5 psu). Each of these zones is characterized by a unique SAV species composition. Other estuaries, like in NC, show a similar pattern. NC has higher salinity SAV, more commonly referred to as seagrasses, with both temperate and tropical species. Most of the documentation for the abundance and distribution of SAV in NC comes from synoptic aerial surveys; however, these surveys have been restricted to the relatively higher salinity regions with good water visibility (NCDEQ 2016; Carpenter 2017). Low-visibility waters in NC tend to occur in oligohaline and mesohaline areas of estuaries where freshwater delivery, colored dissolved organic matter (CDOM) and sediments, as well as wind driven sediment resuspension limit water transparency (Copeland et al. 1984). Hence, estuarine areas of low-visibility have been routinely under-sampled in NC and in many other low-salinity estuarine regions.

The largest and densest cover of high salinity SAV meadows documented in NC occur on the shallow back barrier shelves in the eastern margins of Albemarle, Pamlico, Core, Back, and Bogue Sounds with sparse cover along the inland shores of the estuarine systems (NCDEQ 2016; APNEP 2019). As the systems become more riverine, lower salinity tolerant SAV become more abundant (Ferguson and Wood 1989; Davis and Brinson 1990; Moorman et al. 2014), but their status has been understudied (NCDEQ 2016; Moorman et al. 2014). The salinity in these areas is generally <18 psu (Appendix C.), and turbidity increases near the rivers (Ferguson and Wood 1990). The low-salinity SAV species are highly diverse (approximately 10 species; Table 1) compared to their higher salinity counterparts. Additionally, the low-salinity SAV species are characterized by diverse morphological structures (canopy forming or meadow), morphological plasticity among species, and the intense competition with invasive species (e.g., *Hydrilla verticillata* and *Myriophyllum spicatum*) (Barko et al. 1984; Koch 2001). Kenworthy et al. (2012) indicated that the SAV in these areas are more ephemeral and exhibit a greater temporal and spatial variation than their higher salinity counterparts, which make these species difficult to monitor. However, there have been some attempts in the past to complete inventories of these areas.

In response to the apparent demise of SAV in the Pamlico River, Davis and Brinson (1990) sampled several SAV beds in Albemarle Sound (AS) between 1985 and 1988. Davis and

Brinson (1990) aimed to determine the distribution of SAV in the lower Back Bay, Currituck Sound, and western Albemarle-Pamlico system with ground surveys utilizing underwater viewers and rake samples along predetermined transects. The authors sampled various tributaries and identified monospecific and mixed species beds throughout the Sounds. Unfortunately, they also identified *M.* spicatum, a non-native species to the AS and North America, which has been documented to replace native species affecting the local ecology by modifying vertebrate and invertebrate species assemblages (Keast 1984; Orth and Moore 1984).

In 1990, Ferguson and Wood (1994) surveyed AS for SAV with color aerial photography and in-water sampling during August and September, which is the documented SAV maximum biomass period in this region. Aerial photography revealed a total of 11,962.5 ha of SAV in AS, but Ferguson and Wood (1994) pointed out that the SAV signature in the photographs was low-quality due to reflection and distortion of white caps, sediments, and sun light; furthermore, beds were frequently identified, but in many cases it was not possible to determine their extent due to the poor SAV signatures in the imagery. These surveys identified SAV beds throughout AS, suggesting that SAV have been a persistent underwater feature in the Sound for at least two decades; however, both surveys were limited as aerial photographs failed to capture SAV's signature and in-water samples were only concentrated in a few stations. Davis and Brinson (1990) sampled transects with rakes along the upper, lower, and middle of 10 tributaries and embayments in AS. Ferguson and Wood (1994) visually sampled 89 stations along AS, each covering approximately 370 m radius.

The 2010 NC Coastal Habitat Protection Plan (CHPP) estimated the acreage of mapped SAV between 1981 and 2008 in AS, Currituck Sound, and Chowan River. Based on the aforementioned studies and other projects completed by the NC Division of Marine Fisheries and partner organizations, they estimated there were 8,732 ha of SAV in this area (Deaton et al. 2010).

Quible and Associates (2011) completed the most detailed long-term SAV monitoring survey in AS. At 17 stations, they sampled twice annually in June and September for five consecutive years (2007-2011). The stations were established along the town of Edenton's shoreline at 1.6 km intervals. SAV were present at all sites at some point during their surveys. Only five sites which showed SAV initially did not show SAV in the last year of sampling, and SAV abundance increased at most of the sites during the five years of monitoring. The most dominant species were *N. guadalupensis* and *V. americana*; however, *M. spicatum*, *R. maritima*, and *P. perfolatus* were present as well. According to this study, peak SAV biomass in the AS region varied with seasonal climate trends; however, this study and others (Ferguson and Wood 1994; Kenworthy et al. 2012) suggest that peak abundance of SAV in the area is between July and September. The peak biomass reported for NC low-salinity SAV were similar to other reports in low-salinity regions, like the late-summer peak in the Chesapeake Bay (Moore et al. 2000).

Sampling during maximum SAV abundance has become a standard for several monitoring programs to ensure reliable bed detection (Orth and Moore 1983; Moore et al. 2009; Quible and Associates 2011; Christiaen et al. 2017). However, currently there are no permanent monitoring programs to document low-salinity SAV in NC despite its known historical extent and abundance (Ferguson and Wood 1989; Davis and Brinson 1990; Deaton et al. 2010).

Furthermore, AS has been nominated as one of two estuaries for a pilot study to expand the National Water Quality Monitoring Network (Moorman et al. 2014).

To establish an SAV monitoring protocol for NC, Kenworthy et al. (2012) suggested that the NC low-salinity coastal region could be classified into five different strata: 1) Currituck Sound, 2) Albemarle Sound, 3) Inner Banks of Western Pamlico Sound, 4) Pamlico River, and 5) Neuse River (Appendix C). Kenworthy et al. (2012) also suggested that monitoring should be initiated with a synoptic along-shore survey of the different strata to detect SAV extent. The synoptic surveys could be considered reconnaissance surveys, as they pave the way in identifying SAV extent and selecting intense sampling sites. Identifying intense sampling sites (i.e. sentinel-sites) is crucial, as it is extremely difficult to conduct repeated synoptic surveys due to the large extent of these waterbodies and poor SAV signal detection utilizing conventional SAV synoptic methods (i.e., aerial remote sensing). The sentinel-site approach would ensure the routine monitoring of these large and not easily accessible regions.

Sentinel sites are defined as specific locations selected to conduct intensive and repeated observations to detect changes in the system they represent (Jassby 1998). Sentinel sites have been used in other SAV monitoring programs, and they have been effective in detecting change when it is not feasible to regularly and repeatedly sample an entire system regularly (Jassby 1998; Christiaen et al. 2017). Due to their unique biophysical characteristics, NC low-salinity coastal region strata (Kenworthy et al. 2012) designate the various salinity regimes in APNES, and they may require different monitoring approaches. The high-salinity regions in NC are dominated by ocean tides and characterized by marine-like conditions with the clearest water; whereas, the low-salinity areas are subject to wind-driven tides, freshwater discharges from rivers and creeks, and relatively poorer water transparency. Albemarle Sound, the Pamlico River, western Pamlico Sound, Currituck Sound, and the Neuse River represent the low-salinity regions. Each of these regions have unique environmental conditions, so it is crucial to know the systems and determine the monitoring technique that will better address monitoring needs.

SAV Monitoring Tools

Remote sensing techniques such as aerial photography and satellite imagery have been increasingly used due their ability to cover large areas with high resolution. Aerial photography has been the preferred technique, as it can overcome some of the temporal constraints inherent to satellite imaging, as flights can be executed when conditions are favorable (i.e., sun angle, tide, wind, and water clarity) (Lathrop et al. 2006). Although aerial image can cover a large area, and it is relatively inexpensive; aerial imaging acquisition is limited by several environmental factors: e.g., weather and water clarity (Madsen and Wersal 2017). Further, even if data acquisition is feasible, automated interpretation of aerial imaging requires the development of spectral signatures particular to specific areas and signature detection is severely limited by water clarity and depth (Sawaya et al. 2003). Additionally, automated signature analysis software is proprietary making it costly.

Underwater video is another technique that has been used to survey, map, and monitor SAV (Schultz 2008; Christiaen et al. 2017). However, this method has some severe limitations in turbid water, and it can be time consuming and costly to cover large areas (Kenworthy et al. 2012; Eulie et al. 2013).

Hydroacoustic sampling methods, both single-beam and multi-beam sonar technologies, have also been used to survey and monitor SAV. Single-beam sonar has been used to monitor

SAV for several years and has proven its utility in several applications (McCarthy 1997; Sabol et al. 1998; McCarthy and Sabol 2000; Sabol et al. 2002; Valley and Drake 2005; Winfield et al. 2007; Wilson and Dunton 2009; Kenworthy et al. 2012; Barrell and Grant 2013; Valley et al. 2015; Bučas et al. 2016; Helminen et al. 2019). Single-beam sonar can cover large areas in a short period of time and there are commercially available tools (e.g., Biobase and Biosonics) that automate the analysis at a relatively low cost, making this tool both practical and economically viable. Furthermore, sonar is not limited by water clarity, so it is extremely useful in low-visibility estuaries and deep water, where other remote sensing techniques are not feasible (Bučas et al. 2016). In addition, this remote sensing technique has been shown to be reliable at detecting SAV when compared to in-water samples (Sabol et al. 2002) and underwater video (Kenworthy et al. 2012; Valley et al. 2015; Winfield et al. 2015).

Sonar does have some limitations, such as its inability to differentiate between SAV species, its restrictions to depths > 0.5 m, and a narrow sampling swath. Furthermore, the accuracy of the system must be thoroughly tested and therefore does require some manner of in-water sampling to verify the acoustic signatures. Thus far, single-beam sonar's ability to detect SAV's acoustic signature has been thoroughly established; however, few studies report signal verification. In this dissertation, I report verification estimates.

The multi-beam echosounder has many of the positive characteristics of the single-beam, and it can compensate for the small swath, with a larger swath. However, the multi-beam sonar currently does not have a commercially-available SAV automated analysis tool, so the analysis must be completed manually or by in-house classification algorithms (Kruss et al. 2008). Manual analysis can be time consuming, so proponents of the multi-beam techniques suggest that this technique can be complementary to the single-beam, not a stand-alone technique. Each of these techniques has its own pros and cons, and the decision to use a technique or an array of techniques should be determined by the characteristics of the area under study as well as the overall monitoring goals.

Aerial imaging may be adequate for large-scale monitoring in shallow clear-water estuaries, but single-beam sonar may be more appropriate for turbid environments. Although single-beam sonar can be fast and effective at large-scales, it would be cost prohibitive to sample with single-beam sonar at the same resolution and scale as with aerial imaging or multi-beam sonar. Therefore, the sentinel-site approach along with single-beam sonar offer the best opportunity for scientists and managers to study and monitor the current and future distribution of SAV in low-visibility areas at a large-scale. However, it is not until recently that single-beam sonar SAV automated analysis has become available.

Single-beam sonar SAV automated analysis has opened the door to managers and scientists to develop monitoring strategies that can help determine current and future SAV distributions. Although knowing current and future SAV distribution is crucial to adequately manage this important coastal resource, knowing past SAV distributions is also essential in establishing appropriate baseline abundances (McClenachan et al. 2012). In ecology and conservation, baseline abundances are often used as reference when setting restoration targets; however, in many coastal ecosystems, past distribution data is often lacking. Hence, historical information (e.g., narratives, archival documents, and interviews) is increasingly being used by scientists and managers to estimate past natural resources' abundance (Maynou et al. 2011; Ames 2004; Schuegraf 2004) and set restoration targets based on historic conditions, not just recent ones. Disciplines like social science can be used to collect information about the past per individuals' knowledge through an array of tools and techniques that have been used by sociologist and anthropologists for many years.

SAV and Coastal Communities

People have memories, and social science can be used to draw information from what people remember to gather data that is unavailable through biological sampling. Coastal residents may offer a window to the past distribution of SAV by utilizing social science techniques, like Local Ecological Knowledge (LEK). This knowledge can help managers create historically relevant management and restoration goals. Coastal residents, such as fishers and water-front property owners, develop LEK about the coastal ecosystem. Most knowledge of SAV comes from scientific data and is referred to as Scientific Ecological Knowledge (SEK). However, LEK can help bridge some of the knowledge gaps that exist regarding SAV in NC.

Commercial fishers and local residents are familiar with the environment they work and live in. They have observed the local environment for many years, as the majority of commercial fishers have been working in their area since childhood (Aguilar-Perera 2006). This LEK guides the decisions they make about their livelihoods. Fishers' knowledge can be useful in understanding distribution of natural resources, species richness, and condition of the ecosystems (Berkes et al. 2000). Deaton et al. (2010) summarized anecdotal reports by fishers and citizens of the NC coast on the distribution of SAV. Some of the reports indicated "…elderly fishermen and fishermen's journal accounts from late 1800's describing extensive beds of such vegetation [SAV] in many embayments along the mainland where it's now absent" (Davis and Brinson 1990). In 2007 and 2008, DMF biologists reported extensive SAV growth throughout the estuarine system (attributed primarily to drought conditions and lack of major storm events)" (Deaton et al. 2010). Observations like this can bridge the gap and tell us important information about the habitat suitability for SAV growth. A glimpse into SAV's past distribution through LEK can be especially useful in areas where scientific surveys and monitoring have not been regularly conducted.

LEK was shown to be useful in identifying the historical abundance of herring in Alaska prior to the Exxon Valdez oil spill (Huntington 2000). Similarly, Schuegraf (2004) studied the decline of seagrass beds in Pearl Lagoon, Nicaragua, with a combination of LEK and direct visual census to determine that seagrass had declined in the lagoon. LEK allowed the author to estimate seagrass bed abundance for the last 30 years, information that was not available through SEK data. Likewise, LEK may be useful in understanding the historical distribution of SAV in NC; as well as a tool for coastal resources managers to identify the value that different social groups attribute to natural resources (e.g., SAV). The latter could be useful in facilitating management decisions by helping identify common ground between stakeholders and minimize conflicts when developing management policies.

Purpose of this Project: Objectives and Hypotheses

AS is a large and not easily accessible, low-salinity estuary where there is insufficient knowledge about SAV distribution to properly manage this resource. Therefore, the overall purpose of this study was to conduct a shore-parallel reconnaissance survey for the presence and absence of SAV and identifying suitable location for establishing long-term sentinel monitoring sites. Routine monitoring at sentinel sites would help understand the distribution and temporal changes in SAV at AS, which has seldomly been documented. This dissertation focused on two questions: 1) what is the spatial and depth distribution of SAV in AS, and 2) what is the inter- and intra-annual variation in the AS over a two-year period? To address these questions, I had the following objectives and hypotheses:

1. Complete a large-scale reconnaissance survey of the distribution and abundance of SAV in the Albemarle Sound, NC. [Chapter 1]
2. Establish permanent sentinel sites in Albemarle Sound, NC. [Chapter 1].
3. Quantitatively characterize SAV depth distribution and the temporal (inter- and intra-annual) and spatial variation in SAV the Albemarle Sound, NC. [Chapters 1 and 2].

   Hypothesis 1 (H_1): Mean percent SAV occurrence at all sentinel sites will be greater in 2015 than 2016.

   Hypothesis 2 (H_2): Mean percent SAV occurrence at all sentinel sites will be more abundant in the fall than the spring.
4. To evaluate the perceptions of the ecological value and the distribution of SAV in the AS through LEK. [Chapter 3]

   Hypothesis 3 (H_3): Participants will agree on basic concepts about the value and ecology about SAV (e.g., the cultural belief that SAV are important for the ecosystem and fisheries dependent on it).

   Hypothesis 4 (H_4): Commercial fishers, coastal residents, and fishery managers will have different beliefs about more specific issues rather than the general ecological value of SAV (e.g., SAV abundance trends and factors affecting SAV distribution).

Initial results from the H_4 informed the development of more specific hypotheses:

Hypothesis 4a (H_{4a}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about SAV value.

Hypothesis 4b (H_{4b}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about SAV abundance trend.

Hypothesis 4c (H_{4c}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the Sound's water quality.

Hypothesis 4d (H_{4d}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the effect of seasons on SAV abundance.

Hypothesis 4e (H_{4e}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the effect of storms on SAV abundance.

Hypothesis 4f (H_{4f}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the effect of development on SAV abundance.

Significance of this Study

The effort in this dissertation is unique, as it completed the first large-scale survey for a low-visibility estuary in NC utilizing single-beam sonar. In addition, it established long-term sentinel monitoring sites to help understand SAV depth distribution and the spatial and temporal variation in SAV abundance in AS. The work done in this dissertation can be used by management agencies in NC for their SAV monitoring and assessment programs in low-salinity regions.

Additionally, this study aimed to address some of the potential conflict that coastal managers may encounter while managing SAV in AS. I utilized LEK to understand the perceptions that various stakeholders have about SAV in AS. At the same time, this social science study was applied to further understand the historical distribution of SAV from the stakeholder's perspective. This is the first study to use LEK in AS to evaluate perception and historical distribution SAV patterns in AS.

References

Aguilar-Perera, A. 2006. Disappearance of a Nassau grouper spawning aggregation off the southern Mexican Caribbean coast. *Marine Ecology Progress Series* 327: 289–296.

APNEP. 2019. Submerged Aquatic Vegetation Maps. https://apnep.nc.gov/our-work/monitoring/submerged-aquatic-vegetation-monitoring. Accessed 9 September 2019.

Ames, E.P. 2004. Atlantic cod stock structure in the Gulf of Maine. *Fisheries Research* 29: 10–28. doi:10.1577/1548-8446(2004)29[10:acssit]2.0.co;2.

Barbier, E.B., S.D. Hacker, C. Kennedy, E.W. Koch, A.C. Stier, and B.R. Silliman. 2011. The value of estuarine and coastal ecosystem services. *Ecological Monographs* 81: 169–193.

Barko, J.W., D.G. Hardin, and M.S. Matthews. 1984. Interactive influences of light and temperature on the growth and morphology of submersed freshwater macrophytes. *Aquatic Plant Control Technical Report*: 24.

Barrell, J., and J. Grant. 2013. Detecting hot and cold spots in a seagrass landscape using local indicators of spatial association. *Landscape Ecology* 28: 2005–2018. doi:10.1007/s10980-013-9937-2.

Berkes, F., J. Colding, and C. Folke. 2000. Rediscovery of traditional ecological knowledge as adaptive management. *Ecological applications* 10: 1251–1262.

Bučas, M., A. Šaškov, A. Šiaulys, and Z. Sinkevičienė. 2016. Assessment of a simple hydroacoustic system for the mapping of macrophytes in extremely shallow and turbid lagoon. *Aquatic Botany* 134: 39–46. doi:10.1016/j.aquabot.2016.06.009.

Carpenter, D.E. 2017. Submerged aquatic vegetation conservation in the Albemarle-Pamlico Estuarine Systems. *Habitat Hotline: Atlantic*.

Carpenter, D.E., and L. Dubbs. 2012. *2012 Albemarle-Pamlico ecosystem assessment, Albemarle-Pamlico National Estuary Partnership*. Raleigh, North Carolina.

Christiaen, B., L. Ferrier, P. Dowty, J. Gaecle, and H. Berry. 2017. *Puget Sound seagrass monitoring report monitoring year 2015*. Olympia, Washington.

Copeland, B., R. Hodosn, and S. Riggs. 1984. *The ecology of the Pamlico River, North Carolina: an estuarine profile*. doi:10.1017/CBO9781107415324.004.

Costello, C.T., and W.J. Kenworthy. 2011. Twelve-year mapping and change analysis of Eelgrass (*Zostera marina*) areal abundance in Massachusetts (USA) identifies statewide declines. *Estuaries and Coasts* 34: 232–242.

Davis, G.J., and M.M. Brinson. 1990. *A survey of submersed aquatic vegetation of the Currituck Sound and the western Albemarle-Pamlico estuarine system*. Greenville, North Carolina.

Deaton, A.S., W.S. Chappell, J. O’Neal, K. Hart, and B. Boutin. 2010. *North Carolina Coastal Habitat Protection Plan*. Morehead City, North Carolina.

Eulie, D.O., J.P. Walsh, and D.R. Corbett. 2013. High-resolution analysis of shoreline change and application of balloon-based aerial photography, Albemarle-Pamlico estuarine system, North Carolina, USA. *Limnology and Oceanography: Methods* 11: 151–160. doi:10.4319/lom.2013.11.151.

Ferguson, R.L., and L.L. Wood. 1989. *Submerged aquatic vegetation in the Albemarle-Pamlico estuarine systems*. Beaufort, North Carolina.

Ferguson, R.L., and L.L. Wood. 1990. *Mapping submerged aquatic vegetation in North Carolina with conventional aerial photography*. *Federal Coastal Wetland Mapping Programs*. Washington, District of Columbia.

Ferguson, R.L., and L.L. Wood. 1994. *Rooted vascular aquatic beds in the Albemarle-Pamlico estuarine system.* Beaufort, North Carolina: National Marne Fisheries, National Oceanic and Atmospheric Administration.

Fourqurean, J.W., C.M. Duarte, H. Kennedy, N. Marbà, M. Holmer, M.A. Mateo, E.T. Apostolaki, et al. 2012. Seagrass ecosystems as a globally significant carbon stock. *Nature Geoscience* 5: 1–5.

Helminen, J., T. Linnansaari, M. Bruce, R. Dolson-Edge, and R.A. Curry. 2019. Accuracy and precision of low-cost echosounder and automated data processing software for habitat mapping in a large river. *Diversity* 11: 1–18. doi:10.3390/d11070116.

Hitch, A.T., K.M. Purcell, S.B. Martin, P.L. Klerks, and P.L. Leberg. 2011. Interactions of salinity, marsh fragmentation and submerged aquatic vegetation on resident nekton assemblages of coastal marsh ponds. *Estuaries and Coasts*: 653–662. doi:10.1007/s12237-010-9367-1.

Huntington, H.P. 2000. Using traditional ecological knowledge in science: Methods and applications. *Ecological applications* 10: 1270–1274.

Jassby, A.D. 1998. Interannual variation at three inland water sites: Implications for sentinel sites. *Ecological Applications* 8: 277–287. doi:10.1890/1051-0761(1998)008[0277:IVATIW]2.0.CO;2.

Keast, A. 1984. The introduced aquatic macrophyte, *Myriophyllum spicatum*, as habitat for fish and their invertebrate prey. *Canadian Journal of Zoology* 62: 1289–1303. doi:10.1139/z84-186.

Kenworthy, W.J., C.A. Buckel, D.E. Carpenter, D.B. Eggleson, D. Field, C.S. Krahforst, and J.J. Luczkovich. 2012. *Development of submerged aquatic vegetation monitoring protocols in North Carolina*. Morehead City, North Carolina.

Koch, E.W. 2001. Beyond light: Physical, geological, and geochemical parameters as possible submerged aquatic vegetation habitat requierements. *Estuaries* 24: 1–17. doi:10.2307/1352808.

Kruss, A., P. Blondel, J. Tegowski, J. Wiktor, and A. Tatarek. 2008. Estimation of macrophytes using single-beam and multibeam echosounding for environmental monitoring of arctic fjords (Kongsfjord, West Svalbard Island). *The Journal of the Acoustical Society of America*

123: 3213. doi:10.1121/1.2933397.

Lathrop, R.G., P. Montesano, and S. Haag. 2006. A multi-scale segmentation approach to mapping seagrass habitats using airborne digital camera imagery. *Photogrammetric Engineering & Remote Sensing* 72: 665–675. doi:10.14358/PERS.72.6.665.

Lindquist, N.L., and S.R. Fegley. 2016. *Development of a comprehensive North Carolina salinity database to facilitate management and restoration of critical fish habitats. North Carolina Coastal Recreational Fishing License Final Report: 2013-H-015*.

Lirman, D., G. Deangelo, J. Serafy, A. Hazra, D. Smith Hazra, J. Herlan, J. Luo, S. Bellmund, J. Wang, and R. Clausing. 2008. Seasonal changes in the abundance and distribution of submerged aquatic vegetation in a highly managed coastal lagoon. *Hydrobiologia* 596: 105–120. doi:10.1007/s10750-007-9061-x.

Madsen, J.D., and R.M. Wersal. 2017. A review of aquatic plant monitoring and assessment methods. *Journal of Aquatic Plant Management* 55: 1–13.

Maynou, F., M. Sbrana, P. Sartor, C. Maravelias, S. Kavadas, D. Damalas, J.E. Cartes, and G. Osio. 2011. Estimating trends of population decline in long-lived marine species in the Mediterranean Sea based on fishers' perceptions. *PLoS ONE* 6. doi:10.1371/journal.pone.0021818.

McCarthy, E.M. 1997. Acoustic characterization of submerged aquatic vegetation. In *SACLANTCEN Proceedings Series CP-45, High Frequency Acoustics in Shallow Water*, ed. N. G. Pouliquen, E. Bergem, and A. P. Lyons, 362–369. Lerici, Italy: NATO SACLANT Undersea Research Centre.

McCarthy, E.M., and B.M. Sabol. 2000. Acoustic characterization of submerged aquatic vegetation: Military and environmental monitoring applications. In *OCEANS 2000 MTS/IEEE Conference and Exhibition. Conference Proceedings*, 1957–1961. Providence, Rhode Island: IEEE. doi:10.1109/OCEANS.2000.882226.

McClenachan, L., F. Ferretti, and J.K. Baum. 2012. From archives to conservation: Why historical data are needed to set baselines for marine animals and ecosystems. *Conservation Letters* 5: 349–359. doi:10.1111/j.1755-263X.2012.00253.x.

Moore, K.A., R.J. Orth, and D.J. Wilcox. 2009. Assessment of the abundance of submersed aquatic vegetation (SAV) communities in the Chesapeake Bay and its use in SAV management. In *Remote sensing and geospatial technologies for coastal ecosystem assessment and management, lecture notes in geoinformation and cartography*, ed. X. Jang, 233–257. Berlin: Springer-Verlang. doi:10.1007/978-3-540-88183-4.

Moorman, M.C., K.R. Kolb, and S. Supak. 2014. *Estuarine monitoring programs in the Albemarle Sound study area, North Carolina*. Reston, Virginia.

Mormul, R.P., S.M. Thomaz, A.M. Takeda, and R.D. Behrend. 2011. Structural complexity and distance from source habitat determine invertebrate abundance and diversity. *Biotroica* 43: 738–745.

NCDEQ. 2016. *North Carolina Coastal Habitat Protection Plan Source Document*. Morehead

City, North Carolina.

Oertli, H.J. 1964. The Venice System for the classification of marine waters according to salinity. *Pubblicazioni della Stazione Zoologioca di Napoli* 36: 346–347.

Orth, R.J., T.J.B. Carruthers, W.C. Dennison, C.M. Duarte, J.W. Fourqurean, K.L.J. Heck, A.R. Hughes, et al. 2006. A global crisis for seagrass ecosystems. *Bioscience* 56: 987–996.

Orth, R.J., W.C. Dennison, J.S. Lefcheck, C. Gurbisz, M. Hannam, J. Keisman, J.B. Landry, et al. 2017. Submersed aquatic vegetation in Chesapeake Bay: Sentinel species in a changing world. *BioScience* 67: 698–712. doi:10.1093/biosci/bix058.

Orth, R.J., S.R. Marion, K.A. Moore, and D.J. Wilcox. 2010. Eelgrass (*Zostera marina* L.) in the Chesapeake Bay region of mid-Atlantic coast of the USA: Challenges in conservation and restoration. *Estuaries and Coasts* 33: 139–150. doi:10.1007/s12237-009-9234-0.

Orth, R.J., and K.A. Moore. 1983. Submerged vascular plants: Techniques for analyzing their distribution and abudance. *Marine Technology Society Journal* 17: 38–52.

Orth, R.J., and K.A. Moore. 1984. Distribution and abundance of submerged aquatic vegetation in Chesapeake Bay : An historical perspective. *Coastal and Estuarine Research Federation* 7: 531–540.

Orth, R.J., M.R. Williams, S.R. Marion, D.J. Wilcox, T.J.B. Carruthers, K.A. Moore, W.M. Kemp, et al. 2010. Long-term trends in submersed aquatic vegetation (SAV) in Chesapeake Bay, USA, related to water quality. *Estuaries and Coasts* 33: 1144–1163. doi:10.1007/s12237-010-9311-4.

Quible and Associates. 2011. *A compensatory mitigation plan requierement for The Fund for Sandy Point North Carolina, LLC*. Kitty Wawk, North Carolina.

Rozas, L.P., and W.E. Odum. 1988. Occupation of submerged aquatic vegetation by fishes: Testing the roles of food and refuge. *Oeco* 77: 101–106. doi:10.1007/BF00380932.

Sabol, B.M., R.E.J. Melton, R. Chamberlain, P. Doering, and K. Haunert. 2002. Evaluation of a digital echosounder system for detection of submersed aquatic vegetation. *Estuaries* 25: 133–141. doi:10.1007/BF02696057.

Sabol, B.M., R.E. Meltona, and R.. Kasul. 1998. Method and apparatus for hydroacoustic detection of submersed aquatic vegetation. Washington, District of Columbia: U.S. Patent Office.

Sawaya, K.E., L.G. Olmanson, N.J. Heinert, P.L. Brezonik, and M.E. Bauer. 2003. Extending satellite remote sensing to local scales: Land and water resource monitoring using high-resolution imagery. *Remote Sensing of Environment* 88: 144–156. doi:10.1016/j.rse.2003.04.0006.

Schuegraf, M.J. 2004. Establishment of seagrass decline and causative mechanisms in Pearl Lagoon, Nicaragua through use of traditional ecological knowledge, sediment coring and direct visual census. York University.

Schultz, S.T. 2008. Seagrass monitoring by underwater videography: Disturbance regimes, sampling design, and statistical power. *Aquatic Botany* 88: 228–238. doi:10.1016/j.aquabot.2007.10.009.

Valley, R.D., and M.T. Drake. 2005. *Accuracy and precision of hydroacoustics estimates of aquatic vegetation and the repeatability of whole-lake surveys: Field tests with a commercial echosounder*. *Minnesota Department of Natural Resources Investigational Report*.

Valley, R.D., M.B. Johnson, D.L. Dustin, K.D. Jones, M.R. Lauenstein, and J. Nawrocki. 2015. Combining hydroacoustic and point-intercept survey methods to assess aquatic plant species abundance patterns and community dominance. *Journal of Aquatic Plant Management* 53: 121–129.

Waycott, M., C.M. Duarte, T.J.B. Carruthers, R.J. Orth, W.C. Dennison, S. Olyarnik, A. Calladine, et al. 2009. Accelerating loss of seagrasses across the globe threatens coastal ecosystems. *Proceedings of the National Academy of Sciences of the United States of America* 16: 12377–12381. doi:10.1073/pnas.0905620106.

Wilson, P.S., and K.H. Dunton. 2009. Laboratory investigation of the acoustic response of seagrass tissue in the frequency band 0.5–2.5 kHz. *The Journal of the Acoustical Society of America* 125: 1951–1959. doi:10.1121/1.3086272.

Winfield, I.J., C. Onoufriou, M.J. O'Connell, M. Godlewska, R.M. Ward, A.F. Brown, and M.L. Yallop. 2007. Assessment in two shallow lakes of a hydroacoustic system for surveying aquatic macrophytes. *Hydrobiologia* 584: 111–119. doi:10.1007/s10750-007-0612-y.

Winfield, I.J., J. van Rijn, and R.D. Valley. 2015. Hydroacoustic quantification and assessment of spawning grounds of a lake salmonid in a eutrophicated water body. *Ecological Informatics* 30: 235–240. doi:10.1016/j.ecoinf.2015.05.009.

Tables

Table 1. SAV species found in low salinities in North Carolina. An asterisk indicates the species was identified during my sentinel site sampling (Chapter 2).

Scientific Name	Common Name	Reference
*Ruppia maritima**	Widgeon grass	Ferguson and Wood 1994; Davis and Brinson 1990; Quible and Associates 2011
Stuckenia pectinata	Sago pondweed	Ferguson and Wood 1994; Davis and Brinson 1990
*Vallisneria americana**	Wild celery	Ferguson and Wood 1994; Quible and Associates 2011
*Myriophyllum spicatum**	Eurasian watermilfoil	Ferguson and Wood 1994; Davis and Brinson 1990; Quible and Associates 2011
Potamogeton perfolatus	Redhead grass	Davis and Brinson 1990
*Hydrilla verticillata**	Hydrilla	Quible and Associates 2011
*Najas guadalupensis**	Bushy pondweed	Ferguson and Wood 1994; Davis and Brinson 1990; Quible and Associates 2011
Zannichellia palustris	Horned pondweed	Davis and Brinson 1990
Potamogeton foliosus	Leafy pondweed	Davis and Brinson 1990
*Potamogeton perfoliatus**	Clasping-leaved pondweed	Quible and Associates 2011

CHAPTER 1: Benthic hydroacoustic surveys of Submerged Aquatic Vegetation (SAV) in a large, low-visibility estuary, Albemarle Sound, North Carolina USA

Abstract

SAV are recognized worldwide for providing a wide range of ecological and economic services. However, SAV have declined globally; it is estimated that since the late 1980s more than 90,000 ha have been lost. Changes in SAV distribution have been attributed to both natural (e.g., storms and herbivores) and anthropogenic activities, such as upland development, dredging, propeller scaring, and nutrient loading. The recognized importance of SAV, the reported global declines, and the modest evidence of recovery have motivated scientists and resource management agencies to consider routine quantitative and synoptic monitoring of SAV distribution and abundance. However, SAV monitoring can be difficult in low-visibility regions, where optical remote sensing methods are inadequate. The objective of this study was to conduct a synoptic SAV survey in AS in order to develop an SAV inventory and establish permanent monitoring sites. Scientists and resources managers can use these sites to detect changes in SAV abundance and make informed resources management decisions, if protection and restoration are needed. As an alternative to optical remote sensing, I sampled a low-visibility coastal lagoon estuary, Albemarle Sound, North Carolina, utilizing single-beam sonar. Further, I used the data generated from this survey to establish permanent sentinel sites in the Sound for long-term SAV monitoring. I completed the sampling in a single season between August and October 2014 and surveyed approximately 400 km of shoreline. Three large SAV beds (>10,000 m in length) were identified in Edenton, Kitty Hawk Bay, and East Lake, with various intermediate size beds (<10,000 m in length) and smaller patches scattered throughout the sound. Most of the SAV were present above the 1.7-m isobath. I concluded that single-beam is an effective and efficient

SAV surveying tool, as I was able to survey a large length of shoreline in only three months. Further, this method requires minimal equipment and post-processing compared to in-water surveys or other remote sensing methods. The single-beam sonar along with Biobase, an automated cloud-based SAV signal interpretation platform, has a quick signature interpretation and data processing turnaround time compared to other remote sensing and in-water sampling. The project resulted in the identification of ten candidate sentinel monitoring sites for assessing SAV abundance and distribution. These sites can help managers make better informed decisions regarding the conservation and restoration of this resource.

Keywords

Sonar, underwater video, remote sensing, sentinel sites, and long-term monitoring.

Introduction

SAV are recognized worldwide as important foundation species because of the many ecosystem services they provides, as well as their economic value to humans (Thayer et al. 1984; Orth et al. 2006). SAV provide foraging and nursery habitats for fish (Rozas and Odum 1988; Flaherty-Walia et al. 2015), shellfish (Heck and Thoman 1984; Dealteris et al. 2004), sea turtles (Lutcavage and Musick 1985), marine mammals (Thayer et al. 1984), birds (Lantz et al. 2010), and invertebrates (Voigts 1976; Hovel et al. 2002). SAV methods also help reduce erosion and sediment re-suspension (Madsen et al. 2001), connect other habitats (e.g., salt marshes. oyster reefs, coral reefs, and mangroves; Micheli and Peterson 1999), recycle nutrients (Romero et al. 2006), and sequester carbon (Fourqurean et al. 2012). Scientists and resource managers are also routinely using SAV as bio-indicators of environmental quality; the plants are especially sensitive to changes in temperature, salinity, sedimentation, nutrient loading, and water clarity (Dennison et al. 1993; Orth et al. 2006; Orth et al. 2017).

Human populations have rapidly increased in coastal regions, driving anthropogenic changes in aquatic environments that are responsible for declines in SAV distribution and abundance locally, on the Atlantic coast of the United States (US) (e.g., Chesapeake Bay, Massachusetts, and Florida), and worldwide (Orth and Moore 1983a; Short and Wyllie-Echeverria 1996; Orth et al. 2006; Waycott et al. 2009; Orth et al. 2010; Costello and Kenworthy 2011; Orth et al. 2017; Lefcheck et al. 2018). These declines have motivated scientists and resources management agencies to develop sampling protocols and establish routine monitoring programs to identify the status and trends of SAV distribution and abundance. The information derived from these monitoring programs is being used for conservation and restoration of SAV coastal ecosystems both nationally and globally (Orth et al. 2010; Costello and Kenworthy 2011; Christiaen et al. 2017).

Although SAV are present across various salinities in estuaries around the world, most of the SAV monitoring programs are not as spatially and temporally comprehensive as the monitoring conducted in the Chesapeake Bay. Most of the monitoring programs have focused more on the high- and intermediate-salinity species, or seagrasses (Kenworthy et al. 2012). Many estuaries are turbid and poor water transparency limits the ability to regularly utilize remote sensing technologies (e.g., aerial photography and satellite sensors) to detect submerged bottom features (Orth and Moore 1983b; Finkbeiner et al. 2001; Vis et al. 2003; Winfield et al. 2007). Transparency gradients in coastal water bodies are common and closely coincide with salinity gradients (Ferguson and Wood 1990; Adair et al. 1994; Orth et al. 2010; Jia and Li 2012), such that the submerged deeper portions of SAV meadows in the upper reaches of estuaries are rarely visible to aerially deployed optical sensors. Additionally, the human effort required to monitor sub-tidal environments and the cost of spatially comprehensive and temporally frequent in-water sampling has restricted the implementation of synoptic long-term monitoring programs in low-salinity SAV habitats that cannot be reliably detected by airborne sensors (Davis and Brinson 1976; Ferguson and Wood 1989; Ferguson and Wood 1990; Finkbeiner et al. 2001; NCDEQ 2016; Madsen and Wersal 2017).

Despite NC having the second largest lagoonal estuary in the continental United States (Luettich et al. 2002), a significant portion of the SAV resource located in turbid, lower-salinity regions has not been comprehensively mapped or routinely monitored (Davis and Brinson 1976; Ferguson and Wood 1990; Kenworthy et al. 2012; NCDEQ 2016). The Albemarle-Pamlico Estuary System (APES) has eight major sounds and six major river basins with an estimated

7,530 km^2 of open water and a well-defined salinity gradient extending from east to west (Appendix C). The relatively shallow clear waters located over the back-barrier shelves just behind the islands are an ideal environment for high salinity SAV to thrive (Thayer et al. 1984; Ferguson et al. 1993; Ferguson and Wood 1994; NCDEQ 2016). Periodic remote sensing and mapping of large portions of the eastern region of APES, beginning in 1983 up to as recent as 2013, indicate an estimated maximum extent of seagrass on the order of 130,000 acres (52,609 ha) (Carraway and Priddy 1983; Ferguson and Wood 1989; Ferguson and Wood 1990; Ferguson and Wood 1994; NCDEQ 2016; APNEP 2019). Just this eastern margin of APES alone has approximately five times the acreage of SAV than reported for a large neighboring mid-Atlantic estuary, the Chesapeake Bay (Lefcheck et al. 2018).

The remaining western margin of APES, including Pamlico Sound, the upper reaches of Currituck Sound, AS, and the Neuse and Pamlico Rivers have thousands of km of shoreline adjoining relatively shallow open water known to be potential SAV habitat (NCDEQ 2016). Based on historical data and observations reported from sub-segments of this portion of the estuary, all these waterbodies are known to either have had SAV in the past, or are currently documented to support diverse SAV communities (Davis and Brinson 1976; Davis and Brinson 1990; Ferguson and Wood 1994; Quible and Associates 2011; Carpenter and Dubbs 2012; Kenworthy et al. 2012; NCDEQ 2016). For AS alone, recent estimates have suggested there may be as much as 36,880 acres (14,925 ha) of submerged bottom suitable as potential SAV habitat (Carpenter and Dubbs 2012; Kenworthy et al. 2012; Moorman et al. 2014; NCDEQ 2016). However, previous efforts to remotely detect and comprehensively map and monitor these extensive, relatively lower salinity SAV regions of the estuary have been unsuccessful. Drainage from three large coastal watersheds and the numerous rivers and tributaries associated with these watersheds deliver substantial quantities of freshwater laden with suspended particulate material, CDOM, and nutrients into this shallow and productive region of APES (Li et al. 2007; Jia and Li 2012). Physically isolated from tidal inlets and subjected to both continuous and episodic freshwater discharges and wind driven resuspension of bottom sediments, water transparency is highly variable and frequently limiting visibility of the benthos throughout the SAV growing season. Given the well-documented global (Orth et al. 2006; Waycott et al. 2009), regional (Orth et al. 2010) and local threats to this resource, the recognized ecological services provided by SAV, and the well-established economic value of this habitat to fisheries, wildlife, and human society (NCDEQ 2016); there is a critical need to develop and implement alternative mapping and monitoring tools to assess the status of this vital resource (APNEP 2012).

The use of optical methods such as underwater photography, videography, and acoustic-based remote sensing are alternative methods for locating, mapping, and monitoring SAV (Kenworthy et al. 2012). Underwater videography and photography have been used successfully in some large-scale monitoring programs, for example, in Puget Sound, Washington, US, where the water visibility is suitable (Norris et al. 1997; Christiaen et al. 2017). However, due to poor visibility these optical approaches are neither practical nor reliable for large-scale monitoring in turbid water, like what occurs in the low-salinity estuarine environments in NC (Kenworthy et al. 2012). Alternatively, for waters with poor transparency, acoustic methods, such as single-beam (Sabol et al. 2002; Vis et al. 2003; Valley et al. 2015), multi-beam (Komatsu et al. 2003), and side-scan (Pasqualini et al. 2000; Merkel and Associates 2014) sonar technologies have been used to remotely detect SAV in broad scale SAV mapping and monitoring programs.

Single-beam sonar has been shown to effectively and efficiently identify SAV in fresh and coastal waters (Sabol and Burczinski 1998; Sabol et al. 2002; Jarosław et al. 2003;

Godlewska et al. 2004; Valley and Drake 2005; Kruss et al. 2008; Sabol et al. 2009; Tseng 2009; Kenworthy et al. 2012; Bučas et al. 2016). Initially, SAV sonar estimates were generated through manual interpretation of acoustic echograms (Maceina and Shireman 1980; Maceina et al. 1984; Stent and Hanley 1985; Duarte 1987). However, SAV acoustic signal interpretation gained significant momentum with the military's need to understand SAV sonar signal interference with mine detection (McCarthy and Sabol 2000). Through a military project, McCarthy (1997) used acoustic tanks, mesocosms, and field experiments to document the backscatter created by the gas pockets (or lacunae) in *Zostera marina* when targeted with sonar. The author's results indicated that SAV have a clearly defined backscatter, and that single-beam sonar could be used to distinctly identify SAV. Once the sonar's ability to detect SAV was established (Hermand et al. 1998; Wilson and Dunton 2009), along with advances of GPS, Sabol et al. (2002) developed an automated system for SAV acoustic signal interpretation (i.e., SAVEWS). Their research indicated that the SAV sonar automated signal interpretation and field samples had a close agreement ($r^2 = 0.98$), and sonar could effectively estimate SAV beds in varying substrates and salinities. The sonar's SAV detection capabilities were further confirmed by Valley and Drake (2005) when they compared sonar SAV estimates not only for averaged field measurements, but also SAV detection at the individual plant level. They concluded that sonar and actual plant heights did not differ significantly. As sonar established itself as a reliable SAV remote sensing survey method, affordable automated systems have been developed and are now widely used in lake and estuary surveys (e.g., Biobase and Sonar5-Pro), which have produced several research studies (Spears et al. 2009; Tseng 2009; Kenworthy et al. 2012; Radomski and Holbrook 2015; Winfield et al. 2015; Bučas et al. 2016; Valley 2016; Helminen et al. 2019; Heuvel et al. 2019; Howell and Richardson 2019).

Currently, sonar is the most viable technology to complete synoptic surveys in low-visibility regions where aerial optical remote sensing is not feasible due to water clarity limitations. Sonar significantly reduces sampling times compared to other methods that are not limited by water clarity (Sabol et al. 2002; Tseng 2009). Given the size and geographic complexity of APES, it is neither economically nor logistically feasible to map and monitor SAV along the entire shoreline on a regular basis. However, using acoustics, it is possible to routinely obtain several ecologically relevant metrics of SAV habitat; including percent cover, canopy height, and plant bio-volume (Sabol et al. 2002; Valley et al. 2015; Winfield et al. 2015; Bučas et al. 2016), which could be repeatedly measured at permanent sentinel monitoring stations to determine the status and trends of SAV.

Fixed station sampling, following a “sentinel site monitoring” approach, can draw upon historical knowledge of SAV distribution, recent status and trends assessments where available, and vulnerability of existing SAV to known stressors (e.g., impaired water quality). In this study, I defined sentinel sites as a subset of representative and readily accessible fixed locations in the estuary that have the capacity for intensive monitoring and sustained long-term observations to detect and understand changes in the ecosystems they represent (Jassby 1998; Christian and Mazzilli 2007). Three critical factors govern the scientific rationale behind the selection of representative sentinel sites: 1) the sites should have key physical and biological attributes that represent the larger ecosystem and are representative of the region; 2) the sites should have significant ecological value associated with the presence of key species that are knowingly important to ecosystem function (e.g., SAV); and 3) there is a high likelihood of detecting change. The sentinel sites approach has been used in several SAV monitoring programs in Puget

Sound, Chesapeake Bay, and the Florida Keys National Marine Sanctuary (Fourqurean et al. 2001; Orth et al. 2010; Christiaen et al. 2017).

The specific objectives of this study were to; 1) conduct a large-scale reconnaissance survey of the distribution and abundance of SAV in AS, and 2) to locate and establish permanent sentinel sites for long-term monitoring of SAV status and trends.

Material and Methods

Study Site

I conducted the study in AS; a representative sub-estuary located in the northwestern region of APES (Appendix C). AS is a shallow (mean depth = 5.3 m), wind-driven, microtidal estuary, isolated by distance from the Atlantic Ocean with a water residence time of 45 days, high turbidity, poor water transparency, and persistently low salinity. (Giese et al. 1985; Moorman et al. 2014; NCDEQ 2016). With a surface area of 2,330 km, 800 km of shoreline and the receiving waterbody for three major river drainages (Roanoke, Chowan, and Pasquotank rivers) and numerous other small tributaries, AS is characteristic of the environmental conditions throughout the western APES region. The tributaries of AS are brown-water rivers that drain peatland and swamp forests, farmland, upstream urban and silviculture areas, which create a turbid and optically complex system. The maximum color units for the Chowan River, an AS tributary, has been measured at 320 (Giese et al. 1985). Furthermore, the relatively long water residence time persistently diminishes water clarity, which has limited our ability to optically detect SAV with airborne sensors typically used in submerged habitat monitoring programs. However, both historical data (Davis and Brinson 1976; Ferguson and Wood 1989; Ferguson and

Wood 1994; Quible and Associates 2011) and local knowledge indicate that SAV have been an important component of this estuarine system (NCDEQ 2016).

SAV Field Survey

Sonar

I conducted a rapid assessment survey (RAS) for detecting SAV presence and absence along the shore of AS between August 5th and October 3rd, 2014, using single-beam sonar and underwater video for SAV presence verification. I divided the AS shoreline into 46, 10-km segments; I used these segments to establish transects parallel to the shore (alongshore) at the 1-m isobath. Given the limited knowledge of SAV depth distribution in AS (Quible and Associates 2011), the transects followed the 1-m isobath to maximize SAV bed detection. Using an echosounder, at the start of each transect, I located the 1-m isobath by navigating from the pre-determined start of the transect just offshore towards the shoreline. Once the isobath was located, the sonar sampling was initiated, the boat always aimed to follow the 1-m isobath; however, the depth varied perpendicular to the shore, which required constant maneuvering to maintain the target depth. Some transects were shorter than 10-km long due to boat access limitations in shallow creeks and to avoid underwater obstructions (9 transects were shorter than 10-km). Sixteen transects were longer than 10-km, as I extended these transect' boundaries to include SAV beds outside our pre-establishing sampling route.

The sonar data was collected with a Lowrance/Biobase system, utilizing a Lowrance HDS-5 Gen 2 fishfinder/chartplotter with a 200-kHz frequency transducer with a 20° beam angle (Navico 2014). The Lowrance system has a mapping grade high-sensitivity internal GPS+WAAS antenna for logging latitude and longitude with a positional error of ± 3 m; the HDS-5 Gen 2 does not have a GPS GDOP or HDOP threshold. The transducer was mounted on the side of the boat approximately 0.3 m under the water surface (Figure 1). The sonar ping rate was set at 15 pings per second. The GPS data and acoustic signal were stored in sl2 file format in SD memory cards, and each 10-km transect was saved in a separate file.

Underwater Video

A low-light sensitivity Sartek (model #SDC-MSS) underwater camera was used to collect video data to verify SAV presence or absence. I obtained video samples every 330 m along each 10-km transect, yielding approximately 30 video samples per transect. This sampling frequency was chosen due to time limitations. Additionally, preliminary data indicated that SAV beds in the area have a 424 m mean maximum patch size, and beds can be as large as 1,000 m (Kenworthy et al., 2012), so by sampling every 330-m, it was like to detect most larger beds. The latitude and longitude coordinates of each video point was recorded into the memory of the Lowrance HDS-5 echosounder.

Data Processing and Statistical Analysis

Sonar

The memory card's files with the sonar data were uploaded to the Biobase SAV mapping data analysis and long-term storage cloud (www.cibiobase.com). Biobase is a software platform that automates the analysis of the acoustic and GPS signal from the echosounder, to generate SAV present-absent data (Valley et al. 2015).

The Biobase automated signal-processing algorithm estimates bio-volume which is defined as the percent of water column occupied by plant matter (Navico 2014). Bio-volume is derived from the ratio between plant height, defined as the difference between the sediment surface and the top of the plant canopy, and bottom depth. The bottom usually returns as sharper clearly defined echo with limited changes in depth compared to the SAV canopy echo (Sabol et al. 2002). The GPS position of each ping was recorded approximately every second (15 pings per second), and a bottom feature (i.e., plant height) was estimated based on the signal return. The 15 different GPS positional reports were then averaged for each data point displayed in the final report. Note that the distance covered by each set of 15 pings varied with the boat's speed. The average boat speed was 8 $km \cdot h^{-1}$; therefore, every 15 pings covered a distance of approximately two meters. To generate each report, the pings went through a quality test to determine if a feature (i.e., SAV) could be extracted from the pings. If a feature could be extracted, the data was sent to the feature algorithm detection (Navico 2014), which generated the bio-volume data. Finally, I converted the bio-volume output data generated by Biobase to a binary variable; SAV present (1) or SAV absent (0).

Biobase has a few safeguards against false positive detection as well as some limitations. To avoid false positives, the Biobase system did not consider plant heights from pings within a coordinate point that were shorter than 5% the water depth. Hence, in the SAV maximum depth for the AS (approximately 2.4 m) (Ferguson and Wood 1994), the plants had to be at least 12 cm to be considered SAV in the Biobase algorithm. This height threshold set in the algorithm would likely lead to SAV underestimates in deep waters that have short SAV (<12 cm), which can affect SAV bed's maximum extent estimates. To further avoid false vegetation detections at depths well beyond the deepest rooting depth of vegetation, Biobase discarded 2% of the deepest coordinate points registering vegetation. The maximum depth SAV detection for the sonar depends on the transducer's settings, based in the transducer I used, the maximum detection could be in the tens of meters (Biobase 2019). Due to the low visibility in AS, a substantial amount of SAV is likely to occur at depths shallower than the sonar method can be used (Kenworthy et al. 2012; Bučas et al. 2016). However, the single-beam sonar's nearfield (the distance in front of the transducer where the acoustic cone has not yet formed, and a return signal cannot be adequately analyzed) limits its ability to detect SAV at depths shallower than 0.5 m because the (Navico 2014; Radomski and Holbrook 2015).

After converting the bio-volume data to binomial data, I created a kriging layer from the binomial data utilizing the indicator kriging method in ArcGIS (ESRI 2011). I chose this method as indicator kriging has been used in SAV mapping for its capability to handle non-normally distributed data (Heuvel et al. 2019). In the final kriging layer, I only retained values with a probability of having SAV greater than 50%. This probability percentage threshold is arbitrary, and in some cases it may not yield the highest accuracy; however, previous studies that investigated SAV sonar classification mapping and evaluated different probability threshold values suggested that the 50% threshold may be an acceptable value, especially when conducting binary mapping (i.e. SAV presence and absence) (Osborne et al. 2001; McIntyre et al. 2018). Valley et al. (2005) documented that sonar kriging interpolation yields high accuracy when compared to in-water diver surveys. Nonetheless, I only used the kriging layer to display graphic representations of SAV covered areas. The actual sonar swath at 1-m depth was approximately 10 cm, which was too small to represent in a sound-wide or regional map. In addition, the raw sonar data with each sonar point was cumbersome and difficult to display on a map. I did not use the kriging data to generate any statistics, except to compare the 2014 survey linear distance covered by SAV to historical records of SAV distribution in AS, hereafter referred to as the Maximum Extent Layer.

Maximum Extent Layer (MEL) and 2014 RAS comparison

The Maximum Extent of Reported SAV Presence Layer in AS (MEL) was compiled by NC Division of Marine Fisheries (NCDMF) (2008) comprising observations between 1987 and 2008 (Figure 2). NCDMF utilized various observation methods, such as aerial photography and in- and on-water observations to generate the SAV distribution layer. In this study, the MEL was used as a proxy for historical SAV presence data to compare with the 2014 RAS. To make this comparison, I compared the length of the two layers (2014 RAS vs MEL). However, to standardize the comparison, I excluded areas in the MEL that were not sampled during the 2014 RAS.

SAV Presence Verification

Sonar has been used to effectively identify SAV beds in various aquatic environments (Sabol et al. 1998; Valley et al. 2015; Bučas et al. 2016). However, sonar, like other remote sensing techniques, requires signature verification, as the unique water quality and substrate characteristics of each estuary can affect the signal interpretation (Sabol et al. 2002). In this study, I verified the sonar signal interpretation by comparing underwater video nearest to specific sonar reports.

The video data was analyzed by determining SAV presence-absence using a binomial code (1=SAV present, 0=SAV absent) (Kenworthy et al. 2012). The GPS location of each underwater video point was recorded and later compared to the sonar data in ArcGIS (ESRI 2011). The Spatial Join tool in ArcGIS (ESRI 2011) was utilized to select the nearest sonar point to the video samples with a 10-m threshold matching distance where video points that were located > 10 m from a sonar point were discarded. Preliminary analysis indicated that percent agreement between sonar and video did not significantly vary at distances less than 10 m (Appendix B).

To verify the sonar's signal interpretation, two metrics were estimated: SAV present verification percent (Equation 1) and SAV absent verification percent (Equation 2) where:

$$\text{SAV present verification percent} = \frac{Total\ SAV\ present\ video\ points}{Total\ expected\ SAV\ present\ video\ points}\ X\ 100 \qquad (1)$$

$$\text{SAV absent verification percent} = \frac{Total\ SAV\ \text{absent}\ video\ points}{Total\ expected\ SAV\ \text{absent}\ video\ points}\ X\ 100 \qquad (2)$$

Sentinel Site Selection

One of the main objectives of the RAS, was to identify areas where ten permanent sentinel monitoring sites (SS) could be established. To select the SS, ArcGIS 10.4.1 (ESRI 2011) was used to delineate the 2014 RAS transects with a shapefile layer. The shapefile contained 1,000-m by 500-m rectangles (bins) that followed the AS shoreline. Each of these bins represented potential SS with their corresponding dimensions. A total of 600 bins were created, but only 88 met the selection criteria: 1) SAV present in the MEL, 2) SAV present in 2014 sonar survey, and 3) SAV present in 2014 video survey. A number was assigned to each of the 88 bins, and the "runif" function in R (R Core Team 2014) was used to randomly select ten SS.

Results

SAV Distribution in Albemarle Sound

A total of 46 transects covering approximately 478 km (60%; Moorman et al. 2017) of the AS shoreline and tributaries were sampled in the AS (Figure 3). All the transects detected some SAV present in the sonar survey. The median (or 50th quartile) sampling depth was 1.34 m, the minimum depth 0.77 m, and the maximum depth 5.78 m (Figure 4). The depth 25th and 75th quartiles were 1.15 and 1.68m, respectively, and the sonar sampling depth was not normally distributed (Kolmogorov-Smirnov, $p<0.05$). The median depth for areas with SAV present was 1.27 m, and the 25th and 75th SAV present quartiles were 1.08 and 1.67 m, respectively. The maximum depth for SAV present was 4.66 m and minimum 0.77 m. Whereas, for areas surveyed with no SAV the median depth was 1.36 m, and the 25th and 75th SAV absent quartiles were 1.17 and 1.69 m, respectively (Figure 5).

To further explore the data at depths were SAV were most abundant, I applied a 2.5 m cut-off to the data, rounded from the 2.4 m SAV maximum depth for the area documented by Ferguson and Wood (1994). With the cut-off point, median depth at which SAV were present was 1.26, and the 25th and 75th quartiles were 1.08 and 1.59 m, respectively; whereas, median depth at which SAV were absent was 1.34 m, and the 25th and 75th quartiles were 1.16 and 1.63 m, respectively.

The RAS indicated there were three distinct shoreline areas with relatively large SAV beds (> than 10 km in length) located along 1) the westside of the Sound at Sandy Shores area near the town of Edenton, 2) the eastside of the Sound in Kitty Hawk Bay, and 3) the southeast side of the Sound, near the mouth of the Alligator River, at East Lake (Figure 6). Several smaller beds (<10 km) were identified across the Sound and its tributaries (Figures Figure 7, Figure 8, and Tables

Table 2). I define an SAV bed in the SAV maps as distinct polygons generated from the kriging layer.

Comparison Between 2014 RAS to the Historical Maximum Extent Layer (MEL)

The total vegetated linear distance for SAV coverage indicated by the MEL was 211.72 km while the linear SAV vegetated distance on the sonar kriging map in the 2014 RAS was

114.35 km. The difference between the MEL and the 2014 survey was 97.27 km, a difference of 54%. SAV has persisted in some areas while there were both losses and gains with no clear regional pattern (Figure 9). The Kitty Hawk Bay and Edenton beds were persistent when compared to the MEL; whereas, the bed in the Batchelor Bay area, near the mouth of the Chowan River, appears to have been lost. On the other hand, East lake had not been reported to have SAV in the past, but SAV were present in the 2014 survey (Figure 9).

Sonar Verification with Underwater Video

A total of 1311 underwater video points were obtained during the RAS, but only 871 met the distance matching criteria (<10 m between sonar and video points). For those that met the distance criteria, 237 points were verified in sonar as SAV present (37.2%). Video verification of SAV absence in sonar was 92.15%. SAV presence was verified on video at the most extensive (Edenton, Kitty Hawk, and East Lake) (Figure 10).

Sentinel Site Selection

The RAS transects bin delineation yielded approximately 600 bins, but only 88 bins met the three-point site selection criteria. Ten sentinel sites were selected randomly. Only one site was selected manually, as the south shore of the Sound was underrepresented. I chose a random sentinel site selection, so the sites could be considered representatives of the sound. Fortuitously, the sites are widely distributed across the sound and expose to a diverse range of environmental and anthropogenic condition (Appendix D).

Discussion

Coastal management requires accurate inventories and information on the status and trends of resources to implement knowledge-based management decisions. Hence, there is a great need for reliable and standardized natural resources monitoring among federal and state agencies. This study addressed this need for low-salinity SAV in NC. The results constitute the first attempt to conduct a synoptic sound-wide survey of SAV in AS and portions of the adjoining tributaries using a hydroacoustic detection method. Encouraged by several studies that demonstrated both the practical utility and quantitative capabilities of sonar for assessing the distribution and abundance of SAV in both freshwater and seawater (McCarthy 1997; Sabol et al. 2002; Winfield et al. 2007; Bučas et al. 2016), provided an alternative to other traditional mapping and monitoring approaches (e.g., airborne remote sensing, in-water sampling) (Madsen 1993). Here, single-beam sonar was used primarily as a reconnaissance tool for detecting the presence or absence of SAV and was designed to optimize detection by endeavoring to sample at the 1.0 m isobath where previous studies in AS suggested a high likelihood of SAV occurrence (Davis and Brinson 1976; Ferguson and Wood 1994; Deaton et al. 2010; Quible and Associates 2011).

The transect survey assessed the presence-absence of SAV along 478 linear km of submerged bottom, or approximately 60% of the AS shoreline (800 km). Although the scope of the survey was initially planned to cover the entire Sound and portions of the tributaries, numerous obstructions to navigation and shallow water depths prevented the survey from gaining access to the entire submerged bottom area. The median sampling depth (1.34 m) showed how challenging it was to consistently navigate the vessel along the prescribed 1.0 m isobath. Maintaining the small vessel's course in the wind and in areas with rapid and frequent changes in bathymetry resulted in a lag time between course corrections and reacquisition of the 1.0 m contour. This resulted in a skewed non-normal deviation from the intended sampling depth with less than 25% of the sampling was shallower than the 1-m isobath (1.14 25th depth quartile).

Fortuitously, an unintended consequence of this navigation problem provided an opportunity to evaluate several aspects of SAV depth distribution in the Sound. The median depth of SAV presence (1.27 m) closely coincided with the optimum survey depth (1.0 m) drawn from historical observations in the Sound (Davis and Brinson 1990; Ferguson and Wood 1994; Quible and Associates 2011; NCDEQ 2016), while the absolute frequency of SAV presence was relatively constant between 0.77 m and 1.3 m. The distribution of the presence data suggests SAV can grow to depths well beyond 1.3 m, but the frequency dropped precipitously with increasing water depths. Moreover, the frequency of absence detections initially increased rapidly between 0.77 m and 1.3 m indicating that the maximum SAV coverage occurred at depths < 1.3 m. At deeper depths the meadows were relatively sparse, and occurrence was rare.

Maximum depth of SAV growth and changes in the deep edge distribution of SAV meadows are being routinely used in monitoring programs as one of the primary response indicators for assessing water quality conditions in estuarine environments (Dennison et al. 1993; Kenworthy and Fonseca 1996; Li et al. 2007; Orth et al. 2010; Kenworthy et al. 2014; Greening et al. 2016; Orth et al. 2017). SAV are sensitive to fluctuating optical properties of the water (transparency) and there is a very robust correspondence between SAV maximum depth distribution and optical water quality driven by the concentrations of chlorophyll (chl), total suspended solids (TSS), and colored dissolved organic matter (CDOM) (Dennison et al. 1993; Gallegos 2001; Biber et al. 2008). The sonar data for SAV presence suggested that neither the maximum nor the median depths of SAV alone adequately represented the main distinguishing characteristics of SAV depth distribution in AS. However, the sonar makes it possible to simultaneously measure depth and SAV presence-absence, whereby the distributional properties of these variables (i.e., proportion of SAV presence vs. absence, quartiles, slope of change) could be used to quantitatively characterize the deep edges of SAV meadows and provide a more sensitive, informative, and robust indicator for diagnosing changes in SAV depth distribution and responses to environmental quality. In this study, I chose to report the 25th, 50th, and 75th quartiles, as these quartiles describe at what depth SAV were concentrated.

Except for the notable absence of SAV along the southern shoreline (between the Chowan and Alligator Rivers) in the video verification, meadows were present along most shorelines from the westernmost location at Edenton east to Kitty Hawk Bay. The SAV beds were confined to a narrow band along the shore and comprised of relatively variable sized patches, ranging in length from the most extensive beds covering more than 10,000 m of shoreline (Edenton, Kitty Hawk, and East Lake) to less extensive meadows (<10,000 m, a few 100 m, or smaller). The three most extensive beds were concentrated in shallow areas protected from wind fetch (e.g., sound tributaries and embayments), particularly the strong winter storm northeasterly winds capable of affecting SAV distribution (Short and Wyllie-Echeverria 1996; Cabello-Pasini et al. 2002). This was noticeable in other locations in AS because the mainstem of the Sound had relatively fewer SAV beds compared to the tributaries, which are protected from exposure to strong winds and excessive wave energy by reduced wind fetch.

It was evident from the RAS in 2014, the historical layer in the MEL, and other observations that SAV in AS has been a persistent benthic habitat for more than three decades. However, SAV distribution has experienced substantial fluctuations. When comparing the 2014 RAS to the MEL, SAV were more abundant in some areas in the historical layer than in 2014, for example, Batchelor Bay. In two other regions, Edenton and East Lake, SAV were more abundant in 2014 than in the MEL. In the 1990’s, Davis and Brinson (1990) and Ferguson and Wood (1994) completed some of the most extensive surveys of AS prior to the 2014 RAS. The older surveys identified beds that were not detected in 2014 and vice versa. The SAV bed in Edenton was one of the most extensive in the 2014 RAS and in the period between 2005 and 2010 (Quible and Associates 2011). Yet, Ferguson and Wood (1994) did not report a large bed at this location, though they sampled the Edenton area in the 1990's. Similarly, in East Lake, where one of the most extensive beds was identified in 2014, Ferguson and Wood (1994) did not report a meadow. On the other hand, Ferguson and Wood (1994) reported extensive beds in most of the Perquimans River littoral; however, the only significant bed identified in this study was in Halsey Bay. Similarly, David and Brinson (1990) indicated that Little River had relatively high area coverage and biomass of SAV, but Ferguson and Wood (1994) found no evidence of SAV in Little River except on the southwest shore near the entrance to AS. In the 2014 RAS survey in Little River, only a small patch of SAV were confirmed by video. Kitty Hawk has been the most persistent extensive bed, as it was documented in the 2014 RAS, as well as in Davis and Brinson (1990) and Ferguson and Wood (1994).

Based on anecdotal evidence, it has been reported that as much as 50% of low salinity SAV in NC has been lost during the past century (NCDEQ 2016). This isn't unprecedented; similar scales of SAV loss have been reported in other western Atlantic coastal systems, including neighboring bays and lagoons both north and south of NC (Orth and Moore 1983a; Lefcheck et al. 2018; Morris et al. 2018). Given the spatial and temporal fluctuations of SAV suggested by a comparison between the 2014 RAS and the historical surveys, it is tempting to draw some inferences from similarities in the anecdotal claim of 50% SAV loss and the 54% difference between the 2014 RAS estimate of SAV presence distance and the MEL. However, the linear distance comparison between the two layers are rough estimations given the differences in sampling methodologies. Additionally, the RAS layer was created with an indicator kriging method set with a 50% probability threshold, which in some instances may incorrectly classify SAV presence-absence. Nonetheless, the RAS offers a sense of real SAV distribution (McIntyre et al. 2018) in 2014, and previous studies indicated that the 50% probability threshold is adequate in binary (i.e. SAV presence-absence) classification mapping (Osborne et al. 2001; McIntyre 2019). Therefore, it seems plausible to infer that SAV are declining in AS; however, since it is difficult to assign a level of confidence for either of these estimates, the empirical weight of evidence inferring SAV status and the potential declines of SAV in AS are not sufficiently robust, leading to the second objective of this study.

Based on the sound-wide survey results, the second objective of this study was to identify potential long-term SS in AS. These SS will be incorporated into a larger coast-wide SAV monitoring program in NC and serve as a baseline for assessing future status and trends of SAV in the Sound (APNEP 2012), while providing critical indicators of SAV health and condition during the establishment of a pilot site for the National Monitoring Network (NMN) (Moorman et al. 2014), as well as the implementation of the North Carolina Nutrient Criteria Development Plan (NCDP) for estuarine waters (North Carolina Department of Environmental and Natural Resources 2014). The ten sites that met the prescribed selection criteria span the entire geographic range of the Sound and its salinity gradient, and include shorelines associated with; 1) both high and low wind and wave exposure, 2) the most rural regions of the watershed dominated by wetlands, 3) shorelines and associated drainages affected by agriculture and forestry activities, 4) large river mouths, 5) relatively smaller tributaries, and 6) modestly urbanized shorelines in proximity to Edenton and the highly developed tourist community at Kitty Hawk. The distribution of these sites should provide an opportunity to evaluate many of the most important environmental and anthropogenic stressors potentially affecting the distribution, abundance, and survival of SAV in AS (Orth et al. 2010; Orth et al. 2017; Lefcheck et al. 2018). Furthermore, these strategically located sites can be sampled frequently and at much higher resolution by sonar to evaluate the characteristics of the SAV spatial and depth distributions and both the inter- and intra-annual variation in SAV coverage and abundance.

Benefits and Limitations of the Sonar SAV Survey Method

Practically speaking, as a substitute for other survey approaches, the Lowrance/Biobase system demonstrated the capability to cover extensive areas in a relatively short period of time. More than 400 km of shoreline were surveyed, nearly continuously, in less than three months with a single boat. It is not feasible to achieve this level of resolution at such a large scale with in-water sampling. And since the detection of SAV by high altitude airborne sensors in optically poor waters like AS has not been reliable, sonar can provide a reasonable substitute with the added benefit of a much faster turnaround time for signature interpretation and data processing compared to other remote sensing methods and in-water sampling techniques.

One of the major constraints of sonar is the limitation to water depths deeper than 0.5 m (Navico 2014). Besides the difficulty of navigating a power vessel at shallow depths without severely disturbing the habitat, sonar cannot reliably distinguish the bottom signature from the vegetation signature and may overestimate SAV abundance in shallow water (Radomski and Holbrook 2015). The 2014 RAS avoided this problem by restricting all the sonar detections, both presence and absence, to depths ≥ 0.77 m. Previous studies indicate that SAV regularly occur at depths < 0.77 m in AS (Davis and Brinson 1990; Ferguson and Wood 1994; Quible and Associates 2011; Kenworthy et al. 2012), so it is possible that some of the transects dominated by absence detections may have had relatively more SAV in shallower water closer to shore, and this survey technique underestimated the linear distance of shoreline occupied by SAV.

Clearly, there is a need to improve the scope and accuracy of the survey by adopting some method of sampling perpendicular to shore in order to confirm the presence-absence of SAV in relatively shallower water where the sonar cannot be applied. One practical and cost-effective option would be to complement the sonar survey with aerial imagery acquired by flying a low-altitude (400 ft) drone parallel and inshore of the sonar track. Flying at low altitude and relatively slow speed, the imagery acquired by a quad-copter drone that pauses for each photograph can avoid many of the inherent water penetration issues, as well as some of the logistical problems, typically encountered with high altitude airborne sensors (e.g., fixed wing aircraft and satellites). Affordable drone and high-resolution camera technologies are readily available with programmable software to plot precise flight lines and produce geospatially articulated imagery that could complement the sonar data by filling the SAV information gaps between the sonar transects and the shoreline. Future survey efforts should consider investigating the potential for combining sonar with drone technologies to evaluate whether a combination of these two survey tools can improve the capability for monitoring the status and trends of SAV in low-salinity estuaries.

Signal verification in remote sensing is a necessity, and bottom signal misclassifications is a common problem for remote sensing methods (Congalton 1991). Certain substrates can have a similar acoustic signature to that of SAV, making it difficult for the sonar algorithm to discriminate and classify the substrate correctly; for example, sonar can confuse submerged tree stumps, debris or detritus, and flocculent substrate as SAV (Sabol et al. 2002; Helminen et al. 2019). These and other bottom features may lead to “false positive” classifications of SAV signatures and suggest the need for some level of signature verification (ground truthing) to accompany the acquisition and interpretation of the sonar. As an alternative to in-water sampling by snorkeling or scuba diving, researchers have employed a low-light sensitive video drop camera as the signature verification method (Kenworthy et al. 2012). However, underwater video as a verification method should be used with caution. The limitations of underwater video as a verification tool can be found in Appendix B of this dissertation.

Conclusion

SAV are considered a sentinel species group due to their responsiveness to changes in environmental conditions (Orth et al. 2017). The APES has been experiencing increased pollution due to increased urbanization in the areas (Lin 2007); hence, it is essential to start taking steps to ensure the health of the SAV community by frequently monitoring SAV in the Sound. In my study, I confirmed that SAV in AS is confined to a narrow band along the shallower portions of the shore; more than 75% of the SAV detection were shallower than 2-m. The shallow distribution of SAV and their proximity to the shore, point to SAV's susceptibility to shoreline and water quality changes in AS (Orth et al. 2010). Fortunately, sonar SAV monitoring has the added benefit of providing fine-scale depth information along with SAV presence, which can be very valuable when characterizing SAV beds and detecting change. Changes in SAV beds' deep edge (the transition zone between vegetated and unvegetated substrate along a downward slope) often indicate changes in water quality, like those changes caused by human activity (e.g. nutrient loading, increased sedimentation) (Kenworthy et al. 2014). SAV presence and depth distribution data reported as quartile (50th and 75th) could be adopted as way to characterize beds' edge in the Sound. However, changes in beds' deep edge should be carefully analyzed, as depth limits may be affected by shifts in species composition (Orth and Moore 1988).

SAV in the Sound is susceptible to other emerging stresses like changing climate and rising sea level. Interestingly, in my study, the largest SAV beds in the Sound were in areas protected from strong wind action, likely due to SAV's vulnerability to storms. With an uncertain future climate and the possibility of increasing storm activity (Boyles and Raman 2003) many of these beds could be severely affected. Storms are known to play a major role in shaping SAV abundance and distribution. The largest documented SAV loss in the Chesapeake Bay was followed by Hurricane Agnes in 1972 (Orth 2010). Moreover, two of the largest beds were near urbanized areas (Edenton and Kitty Hawk Bay); urbanized areas tend to have modified shorelines and that can minimize the beds' resilience to sea level changes by inhibiting their ability to migrate up, as sea level changes (Orth et al. 2017). Therefore, there is a heightened need for SAV monitoring and understanding the factors that affect SAV abundance, particularly in relation to water quality, shoreline modification, and climate change. However, identifying factors of change will likely proof difficult due to the SAV's high spatial and temporal variability. Nonetheless, the sentinel sites proposed in this study pave the way to begin understanding SAV status and trends in the Sound.

References

Adair, S.E., J.L. Moore, and C.P. Onuf. 1994. Distribution and status of submerged vegetation in estuaries of the upper Texas coast. *Wetlands* 14: 110–121. doi:10.1007/BF03160627.

APNEP. 2012. *Comprehensive conservation and management plan 2012-2022*. Raleigh, North Carolina.

APNEP. 2019. Submerged Aquatic Vegetation Maps. https://apnep.nc.gov/our-work/monitoring/submerged-aquatic-vegetation-monitoring. Accessed 9 September 2019.

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 seagrasses. *Estuaries and Coasts* 31: 177–191. doi:10.1007/s12237-007-9023-6.

Biobase. 2019. EcoSound FAQs.

Boyles, R.P., and S. Raman. 2003. Analysis of climate trends in North Carolina (1949-1998). *Environment International* 29: 263–275. doi:10.1016/S0160-4120(02)00185-X.

Bučas, M., A. Šaškov, A. Šiaulys, and Z. Sinkevičienė. 2016. Assessment of a simple hydroacoustic system for the mapping of macrophytes in extremely shallow and turbid lagoon. *Aquatic Botany* 134: 39–46. doi:10.1016/j.aquabot.2016.06.009.

Cabello-Pasini, A., C. Lara-Turrent, and R.C. Zimmerman. 2002. Effect of storms on photosynthesis, carbohydrate content and survival of eelgrass populations from a coastal lagoon and the adjacent open ocean. *Aquatic Botany* 74: 149–164. doi:10.1016/S0304-3770(02)00076-1.

Carpenter, D.E., and L. Dubbs. 2012. *2012 Albemarle-Pamlico ecosystem assessment, Albemarle-Pamlico National Estuary Partnership*. Raleigh, North Carolina.

Carraway, R.J., and L.J. Priddy. 1983. *Mapping of submerged grass beds in Core and Bogue Sounds, Carteret County, North Carolina by conventional aerial photography*. Morehead City, NC.

Christiaen, B., L. Ferrier, P. Dowty, J. Gaecle, and H. Berry. 2017. *Puget Sound seagrass monitoring report monitoring year 2015*. Olympia, Washington.

Christian, R.R., and S. Mazzilli. 2007. Defining the coast and sentinel ecosystems for coastal observations of global change. *Hydrobiologia* 577: 55–70. doi:10.1007/s10750-006-0417-4.

Congalton, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* 37: 35–46.

Costello, C.T., and W.J. Kenworthy. 2011. Twelve-year mapping and change analysis of Eelgrass (*Zostera marina*) areal abundance in Massachusetts (USA) identifies statewide declines. *Estuaries and Coasts* 34: 232–242.

Davis, G.J., and M.M. Brinson. 1976. *The submerged macrophytes of the Pamlico River Estuary, North Carolina*. Raleigh, NC.

Davis, G.J., and M.M. Brinson. 1990. *A survey of submersed aquatic vegetation of the Currituck Sound and the western Albemarle-Pamlico estuarine system*. Greenville, North Carolina.

Dealteris, J.T., B.D. Kilpatrick, and R.B. Rheault. 2004. A comparative evaluation of the habitat value of shellfish aquaculture gear, submerged aquatic vegetation and a non-vegetated seabed. *Journal of Shellfish Research* 23: 867–874.

Deaton, A.S., W.S. Chappell, J. O'Neal, K. Hart, and B. Boutin. 2010. *North Carolina Coastal Habitat Protection Plan*. Morehead City, North Carolina.

Dennison, W.C., R.J. Orth, K.A. Moore, J.C. Stevenson, V. Carter, S. Kollar, P.W. Bergstrom, and R.A. Batiuk. 1993. Assessing water quality with submerged aquatic vegetation: Habitat requirements as barometers of Chesapeake Bay health. *BioScience* 43: 86–94. doi:10.2307/1311969.

Duarte, C.M. 1987. Use of echosounder tracings to estimate aboveground biomass of submberged plants in lakes. *Canadian Journal of Fisheries and Aquatic Sciences* 44: 732–735.

ESRI. 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

Ferguson, R.L., and L.L. Wood. 1989. *Submerged aquatic vegetation in the Albemarle-Pamlico estuarine systems*. Beaufort, North Carolina.

Ferguson, R.L., and L.L. Wood. 1990. *Mapping submerged aquatic vegetation in North Carolina with conventional aerial photography*. *Federal Coastal Wetland Mapping Programs*. Washington, District of Columbia.

Ferguson, R.L., and L.L. Wood. 1994. *Rooted vascular aquatic beds in the Albemarle-Pamlico estuarine system.* Beaufort, North Carolina: National Marne Fisheries, National Oceanic and Atmospheric Administration.

Ferguson, R.L., L.L. Wood, and G.J. Davis. 1993. Monitoring spatial change in seagrass habitat with aerial photography. *Photogrammetric Engineering and Remote Sensing* 59: 1033–1038.

Finkbeiner, M., B. Stevenson, and R. Reaman. 2001. *Guidance for benthic habitat mapping: An aerial phographic approach*. Charleston, South Carolina.

Flaherty-Walia, K.E., R.E.J. Matheson, and R. Paperno. 2015. Juvenile Spotted Seatrout (*Cynoscion nebulosus*) habitat use in an eastern Gulf of Mexico estuary: The effects of seagrass bed architecture, seagrass species composition, and varying degrees of freshwater influence. *Estuaries and Coasts* 38: 353–366.

Fourqurean, J.W., C.M. Duarte, H. Kennedy, N. Marbà, M. Holmer, M.A. Mateo, E.T. Apostolaki, et al. 2012. Seagrass ecosystems as a globally significant carbon stock. *Nature Geoscience* 5: 1–5.

Fourqurean, J.W., A. Willsie, C.D. Rose, and L.M. Rutten. 2001. Spatial and temporal pattern in seagrass community composition and productivity in South Florida. *Marine Biology* 138: 341–354. doi:10.1007/s002270000448.

Gallegos, C.L. 2001. Calculating optical water quality targets to restore and protect submerged aquatic vegetation: Overcoming problems in partitioning the diffuse attenuation coefficient for Photosynthetically Active Radiation. *Estuaries* 24: 381–397. doi:10.2307/1353240.

Giese, G.L., H.B. Wilder, and G.G.J. Parker. 1985. *Hydrology of major estuaries and sounds of North Carolina*. Alexandria, Virginia.

Godlewska, M., A. Świerzowski, and I.J. Winfield. 2004. Hydroacoustics as a tool for studies of fish and their habitat. *Ecohydrology and Hydrobiology* 4: 417–427.

Greening, H., A. Janicki, and E.T. Sherwood. 2016. Segrass recovery in Tampa Bay, Florida (USA). In *The Wetland Book I: Structure and Function, Management, and Methods*, ed. C. M. Finlayson, 1st ed. Springer. doi:10.1007/978-94-007-6173-5.

Heck, K.L.J., and T.A. Thoman. 1984. The nursery role of seagrass meadows in the upper and lower reaches of the Chesapeake Bay. *Coastal and Estuarine Research Federation* 7: 70–92.

Helminen, J., T. Linnansaari, M. Bruce, R. Dolson-Edge, and R.A. Curry. 2019. Accuracy and precision of low-cost echosounder and automated data processing software for habitat mapping in a large river. *Diversity* 11: 1–18. doi:10.3390/d11070116.

Hermand, J.P., P. Nascetti, and F. Cinelli. 1998. Inversion of acoustic waveguide propagation features to measure oxygen synthesis by *Posidonia oceanica*. *Oceans Conference Record (IEEE)* 2: 919–926. doi:10.1109/oceans.1998.724372.

Heuvel, M.R., J.K. Hitchcock, M.R.S. Coffin, C.C. Pater, and S.C. Courtenay. 2019. Inorganic nitrogen has a dominant impact on estuarine eelgrass distribution in the southern Gulf of St. Lawrence, Canada. *Limnology and Oceanography*: 1–15. doi:10.1002/lno.11185.

Hovel, K.A., M.S. Fonseca, D.L. Myer, W.J. Kenworthy, and P.E. Whitfield. 2002. Effects of seagrass landscape structure, structural complexity and hydrodynamic regime on macrofaunal densities in North Carolina seagrass beds. *Marine Ecology Progress Series* 243: 11–24.

Howell, A.W., and R.J. Richardson. 2019. Correlation of consumer grade hydroacoustic signature to submersed plant biomass. *Aquatic Botany* 155. Elsevier: 45–51. doi:10.1016/j.aquabot.2019.02.001.

Jarosław, T., N. Gorska, and Z. Klusek. 2003. Statistical analysis of acoustic echoes from underwater meadows in the eutrophic Puck Bay (southern Baltic Sea). *Aquatic Living Resources* 16: 215–221. doi:10.1016/S0990-7440(03)00015-9.

Jassby, A.D. 1998. Interannual variation at three inland water sites: Implications for sentinel sites. *Ecological Applications* 8: 277–287. doi:10.1890/1051-0761(1998)008[0277:IVATIW]2.0.CO;2.

Jia, P., and M. Li. 2012. Circulation dynamics and salt balance in a lagoonal estuary. *Journal of Geophysical Research* 117: 1–16. doi:10.1029/2011JC007124.

Kenworthy, W.J., C.A. Buckel, D.E. Carpenter, D.B. Eggleson, D. Field, C.S. Krahforst, and J.J. Luczkovich. 2012. *Development of submerged aquatic vegetation monitoring protocols in*

North Carolina. Morehead City, North Carolina.

Kenworthy, W.J., and M.S. Fonseca. 1996. Light requirements of seagrasses *Halodule wrightii* and *Syringodium filiforme* derived from the relationship between diffuse light attenuation and maximum depth distribution. *Estuaries* 19: 740–750. doi:10.2307/1352533.

Kenworthy, W.J., C.L. Gallegos, C.T. Costello, D. Field, and G. di Carlo. 2014. Dependence of eelgrass (*Zostera marina*) light requirements on sediment organic matter in Massachusetts coastal bays: Implications for remediation and restoration. *Marine Pollution Bulletin* 83: 446–457. doi:10.1016/j.marpolbul.2013.11.006.

Komatsu, T., C. Igarashi, K. Tatsukawa, S. Sultana, Y. Matsuoka, and S. Harada. 2003. Use of multi-beam sonar to map seagrass beds in Otsuchi Bay on the Sanriku Coast of Japan. *Aquatic Living Resources* 16: 223–230. doi:10.1016/S0990-7440(03)00045-7.

Kruss, A., P. Blondel, J. Tegowski, J. Wiktor, and A. Tatarek. 2008. Estimation of macrophytes using single-beam and multibeam echosounding for environmental monitoring of arctic fjords (Kongsfjord, West Svalbard Island). *The Journal of the Acoustical Society of America* 123: 3213. doi:10.1121/1.2933397.

Lantz, S.M., D.E. Gawlik, and M.I. Cook. 2010. The effects of water depth and submerged aquatic vegetation on the selection of foraging habitat and foraging success of wading birds. *The Condor* 112: 460–469. doi:10.1525/cond.2010.090167.

Lefcheck, J.S., R.J. Orth, W.C. Dennison, D.J. Wilcox, R.R. Murphy, J. Keisman, C. Gurbisz, et al. 2018. Long-term nutrient reductions lead to the unprecedented recovery of a temperate coastal region. *Proceedings of the National Academy of Sciences* 115: 3658–3662. doi:10.1073/pnas.1715798115.

Li, X., D.E. Weller, C.L. Gallegos, T.E. Jordant, and H.-C.C. Kim. 2007. Effects of watershed and estuarine characteristics on the abundance of submerged aquatic vegetation in Chesapeake Bay subestuaries. *Estuaries and Coasts* 30: 840–854. doi:10.1007/BF02841338.

Lindquist, N.L., and S.R. Fegley. 2016. *Development of a comprehensive North Carolina salinity database to facilitate management and restoration of critical fish habitats. North Carolina Coastal Recreational Fishing License Final Report: 2013-H-015*.

Luettich, R.A., S.D. Carr, J. V. Reynolds-Fleming, C.W. Fulcher, and J.E. McNinch. 2002. Semi-diurnal seiching in a shallow, micro-tidal lagoonal estuary. *Continental Shelf Research* 22: 1669–1681. doi:10.1016/S0278-4343(02)00031-6.

Lutcavage, M., and J.A. Musick. 1985. Aspects of the Biology of Sea Turtles in Virginia. *Copeia* 1985: 449–456.

Maceina, M.J., and J. V. Shireman. 1980. The use of a recording fathometer for determnation of distribution and biomass of Hydrilla. *Journal of Aquatic Plant Management* 18: 34–39.

Maceina, M.J., J. V. Shireman, K.A. Langeland, and D.E.J. Canfield. 1984. Prediction of submerged plant biomass by use of a recording fathometer. *Journal of Aquatic Plant Management* 22: 35–38.

Madsen, J.D. 1993. Biomass techniques for monitoring and assessing control of aquatic vegetation. *Lake and Reservoir Management* 7: 141–154. doi:10.1080/07438149309354266.

Madsen, J.D., P.A. Chambers, W.F. James, E.W. Koch, and D.. Westlake. 2001. The interaction between water movement, sediment dynamics and submersed macrophytes. *Hydrobiologia* 444: 71–84. doi:10.1023/A.

Madsen, J.D., and R.M. Wersal. 2017. A review of aquatic plant monitoring and assessment methods. *Journal of Aquatic Plant Management* 55: 1–13.

McCarthy, E.M. 1997. Acoustic characterization of submerged aquatic vegetation. In *SACLANTCEN Proceedings Series CP-45, High Frequency Acoustics in Shallow Water*, ed. N. G. Pouliquen, E. Bergem, and A. P. Lyons, 362–369. Lerici, Italy: NATO SACLANT Undersea Research Centre.

McCarthy, E.M., and B.M. Sabol. 2000. Acoustic characterization of submerged aquatic vegetation: Military and environmental monitoring applications. In *OCEANS 2000 MTS/IEEE Conference and Exhibition. Conference Proceedings*, 1957–1961. Providence, Rhode Island: IEEE. doi:10.1109/OCEANS.2000.882226.

McIntyre, K., K. McLaren, and K. Prospere. 2018. Mapping shallow nearshore benthic features in a Caribbean marine-protected area: Assessing the efficacy of using different data types (hydroacoustic versus satellite images) and classification techniques. *International Journal of Remote Sensing* 39. Taylor & Francis: 1117–1150. doi:10.1080/01431161.2017.1395924.

Merkel and Associates, I. 2014. *Southern California Bight Regional Eeglrass Surveys: Alamitos Bay, San Grabriel River, Anaheim Bay/Huntington Harbour, Agua Hedionda Lagoon, Batiquitos Lagoon, and San Dieguito*. San Diego, CA.

Micheli, F., and C.H. Peterson. 1999. Estuarine vegetated habitats as corridors for predator movements. *Conservation Biology* 13: 869–881. doi:10.1046/j.1523-1739.1999.98233.x.

Moorman, M.C., S.A. Fitzgerald, L.N. Gurley, A. Rhoni-Aref, and K.A. Loftin. 2017. *Water quality and bed sediment quality in the Albemarle Sound, North Carolina, 2012–14*. *Open-File Report 2016-1171*. Reston, Virginia. doi:10.3133/ofr20161171.

Moorman, M.C., K.R. Kolb, and S. Supak. 2014. *Estuarine monitoring programs in the Albemarle Sound study area, North Carolina*. Reston, Virginia.

Morris, L., L. Hall, R.H. Chamberlain, and C. Jacoby. 2018. *Summary report for the Northern Indian River Lagoon*. St. Petersburg, Florida. doi:10.13140/RG.2.2.12366.05445.

Navico, I. 2014. *User reference guide*. Minneapolis, MN.

Norris, J.G., S. Wyllie-Echeverria, T. Mumford, A. Bailey, and T. Turner. 1997. Estimating basal area coverage of subtidal seagrass beds using underwater videography. *Aquatic Botany* 58: 269–287. doi:10.1016/S0304-3770(97)00040-5.

NCDENR. 2014. *North Carolina nutrient criteria development plant*. Raleigh, North Carolina.

NCDEQ. 2016. *North Carolina Coastal Habitat Protection Plan Source Document*. Morehead

City, North Carolina.

NCDMF. 2008. *Inventory of SAV maps and survey work in coastal North Carolina (1981-2008)*. Morehead City, North Carolina.

Orth, R.J., T.J.B. Carruthers, W.C. Dennison, C.M. Duarte, J.W. Fourqurean, K.L.J. Heck, A.R. Hughes, et al. 2006. A global crisis for seagrass ecosystems. *Bioscience* 56: 987–996.

Orth, R.J., W.C. Dennison, J.S. Lefcheck, C. Gurbisz, M. Hannam, J. Keisman, J.B. Landry, et al. 2017. Submersed aquatic vegetation in Chesapeake Bay: Sentinel species in a changing world. *BioScience* 67: 698–712. doi:10.1093/biosci/bix058.

Orth, R.J., and K.A. Moore. 1983a. Chesapeake Bay: An unprecedented decline in submerged aquatic vegetation. *Science* 222: 51–53. doi:10.1126/science.222.4619.51.

Orth, R.J., and K.A. Moore. 1983b. Submerged vascular plants: Techniques for analyzing their distribution and abudance. *Marine Technology Society Journal* 17: 38–52.

Orth, R.J., and K.A. Moore. 1988. Distribution of *Zostera marina* L. and *Ruppia maritima* L. sensu lato along depth gradients in the lower Chesapeake Bay, U.S.A. *Aquatic Botany* 32: 291–305. doi:10.1016/0304-3770(88)90122-2.

Orth, R.J., M.R. Williams, S.R. Marion, D.J. Wilcox, T.J.B. Carruthers, K.A. Moore, W.M. Kemp, et al. 2010. Long-term trends in submersed aquatic vegetation (SAV) in Chesapeake Bay, USA, related to water quality. *Estuaries and Coasts* 33: 1144–1163. doi:10.1007/s12237-010-9311-4.

Osborne, P.E., J.C. Alonso, and R.G. Bryant. 2001. Modelling landscape-scale habitat use using GIS and remote sensing: A case study with great bustards. *Journal of Applied Ecology* 38: 458–471. doi:10.1046/j.1365-2664.2001.00604.x.

Pasqualini, V., P. Clabaut, G. Pergent, L. Benyoussef, and C. Pergent-Martini. 2000. Contribution of side scan sonar to the management of mediterranean littoral ecosystems. *International Journal of Remote Sensing* 21: 367–378. doi:10.1080/014311600210885.

Quible and Associates. 2011. *A compensatory mitigation plan requierement for The Fund for Sandy Point North Carolina, LLC*. Kitty Wawk, North Carolina.

R Core Team. 2014. *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Radomski, P., and B. V. Holbrook. 2015. A comparison of two hydroacoustic methods for estimating submerged macrophyte distribution and abundance: A cautionary note. *Journal of Aquatic Plant Management* 53: 151–159.

Romero, J., K.-S. Lee, M. Pérez, M.A. Mateo, and T. Alcoverro. 2006. Nutrient dynamics in seagrass ecosystems. *Seagrasses: Biology, ecology and conservation*. Springer: 227–254.

Rozas, L.P., and W.E. Odum. 1988. Occupation of submerged aquatic vegetation by fishes: Testing the roles of food and refuge. *Oeco* 77: 101–106. doi:10.1007/BF00380932.

Sabol, B.M., and J. Burczinski. 1998. Digital echosounder for characterizing vegetation in shallow water environments. In *Proceedings of the Fourth European Conference on*

Undewater Acoustics, 165–168. Rome, Italy: CNR-IDAC.

Sabol, B.M., J. Kannenberg, and J.G. Skogerboe. 2009. Integrating acoustic mapping into operational aquatic plant management: A case study in Wisconsin. *Journal of Plant Management* 47: 44–52.

Sabol, B.M., R.E.J. Melton, R. Chamberlain, P. Doering, and K. Haunert. 2002. Evaluation of a digital echosounder system for detection of submersed aquatic vegetation. *Estuaries* 25: 133–141. doi:10.1007/BF02696057.

Sabol, B.M., R.E. Meltona, and R.. Kasul. 1998. Method and apparatus for hydroacoustic detection of submersed aquatic vegetation. Washington, District of Columbia: U.S. Patent Office.

Short, F.T., and S. Wyllie-Echeverria. 1996. Natural and human-induced disturbance of seagrasses. *Environmental conservation* 23: 17–27.

Spears, B.M., I.D.M. Gunn, L. Carvalho, I.J. Winfield, B. Dudley, K. Murphy, and L. May. 2009. An evaluation of methods for sampling macrophyte maximum colonisation depth in Loch Leven, Scotland. *Aquatic Botany* 91: 75–81. doi:10.1016/j.aquabot.2009.02.007.

Stent, C.J., and S. Hanley. 1985. A recording echo sounder for assessing submerged aquatic plant populations in shallow lakes. *Aquatic Botany* 21: 377–394.

Thayer, G.W., K.A. Bjorndal, J.C. Ogden, S.L. Williams, and J.C. Zieman. 1984. Role of large herbivores in seagrass communities. *Estuaries* 7: 351–376.

Tseng, Y.-T. 2009. Recognition and assessment of seafloor vegetation using a single beam echosounder. Curtin University of Technology.

Valley, R.D. 2016. Spatial and temporal variation of aquatic plant abundance: Quantifying change. *Journal of Aquatic Plant Management* 54: 95–101.

Valley, R.D., and M.T. Drake. 2005. *Accuracy and precision of hydroacoustics estimates of aquatic vegetation and the repeatability of whole-lake surveys: Field tests with a commercial echosounder*. *Minnesota Department of Natural Resources Investigational Report*.

Valley, R.D., M.T. Drake, and C.S. Anderson. 2005. Evaluation of alternative interpolation techniques for the mapping of remotely-sensed submersed vegetation abundance. *Aquatic Botany* 81: 13–25. doi:10.1016/j.aquabot.2004.09.002.

Valley, R.D., M.B. Johnson, D.L. Dustin, K.D. Jones, M.R. Lauenstein, and J. Nawrocki. 2015. Combining hydroacoustic and point-intercept survey methods to assess aquatic plant species abundance patterns and community dominance. *Journal of Aquatic Plant Management* 53: 121–129.

Vis, C., C. Hudon, and R. Carignan. 2003. An evaluation of approaches used to determine the distribution and biomass of emergent and submerged aquatic macrophytes over large spatial scales. *Aquatic Botany* 77: 187–201. doi:10.1016/S0304-3770(03)00105-0.

Voigts, D.K. 1976. Aquatic invertebrate abundance in relation to changing marsh vegetation. *The*

American Midland Naturalist 95: 313–322.

Waycott, M., C.M. Duarte, T.J.B. Carruthers, R.J. Orth, W.C. Dennison, S. Olyarnik, A. Calladine, et al. 2009. Accelerating loss of seagrasses across the globe threatens coastal ecosystems. *Proceedings of the National Academy of Sciences of the United States of America* 16: 12377–12381. doi:10.1073/pnas.0905620106.

Wilson, P.S., and K.H. Dunton. 2009. Laboratory investigation of the acoustic response of seagrass tissue in the frequency band 0.5–2.5 kHz. *The Journal of the Acoustical Society of America* 125: 1951–1959. doi:10.1121/1.3086272.

Winfield, I.J., C. Onoufriou, M.J. O'Connell, M. Godlewska, R.M. Ward, A.F. Brown, and M.L. Yallop. 2007. Assessment in two shallow lakes of a hydroacoustic system for surveying aquatic macrophytes. *Hydrobiologia* 584: 111–119. doi:10.1007/s10750-007-0612-y.

Winfield, I.J., J. van Rijn, and R.D. Valley. 2015. Hydroacoustic quantification and assessment of spawning grounds of a lake salmonid in a eutrophicated water body. *Ecological Informatics* 30: 235–240. doi:10.1016/j.ecoinf.2015.05.009.

Figures

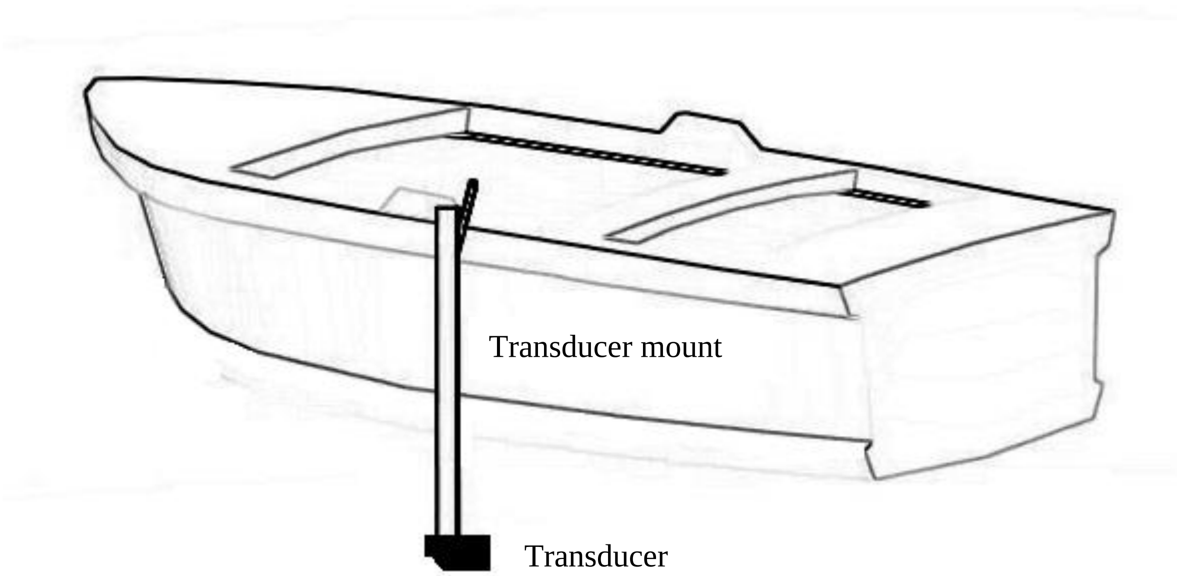


Figure 1. Diagram: Lowrance HDS-5 Gen 2 down-scan mounted mid-way along the gunnel on the hull of the boat.

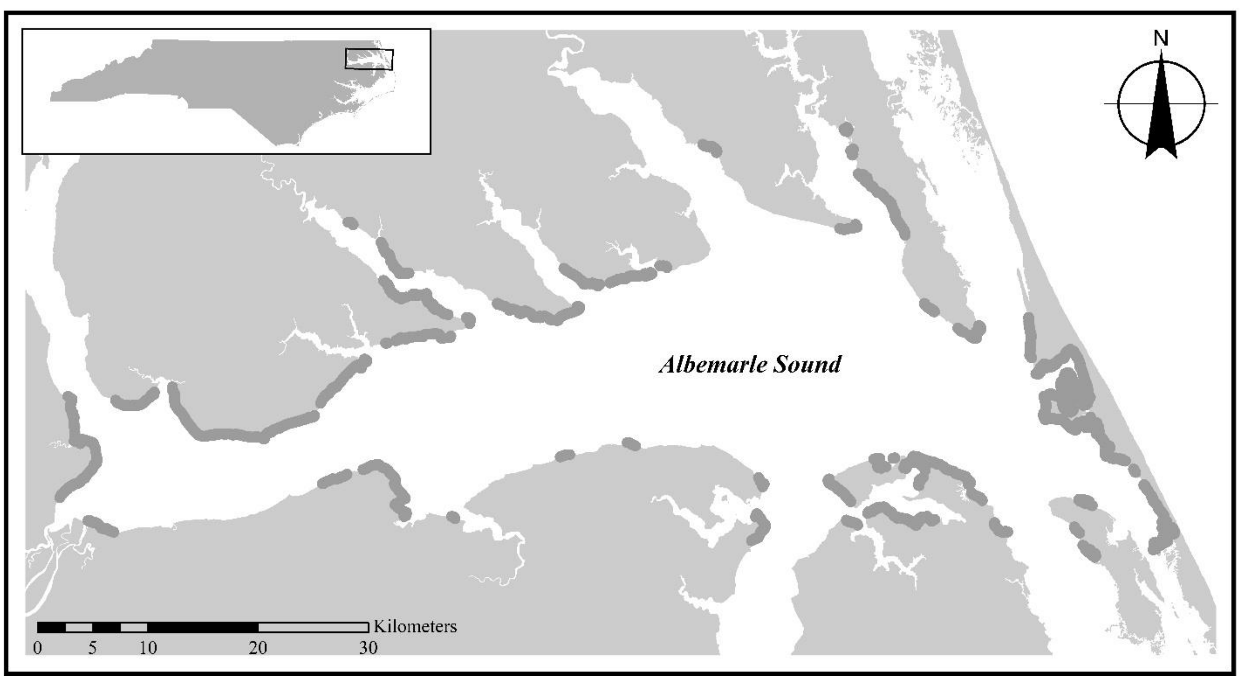


Figure 2 Map of the Albemarle Sound, North Carolina. The shaded areas represent locations with SAV from the Maximum Extent Layer (MEL) along the same shoreline that was sampled in the 2014 RAS sonar survey. The MEL was created by the NCDEQ (NCDMF 2008) comprising observations of SAV presence collected between 1987 and 2008.

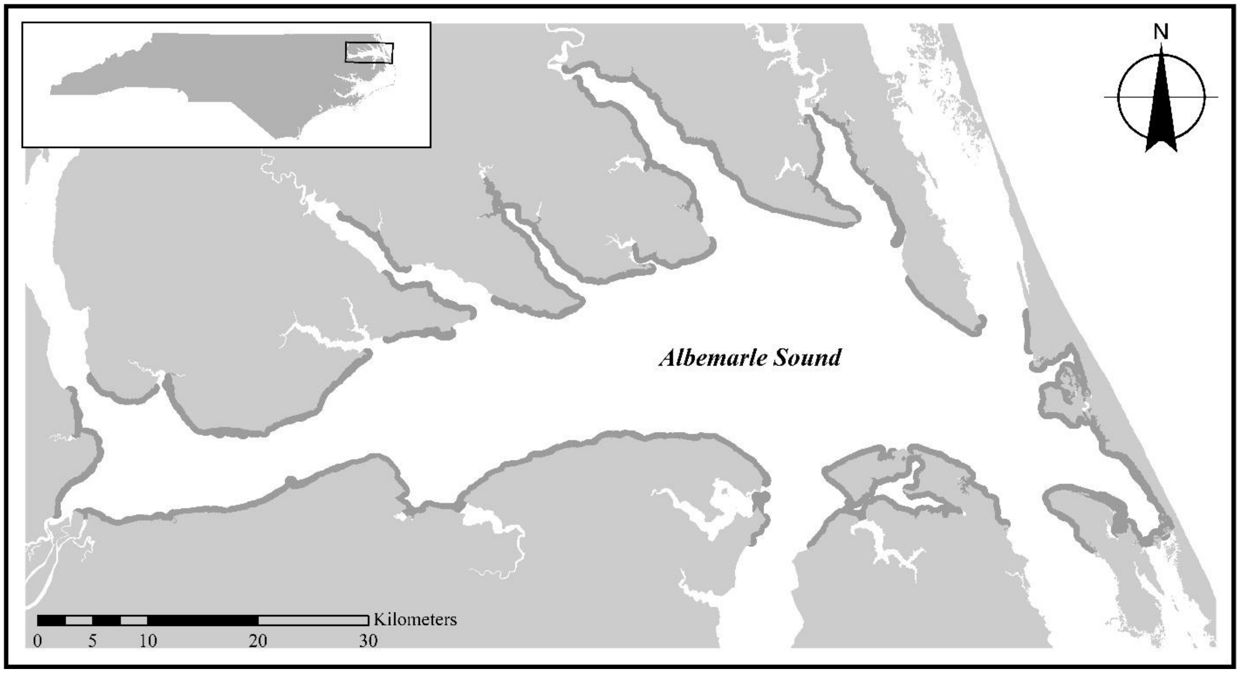


Figure 3. Map of Albemarle Sound, North Carolina. The shaded area along the shore represents the area sampled during the 2014 SAV survey (RAS). Note that the width of the sampled area does not represent the sonar's sampling swath, it only represents the linear distance covered by the sampling.

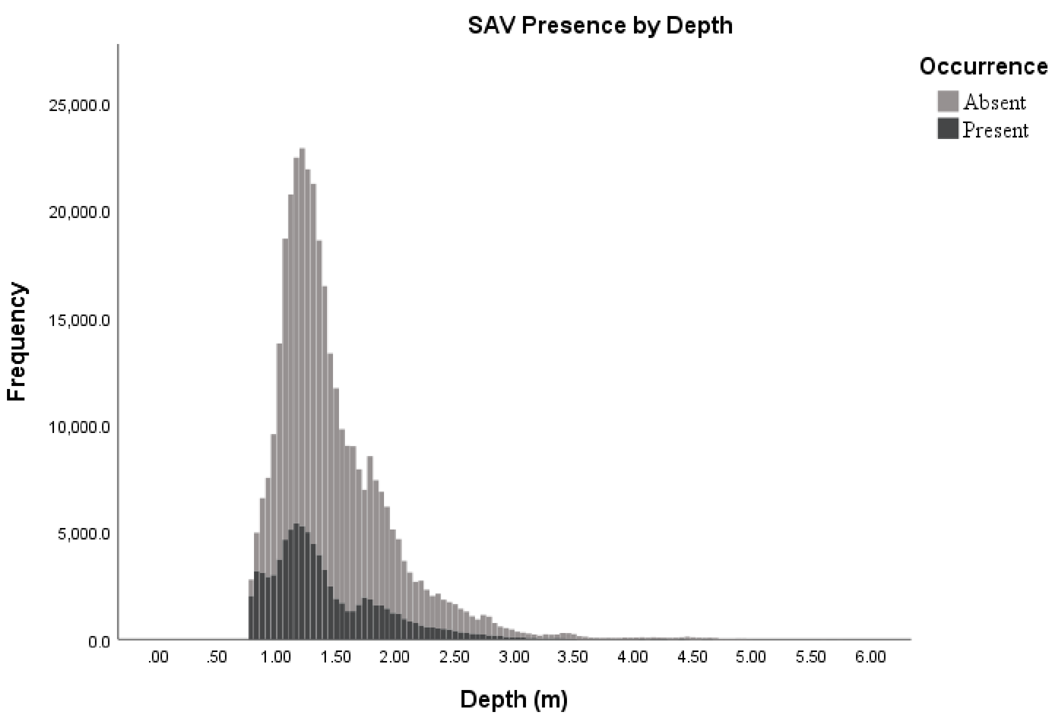


Figure 4. Frequency histogram of sonar sampling depth (m) with SAV present (black) and absent (gray).

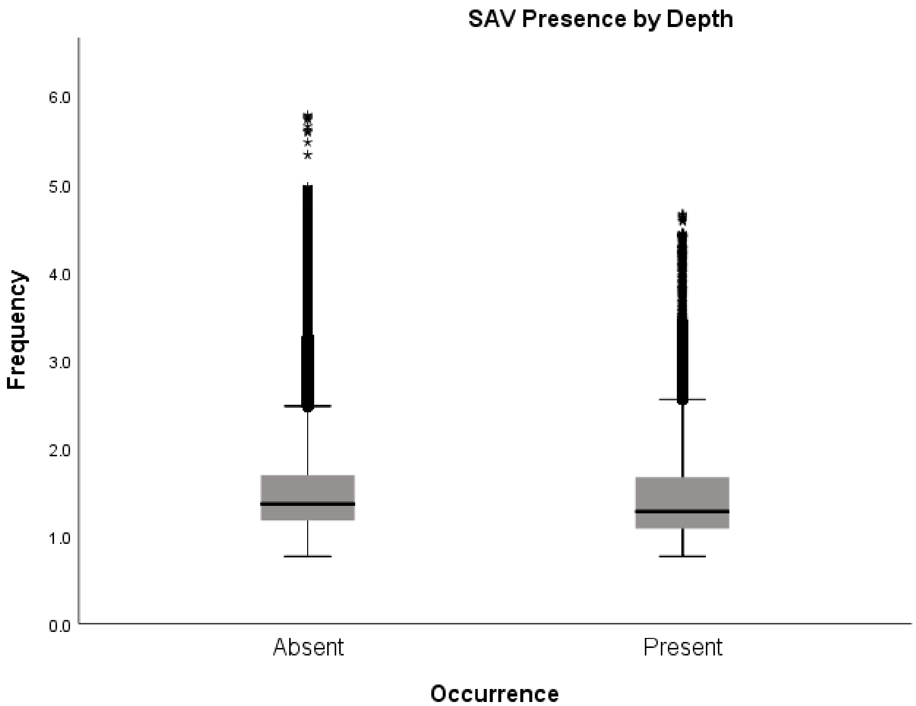


Figure 5. Boxplot showing the median depth (bar), interquartile range (box), and outer quartiles (whiskers) for the depth reported from the sonar between areas with Submerged Aquatic Vegetation (SAV) absent (1.36 m) and present (1.27 m).

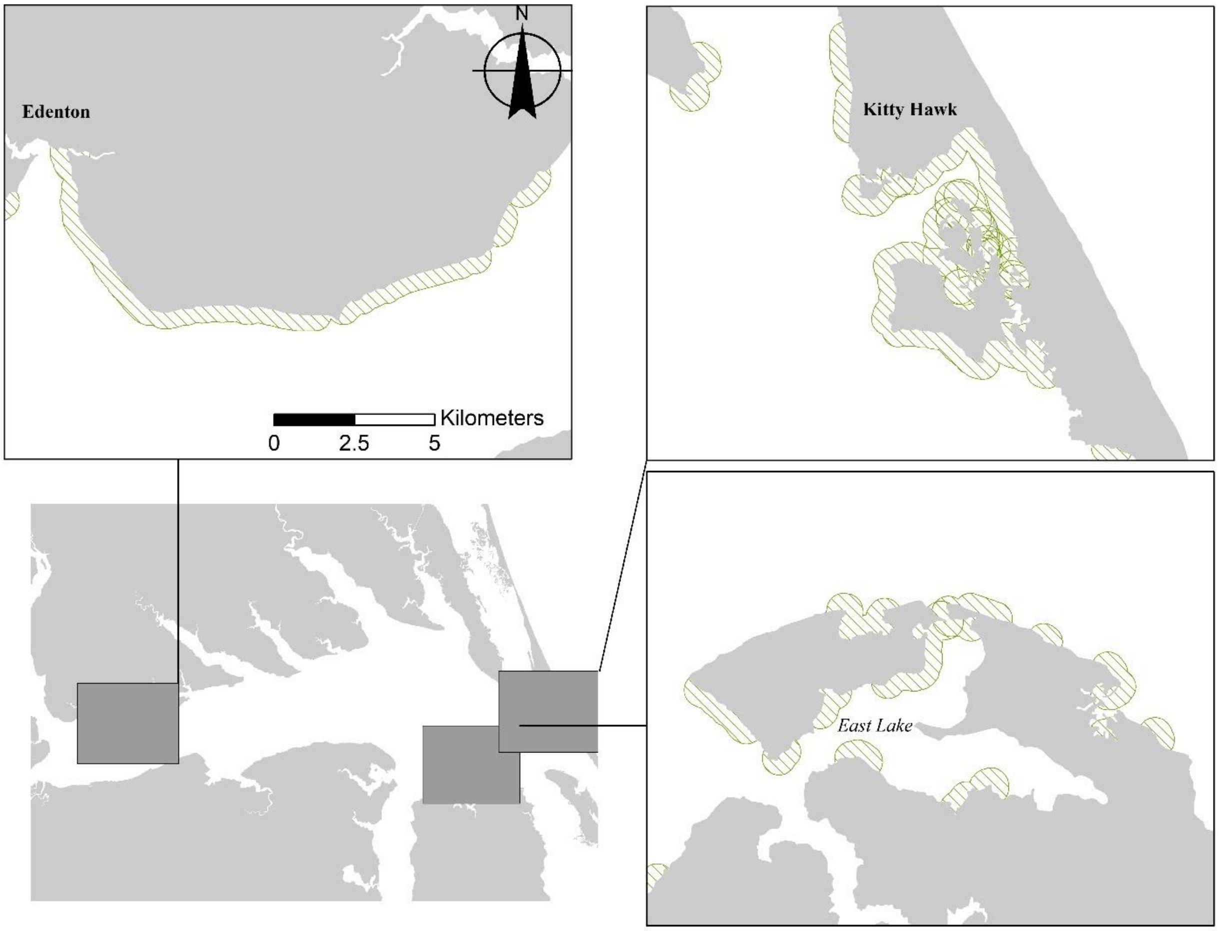


Figure 6. Map showing the location of the three largest SAV beds detected in the 2014 RAS in Albemarle Sound, NC; Edenton (top-left), Kitty Hawk (top-right), and East Lake at the mouth of the Alligator river (bottom-right). The shaded areas represent areas with 50% or greater probability of having SAV based on the sonar data collected in 2014. Note that the width of the polygons does not represent the sonar's sampling swath, it only represents the linear distance covered by the sampling.

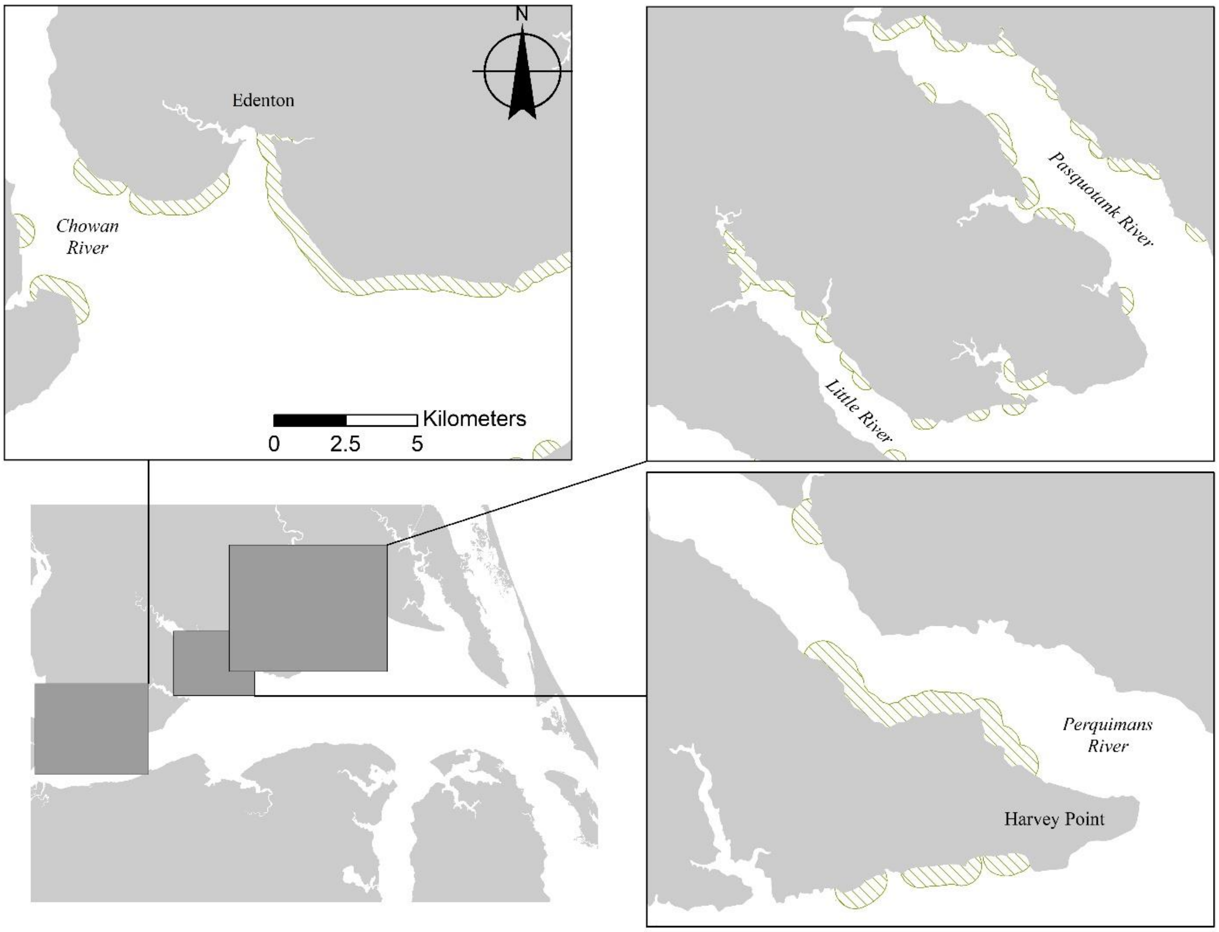


Figure 7. Map showing the location of SAV beds detected in the 2014 RAS in Albemarle Sound, NC; Edenton Bay and mouth of the Chowan River (top-left), Pasquotank River and Little River (top-right), and Perquimans River (bottom-left). The shaded areas represent 50% or greater probability of having SAV based on the sonar collected in 2014. Note that the width of the polygons does not represent the sonar's sampling swath, it only represents the linear distance covered by the sampling.

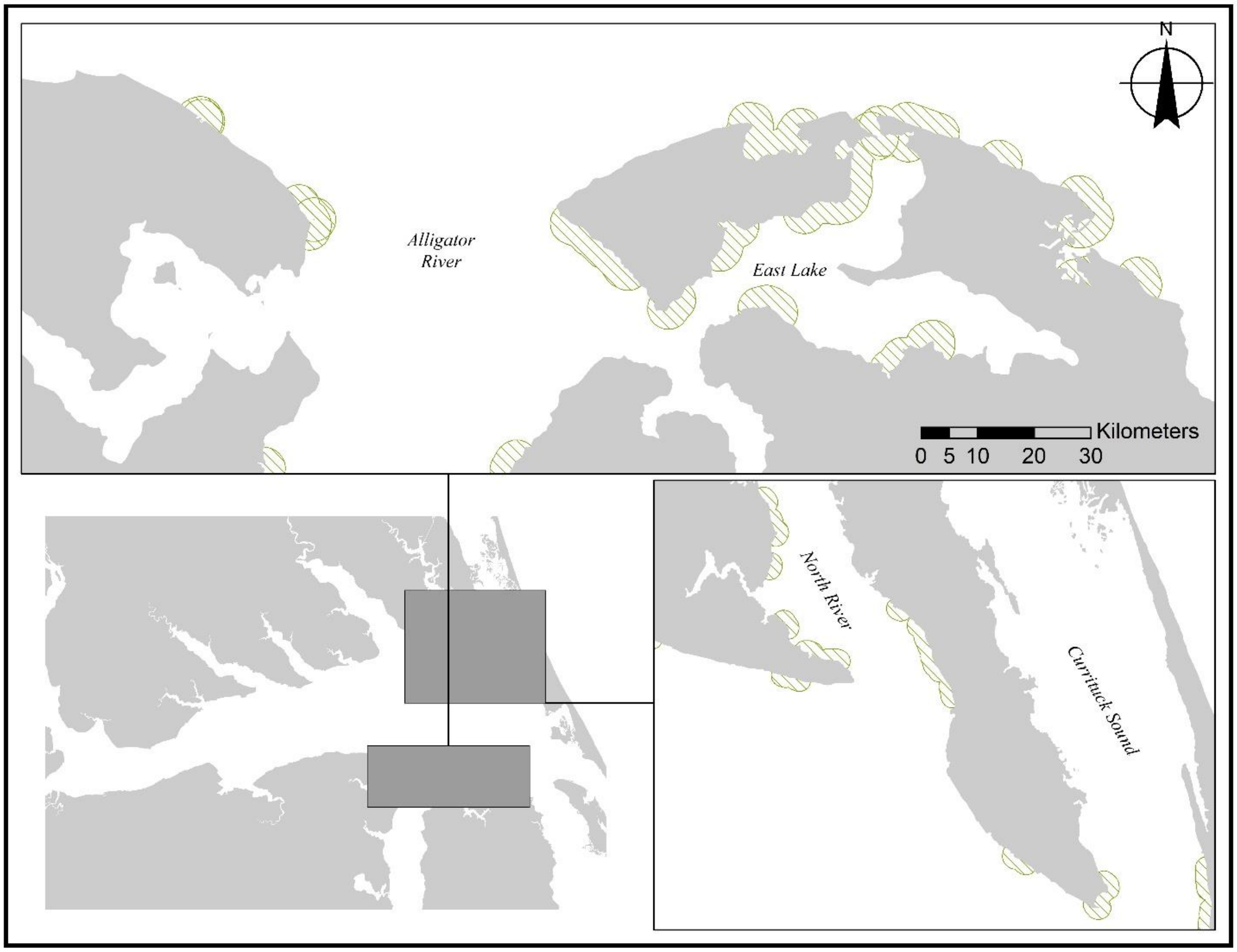


Figure 8. Map showing the location of SAV beds detected in the 2014 RAS in Albemarle Sound, NC; Alligator River and East Lake (top), and at North River (bottom). The shaded areas represent areas with 50% or greater probability of having SAV based on the sonar data collected in 2014. Note that the width of the polygon does not represent the sonar's sampling swath, it only represents the linear distance covered by the sampling.

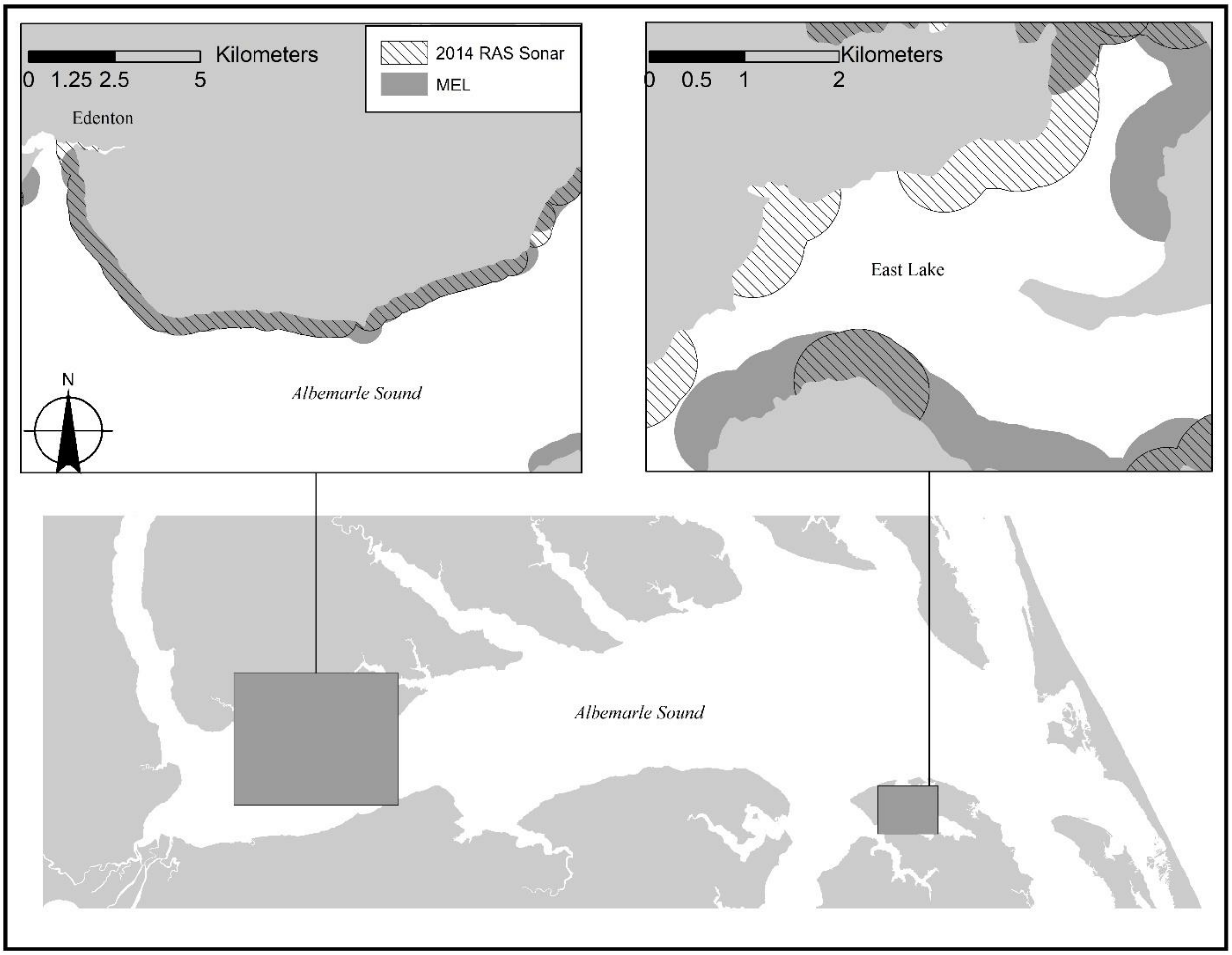


Figure 9. Edenton (top-left), where MEL and RAS overlap and East Lake (top-right), where MEL and RAS reveals areas of loss and gain

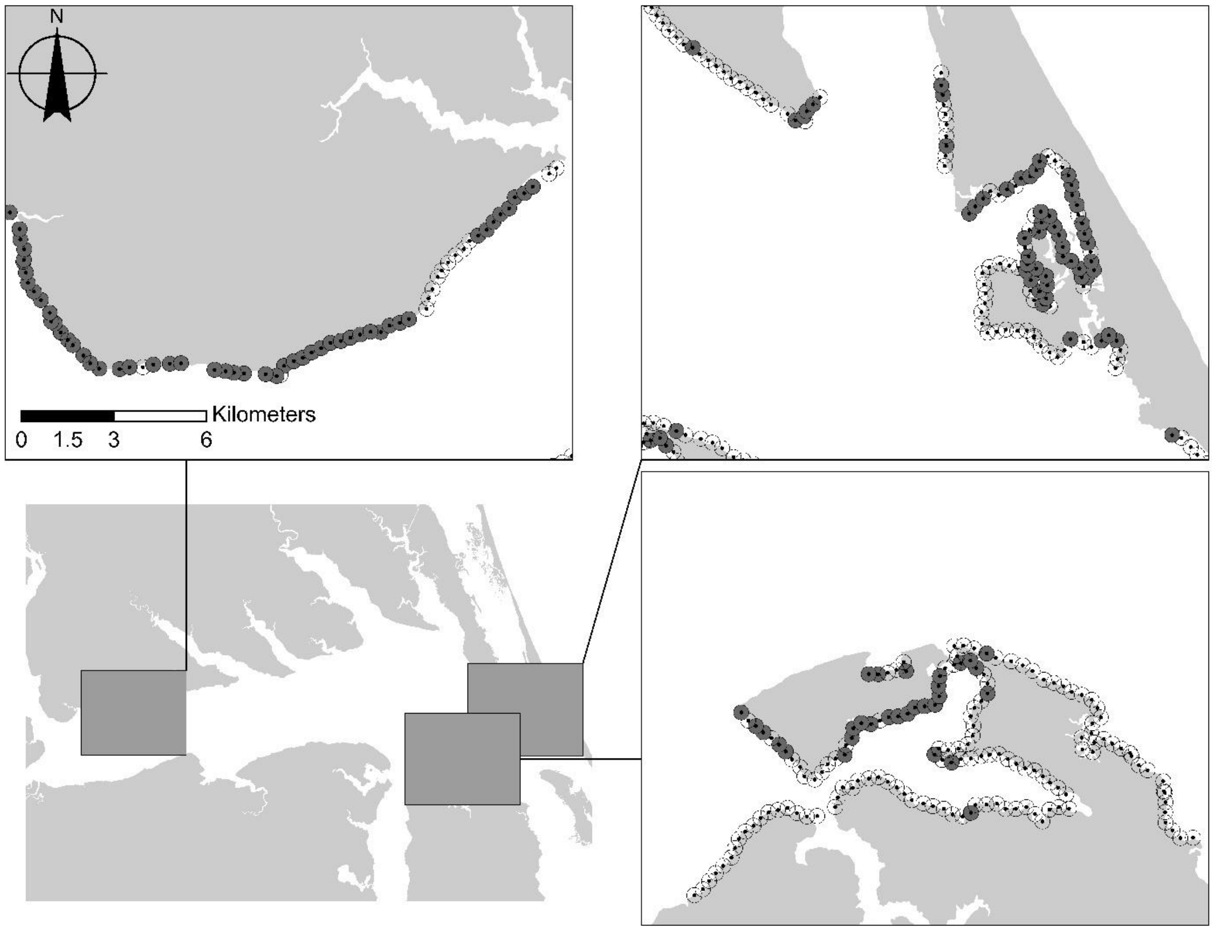


Figure 10. Edenton (top-left), Kitty Hawk (top-right), and East Lake at the mouth of the Alligator river (bottom) were the three areas identified with the greatest abundance of Submerged Aquatic Vegetation (SAV) in AS in 2014. The shaded circles represent SAV positive video-points and the white circles represent SAV negative video-points.

Tables

Table 2. SAV beds identified with sonar and video in the 2014 RAS.

AS region	# beds on sonar	# beds verified (video)	# beds in sonar and MEL	Largest Bed Length (km)	Fig. #	Salinity range (psu)	Temp. range (°C)	Secchi range (m)	Largest bed longitude (meters)	Largest bed latitude (meters)
Kitty Hawk Bay	3	3	3	30	7	2.25 - 8.76	23 - 27.2	0.38 - 0.73	906600.225	260476.766
East Lake	10	4	9	12	7	2 - 4.2	26.5 - 29.47	0.22 - 0.64	891769.355	249224.275
Main stem	24	4	14	17.1	7, 8	0.04 - 1.6	22.8 - 28.92	0.6 - 1.4	826071.882	255243.951
Perquimans River	4	1	4	7.4	8	0.16 - 1.23	20.93 - 26.59	0.66 - 0.9	848879.011	265615.639
Chowan River	3	2	3	2.4	8	0.04 - 0.05	25.69 - 27.57	0.6 - 0.91	818054.991	253047.905
Pasquotank River	14	0	2	2.9	8	1.1 - 2.65	23.1 - 25.8	0.5 - 0.68	873909.661	279362.696
North River	9	5	5	5.7	9	2.06 - 3.1	23.1 - 24.56	0.32 - 0.53	890475.956	273281.326

CHAPTER 2: Intra- and inter-annual variation in the abundance of Submerged Aquatic Vegetation (SAV) at 10 sentinel monitoring sites in Albemarle Sound, North Carolina USA

Abstract

In natural resources management, long-term synoptic monitoring is needed to establish baseline status, understand spatial and temporal variability, and detect changes in resources. Monitoring data can help administrators and managers make better informed decisions about policy and conservation regarding the implementation of actions to address suspected drivers of change. Rarely is it possible to sample an entire resource, and a sentinel-site approach is sometimes used as an alternative by adopting a subset of strategically selected locations to represent the larger ecosystem. Due to limited resources, yet a pressing need to monitor SAV resources in low-salinity low-visibility estuaries in North Carolina, this study investigated SAV distribution and abundance at ten candidate sentinel sites in Albemarle Sound (AS) using single-beam sonar and in-water quadrat sampling. Sampling was conducted twice annually (spring and fall) for two years (2015-2016) to document the inter- and intra-annual variation. I aimed to test two hypotheses; first, SAV would decline inter-annually across my sampling sites. I expected these results, as SAV losses have been reported across the globe and at nearby estuaries (Waycott et al. 2009; Orth et al. 2010). Second, SAV would be more abundant in the fall than the spring across all the sentinel sites. I expected a fall peak, as previous literature for NC low-salinity regions indicated that SAV abundance would be higher in the fall than the spring (Quible and Associates 2011; Kenworthy et al. 2012).

The surveys showed a wide range of SAV abundance (0 – 68% cover) and only three of the 10 sites appeared to have persistent and optimal conditions for SAV to thrive. Intra- and inter-annual SAV variation was highly asynchronous at both regional (sound-wide) and local (site) scales, which makes establishing temporal trends and peak abundances for SAV in AS challenging. Three sites had abundant SAV (>20% SAV occurrence), and two of these sites were near urbanized areas (Edenton and Kitty Hawk Bay). Most sites had little SAV (<10% SAV occurrence). Sonar and quadrat sampling yielded unique temporal variation (inter- and intra-annual variation) results, suggesting that depth plays a factor on temporal SAV distribution. Based on this and a prior longer-term study of temporal variation at one of the sites, it will be necessary to continue monitoring the ten sentinel sites twice annually (spring and fall) for at least five years to improve our understanding of the variability in status and trends of SAV. Future surveys should be supplemented by in-water sampling to assess species composition, as species turnover may play an important role in affecting spatial and temporal changes. Given the minimum depth for sonar sampling (0.5 – 0.79 m), the sonar method under-samples SAV in relatively shallow water, so it will be necessary to adopt alternative methods (e.g., in-water, low altitude AUVs) to comprehensively monitor this resource.

Keywords

Hydroacoustics, sonar, underwater video, synoptic surveys, rapid assessment, low-salinity, North Carolina.

Introduction

Coastal ecosystems are experiencing pressure from recent trends of increased global temperature, sea-level rise, and human population growth (Crowley 1990; Cohen 2005; Miller et al. 2005), and rates of change in coastal ecosystems are occurring at a fast pace (Orth et al. 2006; Barbier et al. 2011). To plan and implement conservation and restoration efforts, it is critical for natural resources management to first know current and past conditions, and the factors that influence change (McDonald et al. 2002). Rigorous and scientific-based monitoring programs are needed to differentiate between natural variability (i.e., intrinsic cycles) and external variability (e.g., anthropogenic factors) (Jassby 1998).

Federal and state agencies, like EPA under the Clean Water Act, are committed to monitor and assess the condition of the nation's aquatic ecosystem, so great effort has been allocated to developing long-term monitoring programs capable of detecting change and assessing environmental risk (McDonald et al. 2002). Through these monitoring programs, agencies responsible for resources management aim to implement informed management decisions. Monitoring efforts often focus on indicator species at landscape and regional levels. Aerial remote sensing methods have allowed agencies to monitor resources that cover large areas, relatively fast; however, these methods are not always adequate due to financial resources or methodological limitations. The sentinel-site approach, where a small number of locations are chosen for intense sampling, has been frequently adopted to identify background and external variability, when sampling an entire system is not feasible (Jassby 1998). This approach is particularly useful when there is previous knowledge about the intrinsic variability across a system. However, extrapolating from a few sites to an entire system can be challenging.

Nonetheless, the sentinel-site approach often delivers the first clues to change and provide some initial understanding about the mechanisms that drive the changes. Here, I used the sentinel-site approach to begin understanding the natural variability of SAV in AS; an important indicator species in coastal systems (Orth et al. 2017).

SAV are one of the most productive and ecologically valuable aquatic habitats on earth. Hundreds of fish and wildlife species depend on SAV for nursery habitat, shelter, and nourishment (Heck and Thoman 1984; Murphey and Fonseca 1995; Barbier et al. 2011). Based on the analysis of 215 SAV studies across the globe, Waycott et al. (2009) reported that marine SAV have been declining at a rate of 110 km^2 yr^{-1} since 1980. Many of the declines have been attributed to increased eutrophication and turbidity in coastal systems, largely the result of activities like watershed and coastal development, deforestation, and shoreline modification, which can impair the productivity, growth, and reproduction of SAV (Chang 2008; Williams et al. 2010; Landry and Golden 2017). The documented SAV losses (Kemp et al. 1983; Orth et al. 2006; Deaton et al. 2010; Costello and Kenworthy 2011; Short et al. 2014; NCDEQ 2016) have encouraged federal and state agencies to become more concerned about the status and trends of SAV resources and the factors responsible for their decline. Despite this heightened awareness for SAV in NC, much of the research and surveys to date have focused on high-salinity estuarine regions, while low-salinity SAV distribution and temporal trends have not been as well documented (Thayer et al. 1984; Ferguson and Wood 1990; Orth et al. 2010; Kenworthy et al. 2012; NCDEQ 2016).

In order to make abundance and trends assessments, coastal managers need routine monitoring data to first identify SAV baseline distribution and temporal variation (Orth et al.

2010; Curran 2011). Low-salinity SAV have high inter-annual variation; therefore, beds need to be monitored for multiple growing seasons before assessing their status (Orth et al. 2010; Patrick and Weller 2015; Bolpagni et al. 2016). To optimize SAV detection, it is also common practice to sample during peak abundance to determine the maximum delineation of the resource's distribution and abundance; hence, initial monitoring efforts should aim to identify the peak signature period for SAV in a waterbody. Understanding SAV's seasonal variation and peak abundance can allow coastal resources managers to develop the most effective SAV monitoring protocols and sampling schedules in order to make informed management decisions.

The distribution and abundance of SAV in low-salinity regions is poorly understood (Davis and Brinson 1990; Stanley 1992; Kenworthy et al. 2012). This is partly because low-salinity SAV species are more taxonomically diverse, ephemeral, and exhibit a greater temporal and spatial variation than their higher salinity counterparts, the seagrasses (Orth et al. 2010; Quible and Associates 2011; Kenworthy et al. 2012). Seasonal and intra-annual variation in low-salinity SAV are sensitive to several environmental factors, such as fluctuations in climate, precipitation, and river discharges; as well as indigenous and non-native species composition (Moore et al. 2000; Burkholder et al. 2004; Orth et al. 2010; Quible and Associates 2011; Kenworthy et al. 2012).

Large-scale synoptic surveys and monitoring of SAV distribution and abundance trends have also focused more on high-salinity regions partially due to the effectiveness of airborne (aerial and satellite imaging) optical remote sensing methods (Ferguson et al. 1993; Orth et al. 2010; Costello and Kenworthy 2011; APNEP 2012; APNEP 2019). However, low-salinity regions frequently have turbid waters resulting from freshwater inflow with higher concentrations of organic matter, tannins, and suspended sediments (Giese et al.1985). These conditions result in poor water transparency and make it difficult to detect SAV with optical remote sensing methods that require clear water to delineate benthic signatures (Finkbeiner et al. 2001; Madsen and Wersal 2017). Aerial remote sensing methods can cover large areas in a relatively short period of time; however, they are constrained by fluctuating water levels (tides and winds) and atmospheric weather conditions (Finkbeiner et al. 2001; Vis et al. 2003). Though aerial surveys have been attempted in low-salinity regions of NC, these surveys have been irregular and incomplete, and they underestimated both presence and general distribution of SAV (Ferguson and Wood 1989; Ferguson and Wood 1990; Kenworthy et al. 2012). Other *in situ* surveying methodologies, like in-water observations, can overcome water clarity issues, but they cannot easily, efficiently, and repeatedly cover large and not easily accessible areas, as they are labor intensive, time consuming, and cost prohibitive (Norris et al. 1997).

Remote sensing methodologies like sonar and underwater video have been proposed as alternative methods to monitor SAV across several scales (Norris et al. 1997; Sabol et al. 2002; Schultz 2008). However, underwater video can be difficult to implement in turbid waters, as it takes too much time for the camera to focus at velocities needed to effectively cover large areas (Norris et al. 1997; Sabol et al. 2002; Lefebvre et al. 2009). Another alternative is the use of acoustic systems, such as single-beam sonar.

Single-beam sonar has been shown to effectively detect SAV in various settings due to SAV's unique acoustic signature generated by the air bubbles and tissue in its blades (McCarthy 1997; Hermand et al. 1998; Wilson and Dunton 2009). Initially, sonar was used to map SAV at small-scales, as most of the signal analysis was done manually (Duarte 1987). After GPS was available, Sabol et al. (2002) developed the first automated SAV sonar signal detection system (SAVEWS), which became the basis for newer more efficient automated detection systems that are currently available (e.g., Biobase and Biosonics). These systems can extract useful information from the SAV's acoustic signal, such as SAV presence-absence, plant height, percent cover, and biovolume (Tseng 2009; Barrell et al. 2015). Hence, sonar has been successfully used in SAV surveys in fresh and marine waters (Vis et al. 2003; Riegl et al. 2005; Winfield et al. 2007; Zhu et al. 2007; Stevens et al. 2008; Guan et al. 2010; Barrell and Grant 2013; Valley 2016), and its effectiveness has been thoroughly evaluated (Valley and Drake 2005; Radomski and Holbrook 2015; Valley et al. 2015; Bučas et al. 2016). Single-beam sonar, coupled with an SAV signal automated processing system, gives sonar the ability to cover long distances and sample large areas repeatedly in a relatively short period of time compared to in-water methods, thereby increasing the possibility of higher frequency sampling at larger scales.

AS is one of several large low-salinity sub-estuaries that make up the greater Albemarle-Pamlico Estuarine System (APES) in eastern NC; one of the largest and most productive estuarine ecosystems in the US. (APNEP 2012; Moorman et al. 2014). A recent (2014) sound-wide shore-parallel rapid assessment survey (RAS) of SAV presence at water depths between 0.77 – 5.78 m determined that the distribution across the Sound was widespread but discontinuous (see Chapter 1). Relatively few locations had nearly continuous SAV detections and visible evidence of large and dense SAV beds, while there were extensive distances along the shore parallel transects and throughout the Sound where SAV were either completely absent, sparse, or very patchy. The RAS appears to corroborate what has been generally considered anecdotal information alleging that there have been large-scale declines in SAV habitat in AS over the past several decades (NCDEQ 2016).

To address the variability evident in the sound-wide distribution and better understand the temporal variation in SAV abundance, I adopted a sentinel site approach for monitoring and assessing SAV in the Sound. I sampled ten sentinel sites using a single-beam sonar detection method (see Appendix D for precise coordinates and code names for each site). The sentinel sites network approach has been proposed for monitoring ecosystems that are too large to frequently sample. Often, the objective of this approach is to repeatedly and intensely sample ecosystem features (e.g., SAV) and environmental parameters at a selected subset of sites to extrapolate the feature's natural variability and responses to stressors at both the local and regional levels (Jassby 1998; Christian and Mazzilli 2007). However, deciding on the location for sentinel sites is difficult, as it requires extensive knowledge about a system's features and its intrinsic dynamics (Jassby 1998). Further, to detect the effect of stressors (e.g., pollution, exotic invasions, coastal development), it is necessary to differentiate the signal (stressor driven variability) to noise (intrinsic variability) ratio, which is difficult, particularly in a highly dynamic system such as AS (Orth et al. 2010; Patrick and Weller 2015; Radomski and Holbrook 2015). Nonetheless, this study is a first step in assessing SAV spatial and temporal dynamics and essential for the development of a long-term monitoring program in AS (Southward 1995).

The specific objectives of this study were twofold. First, I examined the spatial and temporal variation in SAV abundance at ten sentinel sites by analyzing SAV percent occurrence at regional (sound-wide) and local (site) scales, and at different water depths. Because of the large spatial extent of AS and the wide range of factors that might be affecting SAV abundance, I expected that regional variability would be greater than local variation and sentinel sites would be an appropriate long-term monitoring approach. I hypothesized that SAV would be declining from 2015 to 2016 across my sampling sites. Since there is a global consensus that SAV are declining (Waycott et al. 2009). The second objective was to examine the intra-annual variation of SAV abundance at each of the sentinel sites in order to determine the optimum time (peak signature period) for detecting SAV during the year. For the second objective, I aimed to confirm two previous site-specific studies in low-salinity areas of NC which suggested that SAV abundance would be higher in the fall than the spring (Quible and Associates 2011; Kenworthy et al. 2012); hence, I hypothesized that SAV would be more abundant in the fall than the spring across all the sentinel sites. Overall, the objectives of this study aimed to provide a baseline for SAV distribution in the low-salinity, low-visibility waters of AS, so assessments about the status and trends of this resource can be determined in the future.

Material and Methods

Study Area

The study was conducted in AS, NC, USA (Appendix C), a large (2,330 km^2 low-salinity (0-23 psu) coastal plain estuary with a maximum depth of 5.3 m (Moorman et al. 2014; NCDEQ 2016). AS is the receiving water for several large rivers (Chowan, Roanoke, Perquimans, and Pasquotank Rivers) and numerous smaller tributaries that regularly discharge fresh water, sediments, nutrients, and color dissolved organic matter (CDOM) into the system which have a demonstrable effect on optical water quality (Giese et al. 1985). Water levels in the Sound are driven primarily by wind-dominated tides that can vary from 30 to 122 cm on a matter of days. The wind driven tides help mix the water, minimize stratification, and affect the seasonal variability in salinity (Giese et al. 1985; Peng et al. 2004). The Sound is physically isolated from the Atlantic Ocean by a barrier island and two smaller waterbodies to the southeast, Roanoke and

Croatan Sounds, and with the closest oceanic inlet (Oregon Inlet) located approximately 20 km south, AS has a relatively long water residence time of 45 days (Moorman et al. 2014).

Sentinel Site Selection and Sampling Design

Ten rectangular shaped polygons (each 1.0 km parallel to shore by 0.5 km perpendicular to shore) were delineated as candidate sentinel sites (Appendix E and Figure 11). Site selection was based on four criteria; 1) locations were readily accessible for long-term monitoring in a small shallow draft vessel, 2) SAV had been present historically (based on NCDMF (2010) Maximum Extent Layer in Chapter 1), 3) SAV were present in sonar and video sampling in a 2014 synoptic RAS, 4) sites were selected at random, so the sites could be considered representatives of the sound; and 5) the distribution of the sites provided comprehensive sound-wide spatial coverage.

Sampling at each site was conducted along 40 equally spaced (25 m apart) 0.5-km long transects aligned perpendicular to shore. For navigation purposes, the endpoint of each of the transects were loaded as waypoints into a WAAS vessel-mounted GPS. For the regional scale analysis (sound-wide), site was the experimental unit; whereas, in the local scale analysis (site level), each 0.5-km shore perpendicular transect was the designated experimental unit within each sentinel site.

Sonar Sampling

Each sentinel site was monitored for SAV percent occurrence using a boat-mounted Lowrance HDS-7 Gen 2 echosounder equipped with a 200-kHz frequency transducer having a 20° beam angle. The echosounder (mounted approximately 30 cm underwater) recorded water depth and SAV presence-absence data simultaneously. Further, these data were geo-referenced with the echosounder's integrated GPS+WAAS antenna (± 3 m geo-location error). The sonar, GPS, and depth data for each transect was stored separately as sl2 files in an SD card.

Sonar Verification with Underwater Video

A low-light sensitive Sartek (model #SDC-MSS) underwater video camera was used to visually verify the presence or absence of SAV at each sentinel site. The camera was mounted 13 cm above the end of a PVC pole to provide a 20 cm X 20 cm image frame. Video samples were obtained at 100 random points selected *a priori* within each of the ten sentinel sites (Figure 11). The coordinates of the video were recorded into the Lowrance HDS-5 echosounder and later downloaded. Whenever possible, the video samples were acquired immediately after completing the sonar transect sampling, aiming to complete both on the same day. During each camera drop, every effort was made to maintain the vessel in the same position; however, there were times when the wind, water currents, and lag in the GPS signal made it difficult to precisely co-locate the video point with the sonar. Once the camera was lowered, SAV presence or absence was recorded, and the video data were archived on Sony mini DV cassettes.

Water Quality Sampling

Water quality data, including surface water temperature, and salinity were obtained at each sentinel site, each year, and each season, with a CastAway CTD by SonTek. The samples were collected at the center of each sentinel site. Water clarity was measured using a 20 cm diameter Secchi disk lowered over the side of the vessel.

In-water Quadrat Sampling

In situ quadrat sampling at the sentinel sites followed similar methodology as described in Duarte and Kirkman (2001). At each site, ten transects were randomly selected from the 40 transects monitored with sonar. At each randomly selected transect, three replicate samples at four different depths (0.25, 0.5, 0.75, and 1 m) were obtained (Figure 11). Three replicate quadrats at each depth were positioned along a line perpendicular to the transects by randomly selecting 3 distances between 0 and 25 m. At each sampling point, the 1x1-m quadrat with a 100-cell grid was placed on the bottom, and the number of cells with SAV present were counted to estimate SAV percent cover.

In total, there were 120 quadrats per sentinel site (10 transects x 4 depths x 3 replicate quadrats at each depth) except for transect lines extending into areas deeper than 1 m or obstructed by structures. A total of 1481 quadrats were sampled (31% of the total planned), as some of the quadrats fell in areas where I could not sample due to stumps, fallen trees, bulkheads, and manmade structures. This mostly occurred at depths between 0.25 m and 0.5 m, where tree stumps were frequently encountered.

SAV Species Composition

Sediment core samples were obtained during sentinel surveys in 2016 at the sites where SAV were present to determine SAV species composition. The core samples were taken at four depths (0.25, 0.5, 0,75, and 1.0 m) with a 30-cm diameter PVC corer inserted as deep as necessary to ensure the collection of all the roots and rhizomes (ca. 20 cm). I aimed to take three replicate core samples at three of the ten randomly selected transects at each of the sentinel sites at each depth where I located SAV. Nevertheless, at various transects, I did not collect core samples due to high water level (>1.0m) (in some occasions due to periodic water level changes and in others due to higher depths at certain portions of a site) or absence of SAV at the pre-selected transects. Due to the low number of samples, I only reported a species list in this study.

Sonar Data Processing

The sonar data were analyzed with the cloud-based Biobase system (www.cibiobase.com). Biobase utilizes a mathematical algorithm to estimate SAV bio-volume, which is defined as the percent of water column occupied by the plant (Navico 2014). For my analysis, I transformed the Biobase's acoustic reports into a binary variable: SAV presence (1) and SAV absence (0). Using the presence data, I estimated SAV percent occurrence for each of the 40 transects at each sentinel site (each year 2) and season (2). SAV percent occurrence was calculated as (Equation 1);

$$SAV\ Percent\ Occurence = \frac{Number\ of\ positive\ sonar\ points\ in\ a\ transect}{Total\ pumber\ of\ sonar\ points\ in\ a\ transect} \times 100 \qquad (1)$$

Sonar Verification with Underwater Video

First, the SAV presence and absence for the sonar and video data were digitized into ArcGIS 10.4.1 (ESRI 2011). Next, the Spatial Join tool in ArcGIS (ESRI 2011) was utilized to select the nearest sonar point to the video samples with a 10-m threshold matching distance, where points located >10 m from the sonar point were discarded. Preliminary analysis indicated that percent agreement between sonar and video did not vary at distances less than 10 m (Appendix B).

SAV presence or absence in the sonar data were compared to the SAV occurrence on the video data. To verify the sonar's signal interpretation, two metrics were estimated: Present Verified Percentage (PVP) (Equation 2) and Absent Verified Percentage (AVP) (Equation 3).

$$\text{PVP} = \frac{Total\ SAV\ present\ video\ points}{Total\ expected\ SAV\ present\ video\ points}\ X\ 100 \quad (2)$$

$$\text{AVP} = \frac{Total\ SAV\ \text{absent}\ video\ points}{Total\ expected\ SAV\ \text{absent}\ video\ points}\ X\ 100 \quad (3)$$

Statistical Analysis

SAV Percent Occurrence (Sonar)

The sonar data were analyzed at two scales. For the regional scale (sound-wide), I designated the sites as the experimental units and utilized multilevel Linear Mixed Effects Models (LMEM) to analyze the temporal and depth effects on percent occurrence. LMEM is a flexible framework (Verbeke and Molenberghs 2000; McCulloch and Neuhaus 2005) that can handle the SAV's temporal and spatial correlation (Lefcheck et al. 2018). Further, it is possible to detect variability within groups and between groups (i.e., sites). First, I examined the skewness and kurtosis (Hoffman 2015) to determine if the data met normality assumptions. SAV percent occurrence was transformed (log x+1) to meet normality assumptions. Next, I centered the depth values to make the model's intercept meaningful (Heck et al. 2013), as SAV are not found at zero depth. To calculate the centered depth for each transect, the transects' mean depth (2.06 m) was subtracted from each transects' presence and absence mean depth (Equation 4).

$$Centered\ depth\ for\ transect\ i = Transect\ i\ mean\ depth - 2.06 \quad (4)$$

To test for temporal and depth effects, I created an LMEM with site as a grouping variable. In the fixed and random models, I included year (2015 and 2016), season (spring (May-June) and fall (September-October)) and centered depth to determine if any of these variables explained transect variability (i.e., fixed effects) and between sites variability (i.e., random effects). I used a variance components covariance matrix in the random model, as I assumed that the predictor variables were independent. I kept the random model as simple as possible, by excluding interactions, to facilitate results interpretation (Heck et al. 2013).

From the LMEM, year and season had a significantly different effect on SAV mean occurrence across sites, so each site was analyzed individually (i.e., local scale analysis). For the local scale analysis, Generalized Estimating Equations (GEE) were used to analyze each site, as GEE is an extension of GLM, and it accounts for repeated measures in data (Geys et al. 2002). In this analysis, transect was the experimental unit. I fit the model with year (2015 and 2016), season (spring and fall), and mean transect depth as predictor variables. I utilized the transformed percent occurrence (log x+1) as the response variable to meet normality assumptions.

SAV Percent Cover (In-Water Quadrat Sampling)

Analysis of percent cover was very similar to the sonar data. LMEM was utilized to analyze the data at the regional level, with site as the experimental unit. I also transformed SAV percent cover (log x+1) to meet normality assumptions and centered the depth for each mean percent coverer around the mean to make estimates more meaningful (Equation 5).

$$Centered\ depth\ for\ transect\ i = Transect\ i\ mean\ depth - 0.68 \tag{5}$$

The initial fixed and random models were fitted with site (grouping variable), year (2015 and 2016), season (spring and fall), and depth as predictor variables. In the random model, the intercept, year, season, and centered depth were included along with variance components for the variance matrix.

For the local scale analysis, a GEE model was used with year (2015 and 2016), season (spring and fall), and depth as predictor variables for the transformed percent cover, with transect as the experimental unit.

Results

Mean Percent Occurrence (Sonar Sampling)

The spatial distribution and temporal abundance of SAV were highly variable both within and between sites (Table 3; Appendices E and F), with percent occurrence highest at site 4 in spring 2015 (68.33 %) and lowest at site 5 in fall 2015 (zero percent occurrence; Table 3 and Table 4). Site 4 had the widest range of SAV abundance among all the sites (10.43 - 68.33 %). Seasonal peaks were evident in only four of the sites, three of which had peaks in spring while generally the lowest abundance of SAV were more frequently observed in fall (7 out of 10 sites) (Table 4). There was no seasonal difference in 6 of the 10 sites (Table 3 and Table 4).

In the regional analysis, when considering the variance across sites (i.e., random effects model), mean percent occurrence had unique temporal trends at each site (intercept variance; Estimate = 0.1849, Wald Z = 2.049, $p < 0.05$, Table 5). The slope variance for year and season were different across sites (Estimate = 0.0538, Wald Z = 1.981, $p < 0.05$; Estimate = 0.061, Wald Z = 1.968, $p < 0.05$, respectively, Table 5). The depth slope variance had a nearly significant p-value (Estimate = 0.2374, Wald Z = 1.886, $p = 0.06$, Table 5), which would suggest that the effect of depth on percent occurrence varies across sites. It is important to note that even after adding three predictors to the model (year, season, and depth), there was still variance in the intercepts that could not be explained across the sites (residual variance; Estimate = 0.1274, Wald Z = 27.57, $p < 0.05$, Table 5).

The local scale analysis confirmed the findings from the random model, where mean percent occurrence had unique temporal trends at each site (Tables Table 3, Table 4, and Table 6). Eight sites out of the 10 exhibited inter-annual percent occurrence variation (Table 3 and Table 6). Four sites had more SAV in 2016 than 2015 (1, 3, 6, and 10) while four sites had more SAV in 2015 than 2016 (2, 4, 7, and 8) (Table 3 and Table 6). Only four sites had intra-annual variation, with sites 1, 4, and 5 having a greater SAV mean occurrence in the spring than the fall, while only site 8 had greater SAV mean occurrence in the fall (Table 3 and Table 6). Sites 2, 3, 6, 7, 9 and 10 displayed no intra-annual variation (Table 3 and Table 6). However, sites 7 and 10 had a nearly significant seasonal variation (p=0.06), both more abundant in the spring.

SAV Depth Distribution (Sonar Sampling)

The median depth for all sonar sampling was 1.91 m, and SAV were concentrated at depths shallower than 1.79 m (75^{th} percentile). Less than 5 percent (5^{th} percentile) of the SAV present in the sonar data occurred deeper than 1 m, but only 2 percent of all the sampling was done at depths shallower than 1 m (Figure 12). The maximum sampled depth was 5.19 m, and SAV were detected at 4.96 m (site 4 spring 2016; Appendix E). The minimum depth sampled was 0.79 m, and SAV were present at that depth at several sites. Sites 1 and 4 had some of the most abundant SAV with median depths ranging from 1.75 m to 2.15 m at site 1, and from 1.37 m to 1.91 at site 4 (Appendix E). Sites 5 and 10 had some of the lowest SAV values with median depths ranging from 2.4 m to 2.79 m at site 5, and 1.47 to 2.71 at site 10 (Appendix E).

The depth profiles at the ten SS was very variable, some sites were mostly shallow (< 3 m; sites 1 and 5), but some sites were deeper (site 6) (Figure 12 and Appendix F). Generally, the distribution of SAV detections was skewed toward relatively shallower depths with few exceptions (e.g., site 6), and nearly all the sonar monitoring events over-sampled the deeper portions of the SS. Generally, SAV were absent at depths greater than 3 m (Figure 12). Overall, SAV were distributed over a wider depth range in the fall than the spring. The depth 50th and 75th percentiles for SAV present in the spring were 1.80 m and 2.41 m, respectively; and the depth 50th and 75th percentiles for SAV present in the fall were 2.03 m and 2.65 m, respectively.

Sonar Video Verification

Out of the 4,000 planned video camera drops, 3,749 of the samples met the prescribed distance criteria where the sonar waypoint was within 10 m of the camera drop. The video camera drops verified SAV present at 45% of the positive sonar detections (PVP) and 91% of the SAV absence (AVP) detections. Sites 1, 4, and 8 had the most SAV present-verified video points (68%, 61%, and 49%, respectively; Table 7; Appendix G). Sites 2, 5, 6, 7, 9, and 10 had little to no SAV present-verified video points (Table 7).

Percent Cover (Quadrat Sampling)

SAV mean percent cover was highest at site 1 (73%) with a peak in spring 2015 (95.52%) (Table 8). Sites 2, 6, and 10 had some of the lowest SAV cover (<15%). Sites 5 and 9 did not have any SAV; these two sites also had the lowest SAV occurrence in the sonar data (Tables Table 8 and Table 9). Site 8 had large SAV cover fluctuations, for example, in the 2016 spring, SAV cover was at the highest recorded at this site (62%) and by the fall the cover dropped to almost zero (0.69%) (Table 8 and Table 9). Site 4 had a large year to year variation, in 2015 the total cover was 30%, and it dropped to 6% the following year (Table 8 and Table 9).

In the regional analysis (fixed effects), depth slope was positively correlated to percent cover (Estimate = 0.2503, $p > 0.05$; Table 10), which was opposite to the sonar's depth slope. In the quadrat data, the slope's back-transformation revealed that for every unit of change from the mean depth, mean percent occurrence changed 3.46%. SAV declined from 2015 to 2016 (2.8%) and from spring to fall (3.56%) while controlling for other predictors; however, these differences were not statistically significant ($p > 0.05$; Table 10).

When accounting for variation across the sites (random effects), season and depth had different slopes across sites (Estimate = 0.1872, Wald Z = 1.97, $p < 0.05$; Estimate = 0.4052, Wald Z = 1.977, $p < 0.05$, respectively, Table 10); however, year had a nearly significant random slope (Estimate = 0.1319, Wald Z = 1.867, p = 0.062, respectively, Table 10), which indicated that season and depth, and likely year, varied across sites.

After examining each site individually, distinct temporal patterns were evident. Several sites displayed inter-annual variation, four sites had more abundant SAV in 2015 than 2016 (1, 2, 4, and 10) (Table 8 and Table 11), and only site 3 had more abundant SAV in 2016 than 2015. Intra-annual variation was also evident, six sites (1, 2, 3, 4, 8, and 10) were more abundant in the spring (Table 11); however, site 7 had a nearly significant seasonal difference (p=0.6), with higher abundance in the fall. Depth slope was positively correlated with SAV cover at 4 sites (1, 4, 8 and 10), which suggested that SAV were more abundant in deeper areas at these sites. Sites 5 and 9 did not have any SAV during the quadrat sampling, so they were excluded from the GEE analysis.

Core Samples; Species Composition

Five SAV species were identified in the core samples from the sentinel sites (Table 8). *Ruppia maritima* was the only species found at multiple sites (1,3, and 8), while *Myriophylum spicatum*, *Vallisnaria americana*, *Najas guadalupensis*, and *Potomogeton perfolatus* were only detected at one site each (1, 4, 4, and 8, respectively). Three of the four sites where SAV were sampled with the cores (1,4, and 8) had at least two SAV species.

Discussion

In natural resources management and conservation, it is crucial to understand intrinsic and external factors responsible for affecting baseline conditions and detecting changes in resources. Here, a sentinel site approach was applied to a large not easily accessible estuarine system as a first step in understanding the spatial and temporal dynamics of SAV. Through this approach, I confirmed that, like in other regions of North America, SAV abundance and distribution in AS is highly dynamic (Orth et al. 2010; Patrick and Weller 2015; Bolpagni et al. 2016) and identifying intrinsic variability is challenging. It is only through discerning between intrinsic dynamics and external factors that we can begin to understand the effect that factors like climate change, sea level rise, increasing human populations, and water pollution have on natural resources. By monitoring SAV status at these sentinel sites, it is possible to begin formalizing our knowledge of this system. However, predicting habitat changes in association with environmental conditions requires monitoring environmental conditions as well.

This study is the first sound-wide scale investigation of the spatial and temporal variation in the distribution and abundance of SAV in AS. Due to consistently poor optical water quality, attempts to synoptically map and monitor the status and trends of this resource using remotely deployed airborne sensors (photography and satellite) have been unsuccessful (Ferguson and Wood 1989; Ferguson and Wood 1994), while in-water monitoring has been restricted to relatively small areas (Davis and Brinson 1990; Quible and Associates 2011; Kenworthy et al. 2012), resulting in a substantial gap in our understanding of the ecological function and status of

SAV in the Sound (Moorman et al. 2014). To begin to close this gap, single-bean sonar combined with Biobase analytical software, and in-water quadrat sampling were used to detect and analyze the distribution and abundance of SAV at ten pre-determined locations. The geographic distribution of the ten sites encompassed a wide range of environmental conditions (Table 2 and Appendix D) that SAV should normally encounter in AS (e.g., gradients of salinity, wind and wave energy, and substrate type); as well as the potential for exposure to many of the anthropogenic factors known to affect SAV in other comparable low-salinity estuaries, including regional and local watershed discharges, nutrient and sediment loading, land use patterns such as agriculture, silviculture and urban development, and wetland and shoreline modification (Li et al. 2007; Orth et al. 2010; Patrick et al. 2014; Patrick and Weller 2015; Moorman et al. 2014; Lefcheck et al. 2018).

One of the primary objectives of this study was to evaluate the 10 individual locations as candidates for “sentinel sites” where long-term monitoring of SAV distribution and abundance could be incorporated into several resource management programs including APNEP’s Comprehensive Conservation and Management Plan (APNEP 2012), the North Carolina Coastal Habitat Protection Plan (NCDEQ 2016), and the National Water Quality Monitoring Network for U.S. Coastal Waters (Moorman et al. 2014). Collectively, all three of these plans acknowledge the ecological and economic value of SAV in estuarine systems, but also recognize the existence of a large gap in our understanding of the status and trends of SAV resources in AS.

The sonar sampling detected SAV at all 10 sites, but it showed that the sound-wide abundance of SAV varied significantly by location, much more so than either the intra- or inter-annual variation. Three sites with the largest abundance of SAV (1, 4, and 8) stood apart from all seven of the other locations which had sonar frequency of occurrence values generally < 20%, and several of which were < 10%. The large spatial differences and the relative patterns of abundance across the Sound were confirmed with the in-water quadrat sampling, including two sites with relatively low frequency of occurrence in the sonar sampling and no SAV detected in the quadrat sampling (sites 5 and 9).

There were no apparent geographic patterns associated with SAV abundance. The two sites with the lowest abundance (sites 5 and 6), the other four sparsely vegetated sites (2,3 7, 9 and 10), and the locations with the most abundant SAV (sites 1, 4 and 8) were distributed across the entire Sound suggesting that environmental conditions most favorable to SAV growth may be restricted to very specific locations in the estuary. Likewise, the distribution of sites throughout the Sound with relatively low abundance of SAV indicate that unfavorable growing conditions may be more widespread than expected for this primarily rural estuary.

The spatial variability of SAV abundance in AS was comparable to the variability reported in many of the sub-estuaries of neighboring Chesapeake Bay and suggest that conditions operating at relatively small-scales within the Sound may be the most important factors influencing local SAV abundance (Li et al. 2007; Patrick and Weller 2015; Orth et al. 2017). If SAV are going to be used as biological sentinels for distinguishing the effects of human activities and water quality impairment from natural environmental fluctuations, these results indicate there is a compelling need for monitoring multiple stations widely distributed across the Sound. The ten candidate sites selected for this study appear to encompass the full range of SAV abundance characteristics and can serve as a starting point for a long-term investigation of the factors responsible for impacting or enhancing SAV resources.

Ideally, if one of the goals of a monitoring program is to distinguish natural variation from human impacts, monitoring a resource with remote sensing methods should occur at the time of expected peak abundance when the SAV signature is at its maximum extent and least likely to be confused by other benthic signatures, and be frequent enough to accurately characterize the baseline and distinguish it from the stressor-response relationships, sometimes referred as the "signal to noise ratio." Because there is a very limited amount of information characterizing the baseline of SAV in AS, and the timing and magnitude of the SAV stressor-response relationship is expected to fluctuate, establishing the appropriate time to sample is paramount. Hence, one of the main goals of this study was to investigate, both, inter- and intra-annual variation at the ten sentinel sites to help determine the baseline for SAV distribution and abundance and the appropriate signature monitoring period for each location.

Based on the sonar surveys and pooling the data by year over the entire Sound, it was evident that each site had unique annual peaks. For the most part, the three sites with the relatively highest abundance in the sonar survey (1, 4, and 8) and the seven with the least SAV retained their relative abundance attributes inter-annually; stations with high SAV abundance remained relatively high and the low abundance stations remained low.

When the sites were examined individually there were significant differences in SAV abundances between years at eight sites in the sonar sampling and at five sites in the quadrat sampling. However, there wasn't complete agreement for the peak years of abundance between the two sampling methods. Nonetheless, inter-annual variation in absolute SAV abundance detected by both sampling approaches corroborates what was reported in a prior study in AS (Quible and Associates 2011). Quible and Associates (2011) monitored SAV abundance with in-water quadrat sampling during the month of September at 17 stations along a 25 km stretch of shoreline in northern AS for 5 consecutive years (2007-2011). At some stations SAV fluctuated up to 40 % inter-annually, along with shifts in species composition and SAV species dominance. Coincidently, the locations of two Quible and Associates (2011) monitoring stations, SS-5 and SS-6, corresponded with the location of sentinel site 4 in this study. At station SS-5 Quible and Associates (2011) reported that SAV increased every year between 2007 and 2011. In the final year of sampling there was 80-85% SAV cover, but the dominant species during four prior years of monitoring had shifted from *Najas guadalupensis* to a tall canopy forming invasive species *Myriophyllum spicatum*. Comparable quadrat sampling in fall 2015 and fall 2016 at site 4 in this study recorded SAV cover of 12.2% and 8.5%, respectively, substantially less than Quible and Associates (2011) last reported in September 2011. Nearby, at station SS-6 in the Quible and Associates (2011) survey, SAV increased every year from 2007 to 2010 before declining to 5-10% in 2011, which was less than the cover originally recorded in 2007. The sonar survey at site 4 in this study also found a significant inter-annual variation with greater abundance of SAV in 2015 than 2016. Given the results of this study and the five-year Quible and Associates (2011) survey, meadows in the area of site 4 have persisted for at least a decade (2007 – 2016), but with substantial year to year variation in abundance and species composition. These results suggest that sentinel sites in AS will need to be monitored repeatedly for multiple years in order to reliably assess the magnitude of inter-annual variation and how that variation affects the determination of baseline reference conditions and the assessment of status and trends of SAV resources in the Sound.

The intra-annual variation in SAV abundance at the individual sites showed more variability between sites in the sonar data than in the quadrat data. For sonar, there were no seasonal differences at six sites, three sites peaked in spring, and only one site peaked in fall. For the quadrat survey, SAV were more abundant in the spring at six sites; the remaining sites that had SAV in sonar did not have SAV in the quadrats. One other comparison between the two sampling methods is also notable. First, sites 1 and 4 displayed explicit agreement between sampling methods for spring peaks, and these sites had some of the highest maximum values for SAV abundance. Otherwise, all the remaining disagreement between the two sampling methods indicate either a fall peak or no seasonal peak abundance in the sonar. Overall, the preponderance of spring peaks in both the quadrat and sonar samples and the sites with no detectable seasonal difference in the sonar suggests that spring could be considered the primary signature period for SAV abundance during the two years of sampling. This supposition contradicts a previous recommendation that fall should be the preferred season to monitor SAV in low-salinity regions of North Carolina (Quible and Associates 2011; Kenworthy et al. 2012), so I reject my original hypothesis where I expected a fall peak across sites. On the other hand, if sonar is the preferred sampling method, one could also argue that seasonal preference is site specific and further monitoring is needed before making any generalized recommendations. Fewer sites (4) showed intra-annual variability in the sonar; nonetheless, several sites (6) showed seasonal peaks in the quadrat data, all in the spring. Hence, there is compelling evidence supporting the need for both spring and fall sampling. Sampling during both seasons would ensure that any interpretation of inter-annual change is not confounded by shifts in the intra-annual variability.

Many of the low-salinity adapted SAV species are sensitive to small fluctuations in salinity that could result from changing patterns of precipitation, watershed modification, river discharges, and climate (Patrick and Weller 2015). Shifts in species composition and abundance in response to these factors could result in different seasonal distribution and abundance. In lieu of the prospect that the predictions of future climate change in the AS region include altered patterns of precipitation, increasing storm activity, and the potential intrusion of seawater further into the Sound (Goldenberg et al. 2001; Boyles and Raman 2003; Henman and Poulter 2008; Poulter et al. 2009), there is a high likelihood of increasing intra- and inter-annual variability in the environmental factors affecting SAV, especially salinity. Generally, AS is a brackish water environment with a salinity gradient ranging from mostly freshwater conditions in the western region and the smaller tributaries (oligohaline) to mesohaline waters in the mid- and eastern locations of the Sound' main body (Moorman et al. 2014). At times, however, during the two-year monitoring period this gradient appeared to break down. Some stations (e.g., Site 1) exhibited intra- and interannual salinity variation, fluctuating between oligohaline and mesohaline conditions. SAV communities in low-salinity brackish water environments like AS are diverse and highly dynamic and typically display relatively large and sometimes asynchronous intra- and inter-annual variation in species composition and abundance in response to changes in water quality and salinity (Moore et al. 2000; Li et al. 2007; Patrick and Weller 2015; Orth et al. 2017).

In this study, five different SAV species were identified (Table 1); yet, four of the five species only occurred at one location. Further, each site had a unique species composition, suggesting that spatial and temporal variability in the acoustic data and quadrat sampling across sites could have been due to differences in species compositions across sites (Long and McKenzie 1998). SAV species composition is often a reflection of abiotic factors, like salinity, water level, and water clarity particular to an area (Adair el al. 1994; Madsen et al. 2001; Bolpagni et al. 2016), and SAV species tend to have unique growth and maximum extent periods

(Hudon et al. 2000; Kenworthy et al. 2012). Therefore, to better understand SAV abundance and distribution trends, it is essential that future SAV monitoring in AS includes SAV species composition and abiotic factors monitoring.

Water depth also has a significant influence on the distribution and abundance of SAV. Meadows growing in shallow water adjacent to shorelines are the first to experience the direct impacts from land use (e.g., stormwater discharges, sediment and nutrient loading, shoreline modification, etc.) (Landry and Golden 2017). These factors, along with waterfowl grazing, exposure to waves, and periodic fluctuations in water levels due to wind and tides can limit the upper depth distribution and abundance of SAV. Depth is important in limiting the amount of light reaching submerged plants, restricting the spatial distribution of SAV meadows to water depths meeting the species intrinsic light requirements (Dennison and Alberte 1985; Dennison et al. 1993; Kenworthy and Fonseca 1996; Koch 2001). Since the light requirements of many SAV species are generally known (Duarte 1991; Dennison et al. 1993), depth is an important variable to acquire in a resource monitoring program. Unfortunately, the spatial resolution and precision of the existing bathymetry information in many shallow water estuaries, including AS, is insufficient and cannot be readily applied to SAV monitoring programs without acquiring supplemental depth data. Acoustic sonar monitoring offers the dual benefits of detecting SAV presence-absence while simultaneously recording depth, such that the bathymetry of each of the sentinel sites can be mapped along with the depth distribution of the plants. Given the operating restrictions of the sonar to depths > 0.5 - 0.79 m, this approach cannot be reliably used to monitor SAV at the upper depth limit; however, it can be used to determine the maximum depth of SAV growth, and with long-term monitoring it can be used to examine changes in this important metric (Kenworthy and Fonseca 1996; Kemp et al. 2004; Kenworthy et al. 2014).

However, as the characterization of both the deep and shallow edges is crucial to understanding SAV abundance and distribution changes, sonar sampling needs to be complemented with other methodologies (e.g., in-water, low-altitude AUV's) to comprehensively monitor the resource.

Worldwide, SAV are recognized as valuable and practical sentinels of coastal environmental quality and, more specifically, a biological indicator of water quality impairment or improvement (Dennison et al. 1993; Orth et al. 2006; Orth et al. 2017). A commonly used metric in coastal monitoring programs is to determine the maximum SAV depth distribution and monitor the deviations from this value against the expected depth while factoring in the species light requirements (Kenworthy and Fonseca 1996; Kenworthy et al. 2014). As a more robust indicator, changes in the lower depth limit of SAV distribution can be coupled with routinely measured water quality parameters (e.g., chlorophyll, turbidity, CDOM) and calibrated with optical water quality models to identify potential stressors in the system and to set water quality targets for protection and restoration of SAV (Dennison et al. 1993; Gallegos 2001; Kenworthy et al. 2014).

By design, the offshore edge of the permanently located rectangular polygons defining the perimeter of each of the sentinel sites was expected to exceed the lower depth distribution of SAV at each location. Effectively, the sonar transects were designed to "over-sample" in deeper depths to identify the threshold depth where SAV growth terminated, such that the expansion (or contraction) of SAV maximum depth distribution could be identified and tracked in future monitoring events. Generally, the sonar detected maximum depths of SAV growth in the Sound ranging between 1.5 and 2.5 m, depending on the site. These values are well within the range of maximum depths for SAV growth known for other neighboring low-salinity estuaries (Kemp et al. 2004; Orth et al. 2010). Notably, the SAV depth distribution shifted to deeper regions in the fall (2.65 m depth 75th percentile) compared to the spring (2.41 m depth 75th percentile). This shift in depth distribution may be attributed to differences in light availability between the summer and fall due to different freshwater inflows during those seasons (Giese et al. 1985; Jia and Li 2012), fluctuating water levels or possibly differences in the SAV species composition.

There were also a few extraordinary sonar detections exceeding 3.0 m. For example, at site 4 the maximum depths of SAV recorded in spring and fall of 2016 were 4.96 m and 4.29 m, respectively, and were substantially greater than the maximum depths recorded in 2015 (1.71 and 2.98 m). These relatively deep detections may be partly explained by annual or intra-annual shifts in species dominance from low relief canopy taxa to taller canopy forming species able to compensate for low light levels at deeper depths by growing higher in the water column. Alternatively, some of the deeper detections could be false positive sonar readings due to the bottom characteristics of the site. In soft, flocculent substrates the surface sediments can return an echo that appears to be SAV (Kenworthy et al. 2012). Soft, flocculent sediments are not uncommon in estuaries and this methodological artifact could produce outliers that deserve special attention and require some additional verification of the signatures by either video or in-water observations.

Even though tidal effects are minimal in AS, water levels periodically and temporarily rise and fall in response to winds and tributary discharges (Giese et al. 1985). These fluctuations can be quite large and could result in erroneous estimates of the maximum depth of SAV growth. This was evident at several sites which had maximum sampling depths that fluctuated 0.5 to 1.0 m between sampling events. These temporary water level fluctuations could lead to apparent variability in SAV depth distribution and demonstrate the need for establishing fixed water level benchmarks at the sentinel sites in order to standardize the depth values recorded by the sonar during each sampling event.

Summary and Recommendations

One of the main goals of any natural resource monitoring program is to develop the capability of distinguishing natural variation from variability due to unambiguous and manageable stressors (e.g., pollution) (Southward 1995; Christian and Mazzilli 2007; Orth et al. 2010; Patrick and Weller 2015). Clearly, the numerous well-funded programs in neighboring Chesapeake Bay have demonstrated the value of several decades of monitoring by identifying many of the important relationships and applied this knowledge directly to the conservation and restoration of SAV (Orth et al. 2017; Lefcheck et al. 2018). Granted, the Chesapeake Bay estuary is far more urbanized than AS and, depending on location, the types of stressors and their magnitude can be very different. Yet, many of the important stressor-response relationships identified in the oligohaline and mesohaline SAV communities in Chesapeake Bay could be transferred to AS if there was enough monitoring data available. After more than a century of research and monitoring in AS there are still substantial data gaps, including very little information about the distribution and abundance of SAV. However, there are several important local, regional, and national monitoring activities striving to close the gaps through numerous enhancements (Moorman et al. 2014) including the establishment and evaluation of an SAV sentinel site monitoring program reported in this study.

AS is a large and biophysically diverse water body making it very difficult and expensive to synoptically and frequently monitor submerged benthic resources with traditional in-water methods. Prior to this study, it was known that the poor water transparency characteristic of the Sound severely limited the use of airborne remote sensing to detect benthic habitat signatures. Although airborne sensors are regularly used in the Chesapeake Bay and elsewhere, conditions in AS are rarely suitable enough to allow these sensors to reliability and repeatedly penetrate through the water column and detect the deeper water SAV communities. As an alternative to some of the more traditional methods, the feasibility of a sentinel site approach combined with remote sensing of SAV presence-absence using boat-based sonar was investigated. Based on the design, a single site could be monitored, and SAV sonar signal verified with video in approximately two days, weather permitting. While allowing for intervals of data processing and travel logistics between sites, multiple locations can be surveyed over a period of several weeks in order to effectively capture conditions within specified seasonal windows. Another major advantage of the sonar method is the possibility of resampling without the need for costly re-activation of in-water sampling teams or the deployment of aircraft.

The ten locations investigated in this study were selected based on a consideration of three sentinel site selection criteria; 1) the key feature that is important to ecosystem function should be present (e.g., SAV); 2) the sites should have key physical and biological attributes that represent the larger ecosystem (e.g., a salinity gradient, presence of environmental and anthropogenic stressors) and; 3) there is a high likelihood of detecting change. Criteria 1 was satisfied; SAV were present at all sites. But there was significant spatial and temporal variation in SAV distribution and abundance across sites, which suggested that any attempt to characterize the SAV baseline by averaging sites across AS would be misleading. The evidence supporting a need for monitoring individual sentinel sites was compelling.

Criteria 2 was partially satisfied; the ten stations encompassed a salinity gradient, but again there was both substantial intra- and inter-annual salinity variation. Though the sites were randomly selected (Chapter 1); fortuitously, the sites are distributed widely across the Sound and are exposed to a range of environmental conditions and anthropogenic stressors. The variability in SAV abundance suggested that conditions at three of the sites were more optimal than the other seven locations. However, as an indicator of environmental quality (Orth et al. 2017), the relatively low abundance of SAV at seven locations distributed across the Sound may be signaling some problems that need resource managers' immediate attention. As this sentinel site monitoring program proceeds and becomes integrated with other monitoring and assessment programs in AS (e.g., water quality), there will be an opportunity to identify and examine the specific factors responsible for influencing SAV abundance at the individual sites and across the Sound. Additionally, the spatial variability in local SAV abundance could be used as a guide to direct other monitoring efforts in their selection of metrics to be used for distinguishing between the effects of environmental and anthropogenic stressors on SAV and other resources.

Based on the magnitude of the spatial and temporal variability of SAV abundance at the ten sentinel sites, it would be premature to declare that Criteria 3 was met by just two years of monitoring. The spatial and temporal asynchrony of the system makes it very difficult to determine whether the established sites are adequate for monitoring change due to the high signal to noise ratio. At some of the sites the intra-annual variability exceeded the inter-annual variation in abundance, leaving the determination of one optimal sampling period still unresolved, let alone the capability of detecting change. At best, without a reliable quantitative assessment of historical SAV abundance, one can only conclude that SAV have persisted at the 10 sentinel sites, and in one case (Site 4), nearly continuously for at least a decade. Based on the only other monitoring program in AS that spanned multiple years (five), it is known that there can be significant inter-annual variation in SAV abundance that would not be detected in just two years of sampling (Quible and Associates 2011). In order to expect to have a reasonable understanding of the baseline of SAV abundance and develop the capability of detecting meaningful change it will be necessary to continue monitoring the 10 sentinel sites twice annually (spring and fall) for at least five years.

SAV species composition is known to play an important role in inter- and intra-annual SAV abundance (Adair et al. 1994; Kenworthy et al. 2012); therefore, it is crucial to fill the information gap on the relationship between SAV species composition and its temporal patterns at the sentinel sites. SAV is dynamic by nature which makes identifying clear temporal patterns challenging (Orth et al. 2010; Patrick and Weller 2015; Bolpagni et al. 2016). This difficulty is exacerbated in low-salinity regions due to greater species diversity compared to high-salinity regions (Kenworthy et al. 2012). The benefit of adding rigorous species composition monitoring at the sentinel sites is twofold. First, SAV peak abundances, for a location, are often associated with the dominant species' peak abundance (Kenworthy et al. 2012; Patrick and Weller 2017), so characterizing SAV species composition at the sentinel sites should help identify and predict peak abundances. The Chesapeake Bay has 13 oligohaline SAV species (Moore et al. 2000; Orth et al. 2010), yet the low-salinity sub-estuaries in the Bay are often dominated by only one or two species, which are often not the same across sub-estuaries, contributing to the SAV abundance asynchrony across the different waterbodies (Patrick and Weller 2017). In AS, we know very little about species dominance, but we know that there are approximately 10 different low-salinity species in NC, with *R. maritima*, *M. spicatum*, and *N. guadalupensis* being the most frequently reported (Davis and Brinson 1990; Ferguson and Wood 1994; Quible and Associates

2011; Kenworthy et al. 2012; Table 8). Nonetheless, long-term species composition monitoring in the Sound should help understand species dominance and species phenology. Second, SAV species composition often reflects the local environmental conditions, so studying shift is species composition along with environmental parameters (e.g. light availability, salinity, sedimentation, storms) can help better discern SAV temporal variation in AS (Orth et al. 2010; Orth et al. 2017; Patrick and Weller 2017). Case studies in the Chesapeake Bay indicated that a reduction of point-source nutrient loading in the Bay led to increased SAV species diversity and the decline of invasive species (Ruhl and Rybicki 2010). After exploring the literature, Davis and Brinson (1990) reported a total of seven SAV species in AS; whereas, more recent reports by Quibble and Associates (2011) and my own study reported six and five species, respectively. The information from these reports is not sufficient to make conclusive statements about shifts in species composition through time; nonetheless, changes in species composition and diversity should be closely monitored, as they help discern SAV temporal patterns. Moreover, they may also serve as early warning of environmental degradation (Orth et al. 2017).

In other to accurately detect change, ideally, the verification of SAV presence in the sonar should be high. Even though the sampling effort strived to minimize error as much as possible by acquiring 100 video verification points at each site and filtering the data so that video points were within 10 m of the sonar point, the percentage of sonar detections verified for SAV presence (PVP) was poor while the verification of absence (AVP) was very good. Given that the sonar's capability of detecting SAV has been clearly established in several studies, the relatively low PVP can be attributed to a methods design problem. Poor sonar verification in this study was a technical problem associated with three potential sources of error; 1) GPS location error; 2) the co-location error associated with the position of the single camera drop and the position of the sonar report; 3) and the difference in sampling "footprint resolution" between the sonar and the video. Depending on the wind conditions at the time of the camera drop, and the effect the vessel's drift, the precise location of the camera, and the original sonar position can deviate substantially. Low verification of SAV presence could have been also be partly attributed to the sonar's ability to detect smaller patches, due to its higher sampling rate. Similar sonar accuracy issues were ascribed to the co-location error in Puget Sound where accuracy was lower in areas with patchy SAV beds (Stevens et al. 2008). Sonar verification with video could be improved by using DGPS (Differential Global Positioning Systems) in place of standard GPS and more precisely co-locating the positions for the camera drops. These improvements will certainly add to the time and cost of sampling.

Sonar sampling alone will not be enough to fully assess the status and trends of SAV at the sentinel sites. In-water species composition identification and monitoring the fluctuations in the species will be necessary to fully understand the condition of the meadows and their response to environmental changes and stressors. This was evident at the seventeen sites in proximity to site SS 4 where Quible and Associates (2011) found six species of SAV in total over the five years of sampling. Several stations had multiple co-occurring species, thirteen shifted species dominance, only four of the stations had one dominant species over the five-year sampling period and two stations had the non-native species *M. spicatum*. *M. spicatum* is an exotic species that has spread in North America (Nichols and Shaw 1986), and along with other exotic species (e.g., *Hydrilla verticillata*) that occur in low-salinity estuaries, it is known to reduce habitat suitability for fish and macroinvertebrates (Keast 1984) and outcompete local SAV species. Historically, *M. spicatum* was estimated to cover 162 hectares in Currituck and Albemarle sounds (North Carolina Division of Water Resources 1996) and has been present in the system for more than 4 decades (Getsinger et al. 1982). Its presence and possible high abundance should be monitored, as invasive species can be stressors to already fragile systems (Ruiz et al. 1999). Hence, I cannot emphasize enough the importance of supplementing the sonar and video sentinel sites surveys with in-water species composition surveys.

References

Adair, S.E., J.L. Moore, and C.P. Onuf. 1994. Distribution and status of submerged vegetation in estuaries of the upper Texas coast. *Wetlands* 14: 110–121. doi:10.1007/BF03160627.

APNEP. 2012. *Comprehensive conservation and management plan 2012-2022*. Raleigh, North Carolina.

APNEP. 2019. Submerged Aquatic Vegetation Maps. https://apnep.nc.gov/our-work/monitoring/submerged-aquatic-vegetation-monitoring. Accessed 9 September 2019.

Barbier, E.B., S.D. Hacker, C. Kennedy, E.W. Koch, A.C. Stier, and B.R. Silliman. 2011. The value of estuarine and coastal ecosystem services. *Ecological Monographs* 81: 169–193.

Barrell, J., and J. Grant. 2013. Detecting hot and cold spots in a seagrass landscape using local indicators of spatial association. *Landscape Ecology* 28: 2005–2018. doi:10.1007/s10980-013-9937-2.

Barrell, J., J. Grant, A. Hanson, and M. Mahoney. 2015. Evaluating the complementarity of acoustic and satellite remote sensing for seagrass landscape mapping. *International Journal of Remote Sensing* 36: 4069–4094. doi:10.1080/01431161.2015.1076208.

Bolpagni, R., A. Laini, and M.M. Azzella. 2016. Short-term dynamics of submerged aquatic vegetation diversity and abundance in deep lakes. *Applied Vegetation Science* 19: 711–723. doi:10.1111/avsc.12245.

Boyles, R.P., and S. Raman. 2003. Analysis of climate trends in North Carolina (1949-1998). *Environment International* 29: 263–275. doi:10.1016/S0160-4120(02)00185-X.

Bučas, M., A. Šaškov, A. Šiaulys, and Z. Sinkevičienė. 2016. Assessment of a simple hydroacoustic system for the mapping of macrophytes in extremely shallow and turbid lagoon. *Aquatic Botany* 134: 39–46. doi:10.1016/j.aquabot.2016.06.009.

Burkholder, J., D. Eggleston, H. Glasgow, C. Brownie, R. Reed, G. Janowitz, M. Posey, et al. 2004. Comparative impacts of two major hurricane seasons on the Neuse River and western Pamlico Sound ecosystems. *Proceedings of the National Academy of Sciences* 101: 9291–9296. doi:10.1073/pnas.0306842101.

Chang, H. 2008. Spatial analysis of water quality trends in the Han River basin, South Korea. *Water Research* 42: 3285–3304.

Christian, R.R., and S. Mazzilli. 2007. Defining the coast and sentinel ecosystems for coastal observations of global change. *Hydrobiologia* 577: 55–70. doi:10.1007/s10750-006-0417-4.

Cohen, J.E. 1995. How Many People Can the Earth Support (1994, Human Sciences Press, Inc) WW Norton & Company. *New York*.

Costello, C.T., and W.J. Kenworthy. 2011. Twelve-year mapping and change analysis of Eelgrass (*Zostera marina*) areal abundance in Massachusetts (USA) identifies statewide declines. *Estuaries and Coasts* 34: 232–242.

Crowley, T.J. 1990. Are there any satisfactory geological analogs for future greenhouse warming? *Journal of Climate* 3: 1282–1292.

Curran, R.W. 2011. The utility of Digital's Globe's WordView-2 satellite data in mapping seagrass in North Carolina estuaries. East Carolina University.

Davis, G.J., and M.M. Brinson. 1990. *A survey of submersed aquatic vegetation of the Currituck Sound and the western Albemarle-Pamlico estuarine system*. Greenville, North Carolina.

Deaton, A.S., W.S. Chappell, J. O'Neal, K. Hart, and B. Boutin. 2010. *North Carolina Coastal Habitat Protection Plan*. Morehead City, North Carolina.

Dennison, W.C., and R.S. Alberte. 1985. Role of daily light period in the depth distribution of *Zostera marina* (eelgrass). *Marine Ecology Progress Series* 25: 51–61. doi:10.3354/meps025051.

Dennison, W.C., R.J. Orth, K.A. Moore, J.C. Stevenson, V. Carter, S. Kollar, P.W. Bergstrom, and R.A. Batiuk. 1993. Assessing water quality with submerged aquatic vegetation: Habitat requirements as barometers of Chesapeake Bay health. *BioScience* 43: 86–94. doi:10.2307/1311969.

Duarte, C.M. 1987. Use of echosounder tracings to estimate aboveground biomass of submberged plants in lakes. *Canadian Journal of Fisheries and Aquatic Sciences* 44: 732–735.

Duarte, C.M. 1991. Seagrass depth limits. *Aquatic Botany* 40: 363–377. doi:10.1016/0304-3770(91)90081-F.

Duarte, C.M., and H. Kirkman. 2001. Chapter 7: Methods for measurement of seagrass abundance and depth distribitution. In *Global seagrass research methods*, ed. Frederick T. Short and Robert G. Coles, 1st ed., 141–153. Amsterdam, The Netherlands: Elsevier B.V. doi:https://doi.org/10.1016/B978-0-444-50891-1.X5000-2.

ESRI. 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

Ferguson, R.L., and L.L. Wood. 1989. *Submerged aquatic vegetation in the Albemarle-Pamlico estuarine systems*. Beaufort, North Carolina.

Ferguson, R.L., and L.L. Wood. 1990. *Mapping submerged aquatic vegetation in North Carolina with conventional aerial photography*. *Federal Coastal Wetland Mapping Programs*. Washington, District of Columbia.

Ferguson, R.L., and L.L. Wood. 1994. *Rooted vascular aquatic beds in the Albemarle-Pamlico estuarine system.* Beaufort, North Carolina: National Marne Fisheries, National Oceanic and Atmospheric Administration.

Ferguson, R.L., L.L. Wood, and G.J. Davis. 1993. Monitoring spatial change in seagrass habitat with aerial photography. *Photogrammetric Engineering and Remote Sensing* 59: 1033–

1038.

Finkbeiner, M., B. Stevenson, and R. Reaman. 2001. *Guidance for benthic habitat mapping: An aerial phographic approach*. Charleston, South Carolina.

Gallegos, C.L. 2001. Calculating optical water quality targets to restore and protect submerged aquatic vegetation: Overcoming problems in partitioning the diffuse attenuation coefficient for Photosynthetically Active Radiation. *Estuaries* 24: 381–397. doi:10.2307/1353240.

Getsinger, K.D., G.J. Davis, and M.M. Brinson. 1982. Changes in a *Myriophyllum spicatum* L. community following 2,4-D Treatment. *Journal of Aquatic Plant Management* 20: 4–8.

Geys, H., G. Molenberghs, and L.M. Ryan. 2002. *Generalized estimating equations*. *Topics in Modelling of Clustered Data*. Boca Raton, Florida: Chapman and Hall/CRC.

Giese, G.L., H.B. Wilder, and G.G.J. Parker. 1985. *Hydrology of major estuaries and sounds of North Carolina*. Alexandria, Virginia.

Goldenberg, S.B., C.W. Landsea, A.M. Mestas-Nuñez, and W.M. Gray. 2001. The recent increase in Atlantic hurricane activity: Causes and implications. *Science* 293: 474–479. doi:10.1126/science.1060040.

Guan, W., R.H. Chamberlain, B.M. Sabol, and P.H. Doering. 2010. Mapping submerged aquatic vegetation with GIS in the Caloosahatchee Estuary: Evaluation of different interpolation methods. *Marine Geodesy* 22: 69–91. doi:10.1080/014904199273506.

Heck, K.L.J., and T.A. Thoman. 1984. The nursery role of seagrass meadows in the upper and lower reaches of the Chesapeake Bay. *Coastal and Estuarine Research Federation* 7: 70–92.

Heck, R.H., S.L. Thomas, and L.N. Tabata. 2013. Multilevel and longitudinal modeling with IBM SPSS. In , 2nd ed., 443. New York, New York: Routledge.

Henman, J., and B. Poulter. 2008. Inundation of freshwater peatlands by sea level rise: Uncertainty and potential carbon cycle feedbacks. *Journal of Geophysical Research* 113: 1–11. doi:10.1029/2006JG000395.

Hermand, J.P., P. Nascetti, and F. Cinelli. 1998. Inversion of acoustic waveguide propagation features to measure oxygen synthesis by *Posidonia oceanica*. *Oceans Conference Record (IEEE)* 2: 919–926. doi:10.1109/oceans.1998.724372.

Hoffman, L. 2015. *Longitudinal analysis: Modeling within-person fluctuation and change*. 1st ed. New York, New York: Routledge.

Hudon, C., S. Lalonde, and P. Gagnon. 2000. Ranking the effects of site exposure, plant growth form, water depth, and transparency on aquatic plant biomass. *Canadian Journal of Fisheries and Aquatic Sciences* 57: 31–42. doi:10.1139/f99-232.

Jassby, A.D. 1998. Interannual variation at three inland water sites: Implications for sentinel sites. *Ecological Applications* 8: 277–287. doi:10.1890/1051-0761(1998)008[0277:IVATIW]2.0.CO;2.

Jia, P., and M. Li. 2012. Circulation dynamics and salt balance in a lagoonal estuary. *Journal of Geophysical Research* 117: 1–16. doi:10.1029/2011JC007124.

Keast, A. 1984. The introduced aquatic macrophyte, *Myriophyllum spicatum*, as habitat for fish and their invertebrate prey. *Canadian Journal of Zoology* 62: 1289–1303. doi:10.1139/z84-186.

Kemp, W.M., R. Batiuk, R. Bartleson, P.W. Bergstrom, V. Carter, C.L. Gallegos, W. Hunley, et al. 2004. Habitat requirements for submerged aquatic vegetation in Chesapeake Bay: Water quality, light regime, and physical-chemical factors. *Estuaries* 27: 363–377.

Kemp, W.M., R. Twilley, J.C. Stevenson, W.R. Boynton, and J.C. Means. 1983. The decline of submerged vascular plants in upper Chesapeake Bay: Summary of results concerning possible causes. *Marine Technology Society Journal* 17: 78–89.

Kenworthy, W.J., C.A. Buckel, D.E. Carpenter, D.B. Eggleson, D. Field, C.S. Krahforst, and J.J. Luczkovich. 2012. *Development of submerged aquatic vegetation monitoring protocols in North Carolina*. Morehead City, North Carolina.

Kenworthy, W.J., and M.S. Fonseca. 1996. Light requirements of seagrasses *Halodule wrightii* and *Syringodium filiforme* derived from the relationship between diffuse light attenuation and maximum depth distribution. *Estuaries* 19: 740–750. doi:10.2307/1352533.

Kenworthy, W.J., C.L. Gallegos, C.T. Costello, D. Field, and G. di Carlo. 2014. Dependence of eelgrass (*Zostera marina*) light requirements on sediment organic matter in Massachusetts coastal bays: Implications for remediation and restoration. *Marine Pollution Bulletin* 83: 446–457. doi:10.1016/j.marpolbul.2013.11.006.

Koch, E.W. 2001. Beyond light: Physical, geological, and geochemical parameters as possible submerged aquatic vegetation habitat requierements. *Estuaries* 24: 1–17. doi:10.2307/1352808.

Landry, J.B., and R.R. Golden. 2017. *In situ* effects of shoreline type and watershed land use on submerged aquatic vegetation habitat quality in the Chesapeake and Mid-Atlantic coastal bays. *Estuaries and Coasts*. Estuaries and Coasts: 1–13. doi:10.1007/s12237-017-0316-0.

Lefcheck, J.S., R.J. Orth, W.C. Dennison, D.J. Wilcox, R.R. Murphy, J. Keisman, C. Gurbisz, et al. 2018. Long-term nutrient reductions lead to the unprecedented recovery of a temperate coastal region. *Proceedings of the National Academy of Sciences* 115: 3658–3662. doi:10.1073/pnas.1715798115.

Lefebvre, A., C.E.L. Thompson, K.J. Collins, and C.L. Amos. 2009. Use of a high-resolution profiling sonar and a towed video camera to map a *Zostera marina* bed, Solent, UK. *Estuarine, Coastal and Shelf Science* 82. Elsevier Ltd: 323–334. doi:10.1016/j.ecss.2009.01.027.

Li, X., D.E. Weller, C.L. Gallegos, T.E. Jordant, and H.-C.C. Kim. 2007. Effects of watershed and estuarine characteristics on the abundance of submerged aquatic vegetation in Chesapeake Bay subestuaries. *Estuaries and Coasts* 30: 840–854. doi:10.1007/BF02841338.

Lindquist, N.L., and S.R. Fegley. 2016. *Development of a comprehensive North Carolina salinity database to facilitate management and restoration of critical fish habitats. North Carolina Coastal Recreational Fishing License Final Report: 2013-H-015*.

Long, W.J.L., and L.J. McKenzie. 1998. *Preliminary evaluation of an acoustic technique for mapping tropical seagrass habitat*. *Great Barrier Reef Marnie Park Authority*. Townsville, Australia.

Madsen, J.D., P.A. Chambers, W.F. James, E.W. Koch, and D.. Westlake. 2001. The interaction between water movement, sediment dynamics and submersed macrophytes. *Hydrobiologia* 444: 71–84. doi:10.1023/A.

Madsen, J.D., and R.M. Wersal. 2017. A review of aquatic plant monitoring and assessment methods. *Journal of Aquatic Plant Management* 55: 1–13.

McCarthy, E.M. 1997. Acoustic characterization of submerged aquatic vegetation. In *SACLANTCEN Proceedings Series CP-45, High Frequency Acoustics in Shallow Water*, ed. N. G. Pouliquen, E. Bergem, and A. P. Lyons, 362–369. Lerici, Italy: NATO SACLANT Undersea Research Centre.

McCulloch, C.E., and J.M. Neuhaus. 2005. Generalized linear mixed models. In *Encyclopedia of biostatistics*, ed. Peter Armitage and Theodore Colton, 1st ed. New York, New York: John Wiley & Sons, Ltd.

McDonald, M.E., S. Paulsen, R. Blair, J. Dlugosz, S. Hale, D. Heggen, L. Jackson, et al. 2002. *Research strategy: Environmental monitoring and assessment program*. Research Triangle Park, NC.

Miller, K.G., M.A. Kominz, J. V. Browning, J.D. Wright, G.S. Mountain, M.E. Katz, P.J. Sugarman, B.S. Cramer, N. Christie-Blick, and S.F. Pekar. 2005. The phanerozoic record of global sea-level change. *Science* 310: 1293–1298. doi:10.1126/science.1116412.

Moore, K.A., D.J. Wilcox, and R.J. Orth. 2000. Analysis of the abundance of submersed aquatic vegetation communities in the Chesapeake Bay. *Estuaries* 23: 115–127. doi:10.2307/1353229.

Moorman, M.C., K.R. Kolb, and S. Supak. 2014. *Estuarine monitoring programs in the Albemarle Sound study area, North Carolina*. Reston, Virginia.

Murphey, P.L., and M.S. Fonseca. 1995. Role of high and low energy seagrass beds as nursery areas for *Penaeus duorarum* in North Carolina. *Marine Ecology Progress Series* 121: 91–98. doi:10.3354/meps121091.

Navico. 2014. BioBase User Reference Guide.

Nichols, S.A., and B.H. Shaw. 1986. Ecological life histories of the three aquatic nuisance plants, *Myriophyllum spicatum*, *Potamogeton crispus* and *Elodea canadensis*. *Hydrobiologia* 131: 3–21. doi:10.1007/BF00008319.

Norris, J.G., S. Wyllie-Echeverria, T. Mumford, A. Bailey, and T. Turner. 1997. Estimating basal area coverage of subtidal seagrass beds using underwater videography. *Aquatic*

Botany 58: 269–287. doi:10.1016/S0304-3770(97)00040-5.

NCDEQ. 2016. *North Carolina Coastal Habitat Protection Plan Source Document*. Morehead City, North Carolina.

NC Division of Water Resources. 1996. *Economic and environmental impacts of North Carolina aquatic weed infestations*. Raleigh, North Carolina.

Orth, R.J., T.J.B. Carruthers, W.C. Dennison, C.M. Duarte, J.W. Fourqurean, K.L.J. Heck, A.R. Hughes, et al. 2006. A global crisis for seagrass ecosystems. *Bioscience* 56: 987–996.

Orth, R.J., W.C. Dennison, J.S. Lefcheck, C. Gurbisz, M. Hannam, J. Keisman, J.B. Landry, et al. 2017. Submersed aquatic vegetation in Chesapeake Bay: Sentinel species in a changing world. *BioScience* 67: 698–712. doi:10.1093/biosci/bix058.

Orth, R.J., M.R. Williams, S.R. Marion, D.J. Wilcox, T.J.B. Carruthers, K.A. Moore, W.M. Kemp, et al. 2010. Long-term trends in submersed aquatic vegetation (SAV) in Chesapeake Bay, USA, related to water quality. *Estuaries and Coasts* 33: 1144–1163. doi:10.1007/s12237-010-9311-4.

Patrick, C.J., and D.E. Weller. 2015. Interannual variation in submerged aquatic vegetation and its relationship to water quality in subestuaries of Chesapeake Bay. *Marine Ecology Progress Series* 537: 121–135. doi:10.3354/meps11412.

Patrick, C.J., D.E. Weller, X. Li, and M. Ryder. 2014. Effects of shoreline alteration and other stressors on submerged aquatic vegetation in subestuaries of Chesapeake Bay and the Mid-Atlantic coastal bays. *Estuaries and Coasts* 37: 1516–1531. doi:10.1007/s12237-014-9768-7.

Peng, M., L. Xie, and L.J. Pietrafesa. 2004. A numerical study of storm surge and inundation in the Croatan–Albemarle–Pamlico Estuary System. *Estuarine, Coastal and Shelf Science* 59: 121–137. doi:10.1016/j.ecss.2003.07.010.

Poulter, B., R.L. Feldman, M.M. Brinson, B.P. Horton, M.K. Orbach, S.H. Pearsall, E. Reyes, S.R. Riggs, and J.C. Whitehead. 2009. Sea-level rise research and dialogue in North Carolina: Creating windows for policy change. *Ocean and Coastal Management* 52: 147–153. doi:10.1016/j.ocecoaman.2008.09.010.

Quible and Associates. 2011. *A compensatory mitigation plan requierement for The Fund for Sandy Point North Carolina, LLC*. Kitty Wawk, North Carolina.

Radomski, P., and B. V. Holbrook. 2015. A comparison of two hydroacoustic methods for estimating submerged macrophyte distribution and abundance: A cautionary note. *Journal of Aquatic Plant Management* 53: 151–159.

Riegl, B.M., R.P. Moyer, L.J. Morris, R.W. Virnstein, and S.J. Purkis. 2005. Distribution and seasonal biomass of drift macroalgae in the Indian River Lagoon (Florida , USA) estimated with acoustic seafloor classification (QTCView , Echo plus). *Journal of Experimental Marine Biology and Ecology* 326: 89–104. doi:10.1016/j.jembe.2005.05.009.

Ruhl, H.A., and N.B. Rybicki. 2010. Long-term reductions in anthropogenic nutrients link to improvements in Chesapeake Bay habitat. *Proceedings of the National Academy of Sciences of the United States of America* 107: 16566–16570. doi:10.1073/pnas.1003590107.

Ruiz, G.M., P. Fofonoff, and A.H. Hines. 1999. Non-indigenous species as stressors in estuarine and marine communities: Assessing invasion impacts and interactions. *Limnology and Oceanography* 44: 950–972. doi:10.4319/lo.1999.44.3_part_2.0950.

Sabol, B.M., R.E.J. Melton, R. Chamberlain, P. Doering, and K. Haunert. 2002. Evaluation of a digital echosounder system for detection of submersed aquatic vegetation. *Estuaries* 25: 133–141. doi:10.1007/BF02696057.

Schultz, S.T. 2008. Seagrass monitoring by underwater videography: Disturbance regimes, sampling design, and statistical power. *Aquatic Botany* 88: 228–238. doi:10.1016/j.aquabot.2007.10.009.

Short, F.T., R. Coles, M.D. Fortes, S. Victor, M. Salik, I. Isnain, J. Andrew, and A. Seno. 2014. Monitoring in the Western Pacific region shows evidence of seagrass decline in line with global trends. *Marine pollution bulletin* 83: 408–416.

Southward, A.J. 1995. The importance of long time-series in understanding the variability of natural systems. *Helgoländer Meeresuntersuchungen* 49: 329–333. doi:10.1007/BF02368360.

Stanley, D.W. 1992. *Historical trends: Water quality and fisheries, Galveston Bay*. Greenville, North Carolina: East Carolina University.

Stevens, A.W., J.R. Lacy, D.P. Finlayson, and G. Gelfenbaum. 2008. *Evaluation of a single-beam sonar system to map seagrass at two sites in northern Puget Sound, Washington*. *Scientific investigations report 2008-5009*. Reston, Virginia.

Thayer, G.W., W.J. Kenworthy, and M.S. Fonseca. 1984. *The ecology of eelgrass meadows of the Atlantic coast: A community profile*.

Tseng, Y.-T. 2009. Recognition and assessment of seafloor vegetation using a single beam echosounder. Curtin University of Technology.

Valley, R.D. 2016. Spatial and temporal variation of aquatic plant abundance: Quantifying change. *Journal of Aquatic Plant Management* 54: 95–101.

Valley, R.D., and M.T. Drake. 2005. *Accuracy and precision of hydroacoustics estimates of aquatic vegetation and the repeatability of whole-lake surveys: Field tests with a commercial echosounder*. *Minnesota Department of Natural Resources Investigational Report*.

Valley, R.D., M.B. Johnson, D.L. Dustin, K.D. Jones, M.R. Lauenstein, and J. Nawrocki. 2015. Combining hydroacoustic and point-intercept survey methods to assess aquatic plant species abundance patterns and community dominance. *Journal of Aquatic Plant Management* 53: 121–129.

Verbeke, G., and G. Molenberghs. 2000. *Linear mixed models for longitudinal data*. 1st ed. New York, New York: Springer-Verlag New York.

Vis, C., C. Hudon, and R. Carignan. 2003. An evaluation of approaches used to determine the distribution and biomass of emergent and submerged aquatic macrophytes over large spatial scales. *Aquatic Botany* 77: 187–201. doi:10.1016/S0304-3770(03)00105-0.

Waycott, M., C.M. Duarte, T.J.B. Carruthers, R.J. Orth, W.C. Dennison, S. Olyarnik, A. Calladine, et al. 2009. Accelerating loss of seagrasses across the globe threatens coastal ecosystems. *Proceedings of the National Academy of Sciences of the United States of America* 16: 12377–12381. doi:10.1073/pnas.0905620106.

Williams, M.R., S. Filoso, B.J. Longstaff, and W.C. Dennison. 2010. Long-term trends of water quality and biotic metrics in Chesapeake Bay: 1986 to 2008. *Coastal and Estuarine Research Federation* 33: 1279–1299. doi:10.1007/sl.

Wilson, P.S., and K.H. Dunton. 2009. Laboratory investigation of the acoustic response of seagrass tissue in the frequency band 0.5–2.5 kHz. *The Journal of the Acoustical Society of America* 125: 1951–1959. doi:10.1121/1.3086272.

Winfield, I.J., C. Onoufriou, M.J. O'Connell, M. Godlewska, R.M. Ward, A.F. Brown, and M.L. Yallop. 2007. Assessment in two shallow lakes of a hydroacoustic system for surveying aquatic macrophytes. *Hydrobiologia* 584: 111–119. doi:10.1007/s10750-007-0612-y.

Zhu, B., D.G. Fitzgerald, S.B. Hoskins, L.G. Rudstam, C.M. Mayer, and E.L. Mills. 2007. Quantification of historical changes of submerged aquatic vegetation cover in two bays of Lake Ontario with three complementary methods. *Journal of Great Lakes Research* 33: 122–135. doi:10.3394/0380-1330(2007)33[122:QOHCOS]2.0.CO;2.

Figures

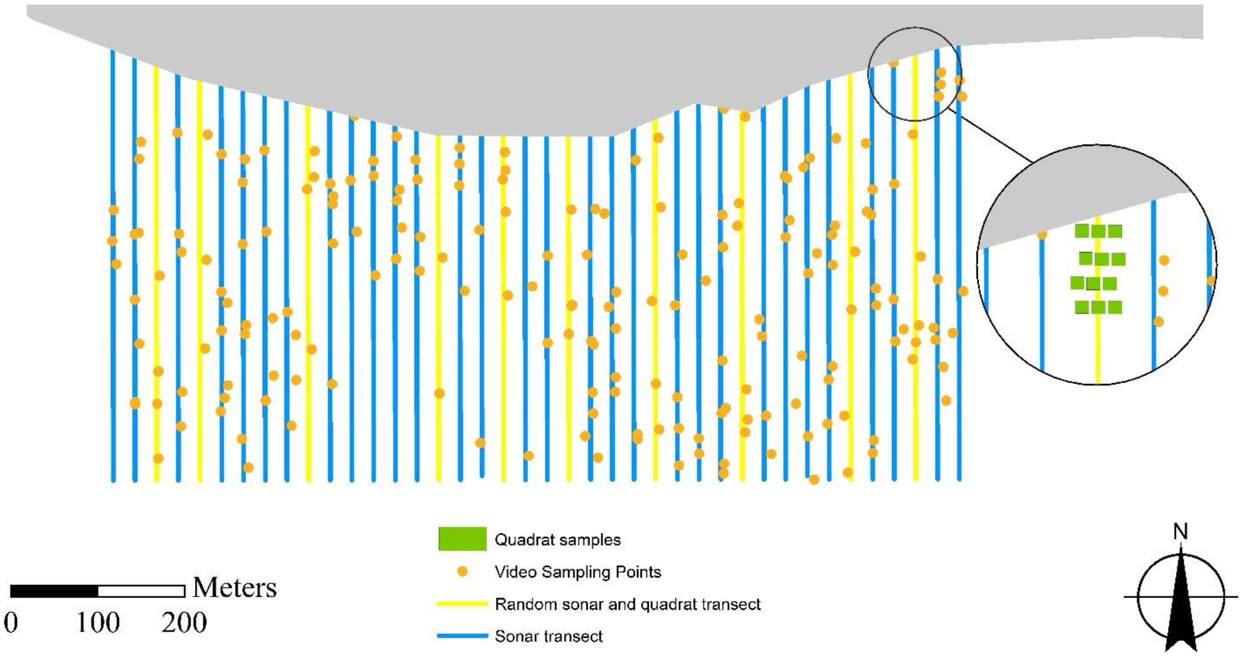


Figure 11. Example of the configuration of one of the Albemarle Sound sentinel sites showing the 40 sonar transect lines with sonar and 100 randomly selected underwater video points. In addition, a detailed inset of the quadrat sampling is shown as well.

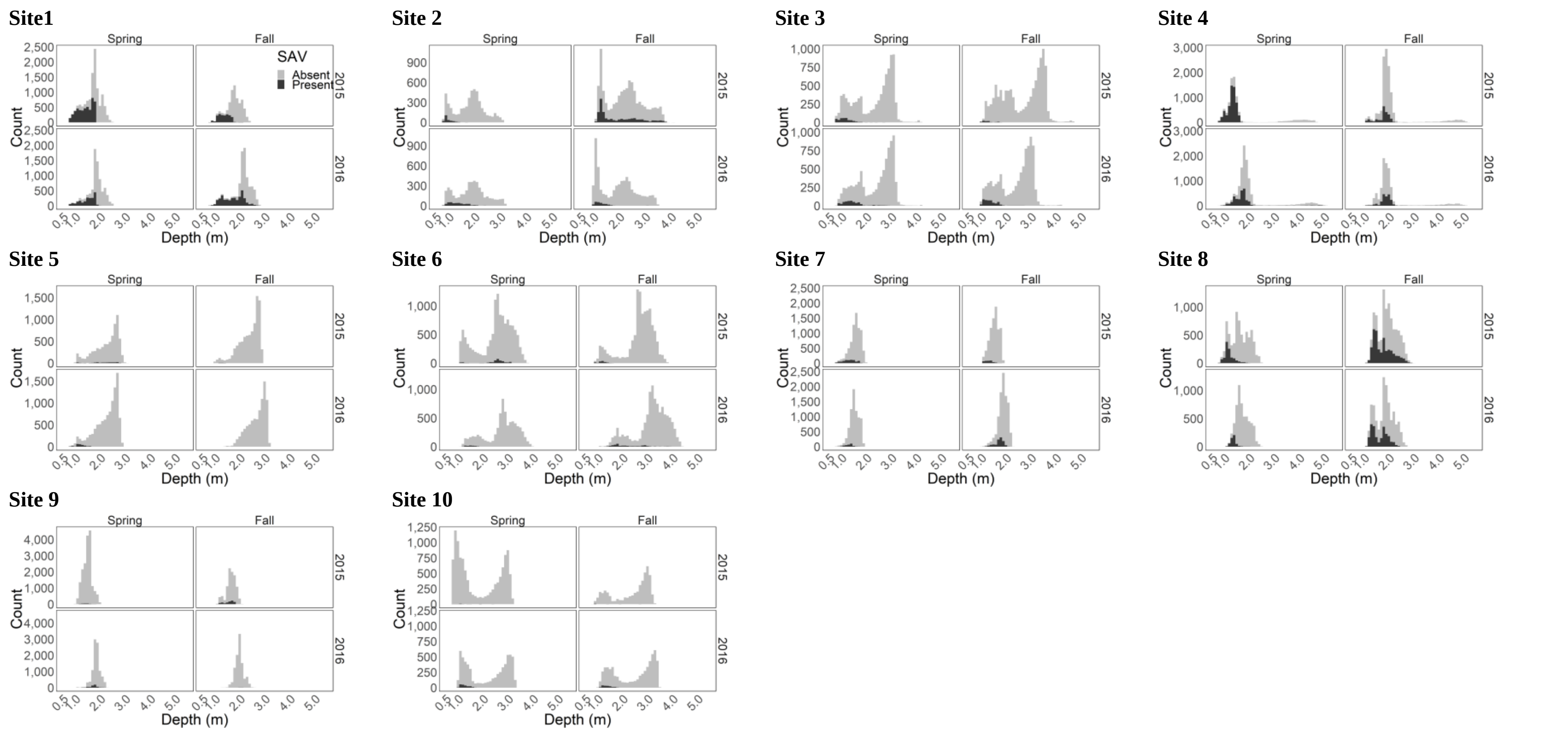


Figure 12. Frequency histogram of SAV presence-absence by depth at the ten sentinel sites in spring and fall of 2015 and 2016. SAV presence are shown in black and SAV absence in grey. See Appendix E for summary statistics and Appendix F for geographic representation of the data.

Tables

Table 3.Sentinel sites characteristics based on sonar and water quality data. SAV mean percent occurrence range (Mean % Occ. range), Peak Abundance (year), Peak Season (spring (S) and fall (F), SAV Median Depth Range, and SAV Maximum Depth Range. ND = no difference.

Site	Mean % Occ. range	Peak Abundance	Peak Season	Sampling depth range (m)	SAV median depth range (m)	SAV maximum depth range (m)	Salinity Range (psu)	Secchi range	Temp. range (°C)
1	24.80 - 43.73	2016	S	0.79 - 2.83	1.37-1.54	1.83 - 2.73	0 - 5.89	0.6 - 0.86	23.75 - 25.38
2	3.40 - 16.6	2015	ND	0.79 - 4.07	0.93 - 1.68	1.75 - 3.81	0 - 4.23	0.35 - 0.75	21. 4 - 28.88
3	0.88 - 6.07	2016	ND	0.79 - 4.73	1.13 - 1.37	1.75 - 2.91	0 - 0.48	0.85 - 1.47	19.57 - 26.41
4	10.43 - 68.33	2015	S	0.79 - 5.19	1.33 - 1.9	1.71 - 4.96	0 - 0.41	0.68 - 1.28	20.87 - 30.62
5	0 - 2.84	ND	S	0.79 - 3.23	1.18 - 2.22	1.5 – 2.79	0 - 0.07	0.77 - 1.5	19.2 - 28.03
6	1.06 - 2.79	2016	ND	0.86 - 4.28	1.18 - 2.59	1.59 – 3.90	0 - 4.75	0.57 - 0.81	21.37 - 27.18
7	3.91 - 10.29	2015	ND	0.79 - 2.27	1.3 - 1.76	1.67 – 2.07	0 - 1.95	0.61 - 1.3	24.53 - 27.83
8	8.29 - 37.36	2015	F	0.82 - 2.98	1.15 - 1.62	1.96 – 2.93	0 - 1.43	0.37 - 0.57	23.85 - 30.1
9	0.11 - 9.85	ND	ND	1.04 - 2.58	1.41 - 2.05	1.81 – 2.88	0 - 0.06	0.38 - 1.3	21.5 - 24.73
10	0.17 - 3.04	2016	ND	0.79 - 3.47	0.91 - 1.35	1.68 – 2.70	0 - 0.05	0.43 - 1.57	18.23 - 24.1

Table 4. Albemarle Sound Sentinel Sites SAV mean percent occurrence and standard deviation for each site based on sonar sampling.

	Site 1		Site 2		Site 3		Site 4		Site 5	
Year/Season	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**
2015 Spring	40	43.77±26.66	30	7.28±14.44	40	4.32±5.53	39	68.33±19.88	39	2.84±2.54
2015 Fall	39	26.7±25.37	39	16.62±6.67	40	0.88±2.15	39	18.43±11.2	39	0.17±0.52
2015 Total	79	35.34±27.25	69	12.56±11.64	80	2.6±4.51	78	43.38±29.79	78	1.5±2.26
2016 Spring	38	24.8±21	38	8.46±8.13	40	6.07±6.06	39	29.7±20.58	39	2.02±2.68
2016 Fall	37	34.39±18.23	40	3.4±4.24	40	5.54±6.9	39	22.04±9.28	39	0±0
2016 Total	75	29.53±20.14	78	5.87±6.88	80	5.81±6.46	78	25.87±16.32	78	1.01±2.14
Spring	78	34.53±25.75	68	7.94±11.27	80	5.19±5.83	78	49.01±27.96	78	2.43±2.62
Fall	76	30.45±22.37	79	9.93±8.65	80	3.21±5.59	78	20.23±10.38	78	0.08±0.37
Site Total	154	32.51±24.15	147	9.01±9.97	160	4.2±5.78	156	34.62±25.5	156	1.26±2.21

	Site 6		Site 7		Site 8		Site 9		Site 10	
Year/Season	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**
2015 Spring	39	2.46±3.11	40	9.92±4.97	39	15.82±10.09	40	0.92±1.57	39	0.21±0.63
2015 Fall	40	1.06±1.71	40	4.26±3.9	40	37.36±7.97	39	9.85±9.29	39	0.17±0.68
2015 Total	79	1.75±2.58	80	7.09±5.27	79	26.73±14.1	79	5.33±7.97	78	0.19±0.65
2016 Spring	40	1.11±1.74	40	3.91±4.06	40	8.29±5.22	40	5.32±2.98	39	3.04±4.01
2016 Fall	40	2.79±3.57	40	10.29±7.69	39	27.69±6.37	39	0.11±0.36	38	2.62±4.57
2016 Total	80	1.95±2.91	80	7.1±6.9	79	17.86±11.34	79	2.75±3.37	77	2.83±4.27
Spring	79	1.77±2.59	80	6.92±5.43	79	12±8.81	80	3.12±3.24	78	1.62±3.19
Fall	80	1.92±2.91	80	7.27±6.77	79	32.59±8.67	78	4.98±8.17	77	1.38±3.45
Site Total	159	1.85±2.75	160	7.09±6.12	158	22.3±13.51	158	4.04±6.23	155	1.5±3.31

Table 5. Linear Mixed Model parameters for the SAV percent occurrence (sonar data) regional analysis.

Model for the Means (fixed)

Model Parameters	Estimate	SD	DF	T	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	0.7135	0.14	9.09	5.14	< 0 .05	0.40	1.03
Year	0.0098	0.08	9.26	0.13	0.90	-0.16	0.18
Season	0.0258	0.08	8.88	0.32	0.76	-0.16	0.21
Centered Depth (m)	-0.3120	0.16	8.59	-1.92	0.09	-0.68	0.06

Model for the Covariance (random)

Model Parameters	Estimate	SD	Wald Z	Sig
Residual Variance	0.1274	0.005	27.570	< 0 .05
Random Intercept	0.1848	0.090	2.049	< 0 .05
Year	0.0538	0.027	1.981	< 0 .05
Season	0.0610	0.031	1.968	< 0 .05
Centered Depth (m)	0.2373	0.126	1.886	0.06

Table 6. GEE Model analysis for sonar SAV percent occurrence (sonar data) at the local level. 95 % CI = 95% Confidence Interval Lower. LB = Lower Bound. UP = Upper Bound. Intc. = Intercept. Depth in meters.

	Site 1				Site 2				Site 3				Site 4			
Parameter	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**
B	3.57	0.36	0.16	-1.36	18.1	-6.84	2.4	-3.51	1.92	0.25	-0.09	-0.64	2.22	-0.18	-0.21	-0.32
SE	0.2	0.05	0.03	0.12	7.16	1.54	1.25	2.99	0.29	0.05	0.06	0.11	0.11	0.04	0.05	0.07
95% CI LB	3.18	0.26	0.09	-1.6	4.06	-9.85	-0.05	-9.38	1.35	0.16	-0.21	-0.86	2	-0.25	-0.31	-0.45
95% CI UB	3.96	0.46	0.22	-1.12	32.14	-3.82	4.86	2.36	2.49	0.34	0.02	-0.42	2.44	-0.1	-0.11	-0.19
P	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0.18	0.10	<0.05	<0.05	0.12	<0.05	<0.05	<0.05	<0.05	<0.05

	Site 5				Site 6				Site 7				Site 8			
Parameter	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**
B	0.65	-0.1	-0.35	-0.09	1.11	0.15	0.12	-0.34	-0.46	-0.17	-0.11	0.84	1.98	-0.17	0.62	-0.54
SE	0.31	0.05	0.05	0.14	0.2	0.06	0.07	0.08	0.32	0.07	0.06	0.21	0.22	0.04	0.04	0.14
95% CI LB	0.05	-0.2	-0.45	-0.36	0.71	0.04	-0.01	-0.5	-1.1	-0.3	-0.22	0.42	1.55	-0.24	0.54	-0.81
95% CI UB	1.26	0.01	-0.26	0.18	1.5	0.26	0.24	-0.19	0.18	-0.04	0	1.25	2.41	-0.1	0.7	-0.27
P	<0.05	0.07	<0.05	0.52	<0.05	<0.05	0.07	<0.05	0.16	<0.05	0.06	<0.05	<0.05	<0.05	<0.05	<0.05

	Site 9				Site 10			
Parameter	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**
B	1.46	0.11	0.06	-0.63	-0.04	0.3	-0.06	0.05
SE	0.74	0.19	0.09	0.5	0.13	0.07	0.03	0.07
95% CI LB	0.01	-0.26	-0.12	-1.6	-0.28	0.16	-0.12	-0.08
95% CI UB	2.92	0.47	0.23	0.34	0.21	0.43	0	0.18
P	0.05	0.57	0.54	0.2	0.78	<0.05	0.06	0.42

Table 7. Total number of video drops and the number of verified SAV present video drops at each sentinel site sampling event (2015 and 2016, spring and fall).

	Site 1		Site 2		Site 3		Site 4		Site 5	
Year/Season	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**
2015 Spring	100	19	100	8	100	0	100	33	101	1
2015 Fall	91	16	65	0	80	1	89	9	81	0
2015 Spring	100	8	100	0	100	4	108	19	100	0
2016 Fall	100	25	100	0	100	0	100	0	100	0
Total	391	68	365	8	380	5	397	61	382	1

	Site 6		Site 7		Site 8		Site 9		Site 10	
Year/Season	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**	**Total video drops**	**SAV verified**
2015 Spring	99	0	58	0	100	20	100	0	100	0
2015 Fall	79	0	89	0	80	18	79	0	50	0
2015 Spring	100	0	100	0	100	1	100	0	100	0
2016 Fall	100	0	100	0	100	10	100	0	100	0
Total	378	0	347	0	380	49	379	0	350	0

Table 8. Sentinel sites characteristics based on quadrat and core data. Sites with NA species indicate that no SAV were found during core sampling. Spring (S,) and fall (F). No statistical difference (ND)

Site	**Percent Cover Range**	**Peak Year**	**Peak Season**	**Species (season)**
1	27.64 - 95.52	2015	S	*R. maritima* (S, F) and *M. spicatum* (S, F)
2	0 - 12.95	2015	S	NA
3	0 - 45.01	2016	S	*R. maritima* (S)
4	2.9 - 72.25	2015	S	*V. americana* (S, F) and *N. guadalupensis* (S)
5	0	all zero	all zero	NA
6	0 - 0.08	ND	ND	NA
7	17.55 - 38.76	ND	ND	NA
8	0.69 - 62.08	ND	S	*R. maritima* (S, F) and *P. perfolialtus* (S)
9	0	all zero	all zero	NA
10	0 - 0.19	2015	S	NA

Table 9. Albemarle Sound Sentinel Sites SAV mean percent cover and standard deviation for each quadrat sampling. Mean PC = Mean Percent Cover.

	Site 1		Site 2		Site 3		Site 4		Site 5	
Year/Season	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**
2015 Spring	27	95.52±15.99	32	12.95±25.63	23	2.06±2.91	12	72.25±43.68	34	0
2015 Fall	20	78.48±31.78	5	0	NA	NA	28	12.27±30.88	40	0
2015 Total	47	88.27±25.18	37	11.2±24.2	23	2.06±2.91	40	30.27±44.42	74	0
2016 Spring	26	63.56±33.58	35	4.22±16.23	16	45.1±35.05	20	2.9±11.13	34	0
2016 Fall	13	37.64±32.02	13	0	23	0±0	19	8.53±18.38	14	0
2016 Total	39	54.92±34.91	48	3.08±13.93	39	18.5±31.46	39	5.64±15.17	48	0
Spring	53	79.84±30.5	67	8.39±21.53	39	19.72±30.82	32	28.91±43.78	68	0
Fall	33	62.39±37.35	18	0	23	0	47	10.76±26.37	54	0
Site Total	86	73.15±34.16	85	6.61±19.39	62	12.4±26.15	79	18.11±35.38	122	0

	Site 6		Site 7		Site 8		Site 9		Site 10	
Year/Season	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**	**N**	**Mean ± SD**
2015 Spring	40	0.08±0.43	33	17.55±28.44	27	18.58±21.8	40	0	34	0.19±0.35
2015 Fall	40	0	31	38.76±40.55	31	20.97±35.29	29	0	40	0
2015 Total	80	0.04±0.3	64	27.83±36.17	58	19.86±29.56	69	0	74	0.09±0.25
2016 Spring	40	0	39	23.35±29.4	31	62.08±47.55	37	0	34	0
2016 Fall	40	0	37	31.17±33.98	24	0.69±2.4	31	0	40	0
2016 Total	80	0	76	27.16±31.74	55	35.29±46.93	68	0	74	0
Spring	80	0.04±0.3	72	20.69±28.91	58	41.83±43.42	77	0	68	0.09±0.26
Fall	80	0	68	34.63±37.03	55	12.12±28.24	60	0	80	0
Site Total	160	0.02±0.21	140	27.46±33.72	113	27.37±39.58	137	0	148	0.04±0.18

Table 10. Linear Mixed Model parameters for the SAV percent cover (quadat data) regional analysis.

Model for the Means (fixed)

Model Parameters	Estimate	SD	DF	T	Sig.	95% CI Lower Bound	95% CI Upper Bound
Intercept	0.4049	0.18	8.71	2.26	< 0 .05	0.00	0.81
Year	-0.0318	0.12	7.91	-0.27	0.80	-0.31	0.24
Season	-0.2695	0.14	8.55	-1.92	0.09	-0.59	0.05
Centered Depth (m)	0.2503	0.21	9.10	1.20	0.26	-0.22	0.72

Model for the Covariance (random)

Model Parameters	Estimate	SD	Wald Z	Sig
Residual Variance	0.2024	0.009	23.319	< 0 .05
Random Intercept	0.2983	0.154	1.943	0.052
Year	0.1319	0.071	1.867	0.062
Season	0.1872	0.095	1.970	< 0 .05
Centered Depth (m)	0.4052	0.205	1.977	< 0 .05

*Table 11. GEE Model analysis for sonar SAV percent cover (quadrat data) at the local level. 95 % CI = 95% Confidence Interval Lower. LB = Lower Bound. UP = Upper Bound. Intc. = Intercept. Depth in meters. * Values were zero, so there was no statistical difference. Sites 5 and 9 had no SAV at any sampling event, so they there were excluded from GEE analysis.*

	Site 1				Site 2				Site 3				Site 4			
Parameter	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**
B	1.77	-0.4	-0.31	0.34	0.8	-0.31	-0.2	-0.42	0.59	1.02	-1.37	-0.3	0.24	-0.53	-0.43	1.2
SE	0.12	0.13	0.14	0.16	0.25	0.13	0.08	0.21	0.23	0.18	0.17	0.27	0.2	0.14	0.16	0.25
95% CI LB	1.53	-0.65	-0.57	0.02	0.32	-0.56	-0.34	-0.83	0.13	0.67	-1.7	-0.83	-0.15	-0.8	-0.74	0.72
95% CI UB	2	-0.16	-0.04	0.66	1.28	-0.06	-0.05	0	1.04	1.38	-1.03	0.22	0.62	-0.25	-0.13	1.69
P	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	0.05	<0.05	<0.05	<0.05	0.25	0.22	<0.05	<0.05	<0.05

	Site 6				Site 7				Site 8				Site 10			
Parameter	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**	**Intc.**	**Year**	**Season**	**Depth**
B	0.02	-0.01	-0.01	-0.01	0.86	0.1	0.28	-0.26	-0.03	-0.04	-0.78	1.64	0.01	-0.03	-0.03	0.04
SE	0.01	0.01	0.01	0.01	0.24	0.16	0.15	0.24	0.16	0.11	0.11	0.24	0.01	0.01	0.01	0.02
95% CI LB	-0.01	-0.02	-0.02	-0.02	0.4	-0.22	-0.02	-0.73	-0.34	-0.24	-1	1.16	0	-0.05	-0.05	0.01
95% CI UB	0.05	0	0	0.01	1.32	0.41	0.57	0.2	0.28	0.17	-0.56	2.12	0.03	-0.01	-0.01	0.07
P	0.18	0.14	0.14	0.46	<0.05	0.55	0.06	0.27	0.86	0.74	<0.05	<0.05	0.06	<0.05	<0.05	<0.05

CHAPTER 3: Perceptions of the distribution of Submerged Aquatic Vegetation (SAV) in a low-salinity estuary in North Carolina: A comparison of casual and expert observers.

Abstract

Coastal resources managers are charged with the task of monitoring and managing resources in order to make informed decisions about conservation and restoration. However, in many cases, though a resource may be already experiencing the negative effects from external pressures, managers do not have enough information about people's perspectives about the resource. Further, they may not have enough historical information to develop successful management strategies that will address stakeholders' issues, will minimize conflict, and set adequate conservation and restoration goals. Including historical data (e.g. archives, interviews, narratives, and zooarchaeological remains) in resources monitoring can help identify baselined distributions. Disciplines likes anthropology and social science already have the protocols to collect and analyze these types of data. The purpose of this phase of the study was to evaluate the effectiveness of Local Ecological Knowledge (LEK) to evaluate people's perceptions about SAV and collect historical abundance and distribution information about an important resource. SAV are considered an indicator species in coastal systems, as they provide valuable ecosystem services and are highly responsive to environmental changes. Yet, their abundance has declined across the world due to increasing human populations along the coast. LEK is defined as the knowledge, practice, and belief held by a group of people about their local ecosystem. To study the effectiveness of LEK at identified people's value and knowledge, I tested two hypotheses. The first hypothesis was that stakeholders (coastal residents, commercials fishers, and fishery managers) in a low-salinity region in North Carolina, the western Albemarle Sound (AS), will agree on the basic values of SAV. The second hypothesis was that different groups of

stakeholders will have different beliefs about specific issues related to SAV. The LEK data in this study were collected in two phases: oral interviews with key informants and a written mail-in survey. In addition to using LEK to test these two hypotheses, the written survey was also utilized to assess the historical SAV distribution knowledge of the respondents for the western AS. Results indicated that commercial fishers and fishery managers have similar knowledge about SAV; however, coastal residents and the other two groups differed in their perceptions. Some important areas of disagreement between the three social groups are SAV's ecosystem value and the effect of development on SAV. While the groups agree that there has been an increase in SAV distribution in the last decade in the AS, a surprising result in light of the reported SAV decline in AS and other areas. Areas of agreement and disagreement can be used by coastal resources managers to initiate communication with stakeholders and develop management policies that are more likely to be accepted when stakeholders participate in the policy-making process (Keeney et al. 1990). Further, stakeholders can have a sense of resource ownership (Tomasini and Theilade 2019). In addition, the results from the historical distribution map question in the survey revealed that the respondents' knowledge about SAV distribution agreed with biological data collected in the region.

Introduction

Ecosystems provide different functions, and these functions depend on factors like temperature, salinity, water chemistry, and plant species composition, and these functions take place independently of humans (Costanza et al. 1997). However, humans and the natural environment may benefit from these functions, providing ecosystem services. Ecosystem services are value-centered as opposed to ecosystems functions - for example, a farmer may value a wetland downstream from their fields, as they help regulate flooding. This study focused on SAV, which is recognized worldwide for its many important ecosystem services and economic value to humans (Orth et al. 2006)

Importance of SAV

SAV are marine and freshwater angiosperm found in estuarine systems. SAV provide foraging and nursery habitat to fish, shellfish, sea turtles, birds, and invertebrates (Heck and Thoman 1984; Thayer et al. 1984). SAV can also reduce erosion (Madsen et al. 2001), connect habitats (e,g., oyster reefs, coral reefs, and mangroves; Micheli and Peterson 1999), and aid in carbon sequestration (Fourqurean et al. 2012). SAV are frequently used as a water quality indicator, as they are responsive to changes in salinity, sedimentation, and nutrient loading (Dennison et al. 1993).

As essential fish habitat, SAV are protected by the Magnuson–Stevens Fishery Conservation and Management Act, which make SAV a habitat of high management priority to state and federal management agencies. The management of SAV requires understanding their distribution, abundance, and fluctuations, along with the stressors responsible for the fluctuations. SAV frequently occur near the shore, so human activity has been linked to their abundance and distribution (Patrick et al. 2014), with commercial fishers, coastal residents, and scientists among the most concerned or affected stakeholders. Therefore, managers also need to understand how SAV management decisions may affect or be perceived by SAV stakeholders.

Problem Statement

As human coastal populations have increased across the world, anthropogenic changes in the aquatic and marine environments have altered natural resources and created increased demand on coasts for leisure and recreation (Van Holt 2009). The increasing population and the variety of stakeholders in coastal areas make resource management ever more complex. Stakeholders come from different socio-economic groups, so they tend to assign different values to and possess varying knowledge about natural resources. All these complexities require coastal managers and decision-makers to have a broad understanding about their constituencies (Bennett et al. 2017). When user groups assign different values to natural resources, managing them becomes complex and conflict prone (Johnson and Pollnac 1989); hence, to minimize conflict, decision-makers need to be increasingly aware of the value and knowledge stakeholders have about costal resources (Rockloff and Lockie 2004).

Many environmental decisions require making trade-offs, and frequently these trade-offs involve choosing between financial and environmental costs and benefits. Decision-makers make these decision behind closed doors (Gregory and Keeney 1994). However, the growing involvement of advocacy groups and a demand for transparency has forced decision-makers to involve different constituencies in the decision-making process through public hearings required by some legislation (Orbach 1989; NCDEQ 2016). Nonetheless, it has been difficult for decision-makers to involve stakeholders because these trade-offs can be difficult to explain, may appear unfair, and are seldom embraced by all stakeholders (Gregory and Keeney 1994).

Understanding the stakeholders' values can allow policy-makers to create improved policy alternatives that may be more readily accepted by all groups (Gregory and Keeney 1994). According to Gregory and Keeney (1994), decision-makers need to know the values that each stakeholder group assigns to a resource, so they can identify all the stakeholders' objectives, and devise policies that address many of the stakeholders' goals and strike a balance between "winners" and "losers".

Johnson and Pollnac (1989) indicated that competing values or knowledge between stakeholders leads to conflict between users. Valdés-Pizzini (1990) documented the conflict that developed after resource managers introduced the idea of establishing a marine sanctuary in La Parguera, Puerto Rico. The objective of the proposed sanctuary was to protect the environment, as well as to provide recreational facilities for visitors and keep the area open for fishers' activities. During the development process, the resource managers failed to clearly inform the fishermen on the objective and purpose of the sanctuary, so the fishers feared they were going to be alienated from their fishing resources and their fisheries collapse; hence, the fishers' perceived their values opposed those of the resource managers. Though the resources managers included the fishers in an opinion poll, the resources managers failed to consult the fishers throughout the sanctuary's management plan development. These compounding factors led the fishermen to lobby against the creation of the sanctuary, and successfully stalled its development. The conflict originated, in part, from misconceptions of the fishers, as resources managers failed to consider the social and cultural aspects in resources management. This case study highlights the importance of developing management steps that consider the knowledge and value of all stakeholders. After the confrontation between fishermen at La Parguera and resource managers, the managers leaned valuable lessons; since then resource managers have requested the fishers' involvement in developing a management plan (Valdés-Pizzini 1990).

A more extreme example of social conflict over coastal resources is found in southeast Asia, where a large population depends on fisheries as their main source of protein. Violence surrounding fishing rights is common between Vietnam, Cambodia, Philippines, and China (Pomeroy et al. 2007). From these examples, it is evident that natural resource managers have a complex job, and they are tasked with developing strategies and policy that manage resources and minimize conflict. When conflict arises, managers can often ameliorate them by finding consensus between the users and implementing policies that are anchored in the agreements between user groups (Rockloff and Lockie 2004). Biological data is crucial during decision-making. However, management decisions need to be made beyond biological data alone: managers need to identify areas of agreement and disagreement between users, and social scientists can provide this information. There is growing evidence that LEK can be used to identify users' value and knowledge of a resource (Keeney et al. 1990; Gregory and Keeney 1994).

LEK as a Tool

In social science various approaches have been used to identify user's values and knowledge; among them, LEK has been increasingly used by social scientists and coastal resources mangers. LEK is defined as the knowledge, practice, and belief held by a group of people about their local ecosystem (Olsson and Folke 2001). LEK is a mixture of scientific and practical knowledge that is often embedded in socio-economic relations (Griffith 1999). García-Quijano (2009) indicated LEK can provide information about natural resources in coastal systems, particularly those that are in constant change. In this study, LEK was especially useful, as SAV's abundance and distribution are in constant flux (Li et al. 2007; Patrick and Weller 2015; Orth et al. 2017). Though, LEK has been described as an excellent tool for ecosystem management and conservation, it has been difficult to translate LEK into applicable ways for Western science (García-Quijano 2007). However, managers cannot afford to ignore the useful information it provides. Further, LEK has been used to create management strategies and contribute to scientific knowledge (Poizat and Baran 1997; Calheiros et al. 2000; Hunn et al. 2003; García-Quijano 2009; Tomasini and Theilade 2019). Note that LEK is not to be confused with Traditional Ecological Knowledge (TEK); LEK differs from TEK where the ecological value of a resource has historical depth and cultural dimensions. Berkes et al. (2000) defined TEK as "a cumulative body of knowledge and beliefs, evolving by adaptive processes and handed down through generations by cultural transmission, about the relationship of humans with one another and their environment."

Various tools have been used to collect LEK, including surveys, value elicitations, focus groups, and public involvement (Keeney et al. 1990). This study focused on utilizing LEK through a social survey to identify the value and beliefs that some of the stakeholders have in relation to SAV in AS , NC. Though SEK surveys have been limited and incomplete in the sound, extensive SAV beds have been already identified (Ferguson and Wood 1994; David and Brinson 1990; Quible and Associates 2011; Kenworthy et al. 2012; Chapters 1 and 2 in this dissertation) which make the Sound a potentially fish and wildlife habitat in the area. Literature indicates that LEK is useful in understanding stakeholder's values and objectives, which can facilitate and legitimate natural resources management (Berkes et al. 2000; Olsson and Folke 2001). Gregory and Keeney (1994) described how the opening of a coal mine in a pristine wilderness forest in Malaysia caused polarization between the various stakeholders (mine company, Malaysian government, environmental groups, and representatives of social interests). These authors identified each group's values and invited them to discuss and to generate alternative policies that addressed all the stakeholders' objectives. Hence, these discussions opened the communication and negotiations between the stakeholders and policymakers. Similarly, managers in a Swedish rural community utilized LEK to create the framework for crayfish fisheries management (Olsson and Folke 2001). Their study indicated that local users have a deep knowledge about the ecology of the system, and their knowledge was valuable in developing successful management strategies. These studies indicate that LEK can be useful in gathering important ecological knowledge to create management solutions and the co-management of natural resources between users and managers is more successful than when users are not directly involved. LEK not only allows managers and social scientists to identify users' values, but it can be also useful to biologists and ecologists, providing valuable ecological insight.

LEK and Historical Information

Most of our knowledge on SAV comes from biological scientific data, and many natural scientist are skeptical of incorporating LEK into their scientific methods, arguing it is biased and anecdotal (Calheiros et al. 2000). While LEK, undeniably is biased, it is based on repeated observations and often it has more time depth than scientific knowledge. Nonetheless, the integration of LEK with scientific knowledge can help create a better decision-making process for coastal resources management (Jacobs et al. 2005). Furthermore, LEK can help biologists and ecologists gain knowledge that would not otherwise be available through biological science (Olsson and Folke 2001; Schuegraf 2004). For example, Ambrose, et al. (2014) found that Inupiaq hunters and fishers of Kotzebue Sound, Alaska were able to describe near-shore marine food webs in more detail than those available from biological studies. However, in most cases, they found close correspondence between Inupiaq and scientific knowledge.

In Alaska, LEK was useful in identifying the historical abundance of herring (Huntington 2000) and the relationships between changing ice cover and local food webs (Ambrose et al. 2014). Similarly, Schuegraf (2004) studied the historical decline of seagrass beds in Pearl Lagoon, Nicaragua with a combination of LEK and direct visual census. LEK allowed Schuegraf (2004) to estimate seagrass bed abundance for the last 30 years, information that would not be available otherwise by interviewing local people who lived or worked around the lagoon. To verify LEK information, Schuegraf (2004) took sediment cores at 64 different locations in the lagoon, and she found a strong correlation (92%) between seagrass presence (LEK responses) and the sediment cores (biological data). Based on the LEK information, the author concluded that seagrass coverage had declined 75% over the last three decades. Furthermore, the people she interviewed gave her important insight on the causes for the decline (e.g., hurricane disturbance, dredging, and sedimentation). The current study used LEK as a tool to understand the historical distribution of SAV in AS, NC.

To manage a natural resource, it is vital for managers to know the resource's status and how human activity affects it. Otherwise, it is not possible to determine what kind of management is needed. Managers are increasingly relying on scientific data to make management decisions (Lemos and Morehouse 2005), yet such data may be limited. This is particularly true for some large and difficult to access coastal areas with large SAV resources where there is a lack of historical information and synoptic biological surveys are not available. This paper focuses on the western AS, NC because of the potential importance of SAV resource in the area (Ferguson and Wood 1994; Deaton et al. 2010). It has been difficult to manage SAV in the area because SAV in AS is considered “invisible.” In other words, it occurs in low-salinity areas, where water clarity is poor due to river inputs of dissolved organic matter and sediments (Fonseca et al. 1998; Kenworthy et al. 2012). The turbidity of the water has limited the ability of federal and state agencies to monitor SAV abundance and distribution with commonly used synoptic methods, such as aerial remote sensing (satellite or airborne). Therefore, management agencies lack a robust baseline for historical and present SAV abundance and distribution. This situation is common in other high-turbidity areas of the world like in the Curonian Lagoon in the Baltic sea (Bučas et al. 2016), in the upper reaches of the Chesapeake Bay, and other portions of NC estuaries (Dobson et al. 1995; Kenworthy et al. 2012). Monitoring SAV in regions with clearer waters has been more successful, like in parts of the Chesapeake Bay (Orth et al. 2010), where the SAV monitoring program has historical information going back the 1970’s. In AS, there is limited historical SAV distribution data (Davis and Brinson 1990; Ferguson and Wood 1994; Deaton et al. 2010; Kenworthy et al. 2012), so I implemented LEK to not only help address the need to identify users’ values and knowledge, but to address the need for historical information about the distribution of the SAV.

This study is unique in that it utilized LEK as a tool to understand SAV stakeholders’ knowledge in an area of NC that has been studied before with SEK, but SAV information remains incomplete. Additionally, this study is the first to generate a historical SAV maximum-extent distribution map for the area, solely based on social knowledge. This map could be considered a steppingstone for finer-resolution, maximum-extent SAV distribution maps that describe past SAV distribution through LEK for the entire AS, including interviewing more people familiar with SAV.

Goals and Hypotheses

The purpose of this phase of the study was to identify users' values and beliefs about SAV through LEK, and to complement a larger study of the condition of SAV in the AS (Chapters 1 and 2). The objectives of the study were twofold. The first objective was to identify the value that users assign to SAV with a written survey. This information could be particularly useful to help scientists, managers, and stakeholders understand the historical distribution of SAV in western AS. In addition, the information can be used to gain insight into the potential causes for change in the SAV distribution and abundance.

Initially, two hypotheses related to SAV cultural belief in the western Albemarle Sound were tested:

Hypothesis 1 (H_1): Participants will agree on basic concepts about the value and ecology of SAV (e.g., the belief that SAV are important for the ecosystem and fisheries dependent on it).

Hypothesis 2 (H_2): Commercial fishers, coastal residents, and fishery managers will have different beliefs about more specific issues.

Initial results from the second hypothesis informed the development of more specific hypotheses:

Hypothesis 2a (H_{2a}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about SAV value.

Hypothesis 2b (H_{2b}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about SAV abundance trend.

Hypothesis 2c (H_{2c}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the Sound's water quality.

Hypothesis 2d (H_{2d}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the effect of seasons on SAV abundance.

Hypothesis 2e (H_{2e}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the effect of storms on SAV abundance.

Hypothesis 2f (H_{2f}): Commercial fishers, coastal residents, and fishery managers will have different beliefs about the effect of development on SAV abundance.

Fishers, who depend on coastal resources for their livelihoods, and scientists, who study estuarine environments and SAV, are likely to understand the ecological value of SAV, including the ecological services SAV provides other, related natural resources. However, some coastal residents find SAV a nuisance, as it impedes their ability to swim and operate watercraft (Nichols and Shaw 1986; Sprecher et al. 1998). On the other hand, fishers and scientists in NC value SAV's ecosystem services, as it provides nursery habitat to many fish and invertebrate species (Griffith 1999; Dealteris et al. 2004; Flaherty-Walia et al. 2015; Miller 2015) (Dealteris et al. 2004; Flaherty-Walia et al. 2015; Miller 2015). I expected fishers and scientists to have a positive belief about the value of SAV, but also expected that coastal residents would likely disagree with fishers and scientists. H_2 arose from evidence that groups tend to disagree about specific concepts about natural resources (Johnson and Griffith 2010). Fishers, fishery managers, and coastal residents spend different amounts of time in the water, which are likely to generate different knowledge levels and beliefs; each of these groups is also likely to have different degrees of economic and environmental interest in SAV, which also has been shown to generate different levels of knowledge (Griffith et al. 2013). These variations in knowledge levels are likely to produce differences in how stakeholders perceive factors that can affect SAV.

Methods

Study Area

This study focused on western AS (Figure 13), which is part of the Albemarle-Pamlico Estuarine System (APES). APES is the largest lagoon system and the second largest estuary in the US. AS covers an area of about 480 m^2, with a west to east distance of about 89-km. AS is a shallow sound (mean depth =3.5 m) where wind has a major influence on water levels and tides; astronomical tides are almost negligible. AS is a low-salinity estuary, as characterized by The Venice system (Oertli 1964); salinity is lowest in the western part of sound (<6 psu), and salinity increase eastward (6-18 psu). Turbidity increases near the rivers (Ferguson et al. 1990), as brown-water drains from the peatland and swamp forests (Giese et al. 1985).

SAV in the Western AS

Low-salinity SAV species (Table 1) present in AS are more ephemeral and exhibit a greater temporal and spatial variation than their higher salinity counterparts (Davis and Brinson 1990; Quible and Associates 2011; Kenworthy et al. 2012). Synoptic SAV surveys of AS are difficult because aerial imaging cannot detect SAV in a low-visibility system, and it often underestimates SAV abundance and bed extent (Ferguson and Wood 1994; Davis and Brinson 1990). Nonetheless, APNEP has monitored SAV in the western area of AS in the past and studies indicated there has been SAV in the area for at least the past 30 years (Quible and Associates 2011; Kenworthy et al. 2012; Chapters 1 and 2).

Participants

I included fishers, fishery managers/experts, and coastal residents as respondents to the surveys. These groups were selected because they are major stakeholders in the management of SAV (Borsuk et al. 2001). Commercial fishers are defined as individuals who work full-time fishing and have a commercial license. Fishery managers/experts are defined as individuals whose primary responsibility is NC fisheries management or they are scientists knowledgeable about the SAV in the area. Coastal residents are defined as those permanent residents on the coast of AS, residing no more than 100 meters from the shore.

The commercial fishers and expert groups were clustered into a single group, hereafter referred to as the “expert” group. The rational for clustering the two groups was twofold. First, commercial fishers and fishery managers are likely to be more knowledgeable about SAV than coastal residents, for two reasons: fishery managers in my sample were familiar with SAV from scientific studies and ongoing environmental monitoring of AS; and commercial fishermen depend on SAV for their livelihoods. While I acknowledge that their beliefs about SAV would not necessarily be in complete agreement, a factor that is often reflected in disputes over the management of fishery resources, literature comparing LEK with scientific knowledge suggests that they both constitute “expert” knowledge systems (Ambrose et al. 2014). In this survey, this was further supported by a comparison between means (Tukey Test), which revealed that the two groups had similar answers to my survey ($p=0.213$). Second, there was a very small sample for the fishery managers. In the AS, only a limited number of individuals work as fisheries managers or study SAV in the area. For example: three scientists at different divisions of North Carolina Department of Environmental Quality (NCDEQ), the technical members of APNEP, and two scientists at East Carolina University and NC State University. Finally, many studies that rely on LEK have small samples, assuming that cultural knowledge is widely shared and assessing requires only a few individuals (Hunn et al. 2003; García-quijano 2007; García-Quijano 2009; Tomasini and Theilade 2019).

The commercial fishers' sample was obtained by intercepting fishers at landing sites and from a boat seller's mailing list. The fishery manager group respondents were obtained by interviewing fisheries managers from the NC Division of Marine Fisheries and university affiliates. The coastal residents' sample was obtained through the Chowan County Land Records Office.

Phase 1: Semi-structed Interviews and Key Informants

In the first phase of this study, oral interviews were conducted with twelve key informants, three from each social group: commercial fishers, scientists, and coastal residents. A key informant was defined as individuals exposed to information about SAV and AS based on their role in the community. These individuals were also knowledgeable about SAV and AS, and they were able and willing to communicate with interviewers, and tend to be unbiased (except for biases known to the interviewer) (Marshall 1996). The key informants were identified by contacting commercial fishers and fisheries managers known to Dr. Griffith at East Carolina University, who has worked for several years with commercial fishers in the area. I also asked some of the key informants if they could name individuals who were knowledgeable about SAV in the area, and I interviewed them as well.

The information collected in the interviews was used to develop a survey instrument that was implemented during the second phase of the data collection. Semi-structured interviews were conducted in the fall and winter of 2017. The open-ended questions covered topics such as their opinion on SAV ecosystem services, the distribution of SAV in the western AS, and the potential causes for change in SAV distribution and abundance. The oral interviews statements were reviewed by two researchers (Dr. Griffith and Hilde Speight) to identify the 33 most common statements, which were selected to be part of the written survey.

Phase 2: Written Survey

The second phase consisted of a written survey with the 33 statements, in which the respondents were asked to reply by indicating: strongly agree, somewhat agree, somewhat disagree, strongly disagree or don't know statements (Likert Scale responses). I balanced the items (50% of the expected answers should be agree and 50% disagree) to limit potential agreement and disagreement biases (Johnson and Griffith 2010).

In addition to the 33 items, the respondents were asked if they have lived in the western AS for less than 10 years, more than 10 years, or more than 20 years. Finally, a map of western AS was included in the survey instrument. In this section, the respondents were asked to select the areas where they have seen SAV in the past 10 years (Table 12 and Figure 13). The purpose of this map was to generate a composite map that would indicate the maximum extent of SAV in the western AS based on LEK. Note than all the respondents are not likely to have visited each possible grid, so there is an inherent bias to the data. Additionally, very few respondents are likely to be familiar with the entire area shown in the map.

At least 15 respondents from the expert group and coastal residents were selected to respond to the survey. While this is too small a sample to statistically represent all commercial fishers and coastal residents on the AS, and certainly cannot be correlated with factors such as ethnicity, age, and socioeconomic status, it is not an uncommon sample size for studies of belief systems that are, like language, shared across populations (Romney et al. 1986; Bernard 2017).

In the same way that you only need a few speakers to understand an entire language, many studies only require a handful of informants to understand local belief systems. Because of the small number of fishery managers who answered the survey, and for other reasons noted above, I pooled them with the fisher/expert sample. Scientists were the only group with less than 15 respondents because of the limited number of scientists in the areas. The small sample does not represent an issue, as social scientists indicate that LEK is widely shared by individuals that work with the same natural resources, which does not necessitate a very large or random sample. The surveys were mailed to most of the respondents, except for a few of the commercial fishers. Some of the fishers were intercepted at a landing center near the western AS (Full Circle Crab Company in Columbia, NC). A total of 97 surveys were mailed with a return rate of 43%, with similar studies reporting return rates lower than 40% (Johnson and Griffith 2010)

Data Analysis

All the data were analyzed using SPSS v25 (IBM Corp. 2017). Analysis of Variance (ANOVA) was used to determine the difference in beliefs between the groups. Beliefs for a given group was determined by the group's mean response to a set of questions. Therefore, in ANOVA, the response variable used in the analysis was the mean responses across a set of questions made by each respondent. Consequently, the scale data, inherent to the Likert scale, can be considered continuous (Johnson and Creech 1983; Sullivan and Artino 2013). First, I compared the two groups' answers (coastal resident and expert) to the entire survey as a whole. Next, I compared the two groups considering questions that related to general SAV ecology, and SAV value. Then, I compared the two groups questions, as they related to specific concepts about SAV ecology, and its value. Finally, I compared the two groups' answers by grouping their answers into specific topics or concepts. These topics were: SAV value, trend, water quality, seasonality, storms, and development. On four occasions, the questions were grouped in more than one topic category, as questions related to more than one topic (i.e., seasonality and water quality in questions 10 and 11, and development and water quality in question 21 and 22). Some of these topics are reflected in the following statements made by some respondents during the open-ended interviews:

> It [SAV distribution] changes every year
>
> In 2007 we had a tremendous bloom of SAV… the crabs that year were unbelievable… I'm sure it's [great abundance and large size of blue crabs] directly tied to SAV…the next year wasn't as extensive.
>
> During dry years you see a difference in the species composition than you do during extreme wet years.
>
> A year before [hurricane] Isabel … we saw SAV like we never seen before then things died out.
>
> One of the reasons it's still profitable [to fish for crab] there [Alligator River] is no development.

Results

A total of 41 people were surveyed, 20 (49% of the total sample) of the respondents were experts (15 fishers and 5 fishery managers) and 21 (51% of the total sample) were coastal residents. The results revealed that the expert group and the coastal residents represent different subcultures. Each of the two groups differ in their general and specific beliefs and knowledge about SAV. When I compared the answers to the entire survey between the groups, I identified a significant difference between the groups (df= 1, F= 11.59, p= 0.001). When I only compared general statements about SAV's ecology and its value between the two groups, my original hypothesis (H_1) was supported because both groups agreed on the generalities about the value of SAV (df=1, F= 0.091, p= 0.764; Table 13). When I compared the two groups' answers to more specific issues (e.g., SAV abundance trends and factors affecting SAV distribution), I did not find evidence that supported my second hypothesis (H_2) because the results indicated that the two groups did not significantly differ about specific issues (df= 1 F= 0.288, p= 0.595; Table 13).

As the comparison between groups in specific issues did not yield any significant difference, I further classified the specific questions of the survey into narrower ecological topics. I grouped the questions into six categories as they relate to SAV: SAV Value, Trend, Water Quality, Seasonality, Development, and Storms. Then, I compared each group again by each of these categories.

SAV value, water quality, and development were the only topics that were significantly different between the two groups, while trend, seasonality, and storms were not significantly different (Table 13). Therefore, I accepted hypotheses H_{2a}, H_{2c}, and H_{2f}, but accepted hypotheses H_{2b}, H_{2d}, and H_{2e},.When looking at the means for the questions used to evaluate SAV value between groups (Questions 23, 29, and 30;Table 12), experts assigned a greater ecological value to SAV as a fish and invertebrate habitat than the coastal residents (F=0.604, DF=1, P=0.0442); however, both groups value SAV as an important habitat. For the water quality topic, both groups responded that the overall water quality has declined in the last ten years; however, experts' beliefs were stronger than the coastal residents'; in other words, the expert grouped had a stronger belief that water quality has declined compared to the coastal residents. Regarding development, both groups think that development negatively affects SAV abundance, but, the expert group had a stronger belief than the coastal resident group. The two groups have several areas where their beliefs agree. Both groups agreed that SAV have increased within the last 10, 20, and 50 years (F=0.463, DF=1, P=0.463; Table 12), and that storms have a major role in the distribution and abundance of SAV ((F=1.085, DF=1, P=0.304; Table 12).

SAV Maximum Extent Map

In the written survey, people were asked to shade areas where they had seen SAV in the past 10 years. (Figure 14). Respondents from all the groups agreed that there has been an extensive (>10 km in length) bed off the town of Edenton, especially on the eastern shore (Figure 15). Respondents also agreed that there has been some SAV in the Chowan River and at the mouth of the Yeopim River (Figure 15). Very few people (less than 6 people) agreed that there has been SAV present on the southwestern shoreline of AS, except for the mouth of Scuppernong River.

The NCDEQ created an SAV composite geographic layer *(NCDMF 2008)* that compiled SAV distribution data collected with various sampling methods between 1987 and 2008. A visual comparison between these data and LEK data showed that the SAV biological distribution data tends to agree with the social science data collected from the respondents. Areas where very few respondents reported the presence of SAV seemed to have very sparse SAV beds during biological surveys (MEL and RAS).

Discussion

While the sample size in this study does not warrant extrapolating this study to the entire population, whether fishers, managers, or coastal residents, this study provides a starting point, a kind of pilot, for SAV managers to identify common interests between two major groups of SAV stakeholders: experts and coastal residents. In addition, the information reported here revealed some areas of potential disagreement between stakeholders. First, it is important to know that although residents and experts value SAV as a habitat for fish and invertebrates, the strength of their belief is significantly different. This result was expected, as anecdotal reports and research studies indicate that some coastal residents see SAV as a nuisance (Nichols and Shaw 1986; Kantrud 1990). Nonetheless, both groups value SAV as a habitat, which offers an important common ground for coastal managers when developing policies, as it shows that both groups could be interested in protecting the ecological function that SAV provides.

Another important area of agreement was that both groups believe SAV have increased in last decades. However, before extrapolating these results to the entire Sound, it is important to highlight the possibility that the LEK data could be spatially biased. Most of the respondents are likely to reside near or within Edenton, NC, as that is the most densely populated area in western AS; additionally, most respondents were sourced from Edenton. Therefore, respondents can be assumed to be most familiar with SAV beds near Edenton, and they likely answered the survey according to their knowledge about SAV in reference to the Edenton area. This spatial bias could yield biased abundance perceptions, which make it difficult to extrapolate abundance findings to the entire sound. The perceived increased abundance could be because Edenton has one of the largest beds in the Sound, per recent biological survey (Quibble and Associates 2011; Kenworthy et al. 2011; Chapters 1 and 2); however, surveys in AS before the 1980's did not document a large bed off the Edenton area (Davis and Brinson 1990; Ferguson and Wood 1994). Nonetheless, this seemed agreement could be a potential obstacle to coastal managers when developing policies that involve protection of SAV resources, as the two groups do not perceive it as declining or endangered. Hence, these groups may not welcome policies that are perceived as unnecessary. Further, coastal managers need to consider potential areas of disagreement between groups.

Biologists know that SAV abundance and distribution is significantly affected by water quality (Fourqurean et al. 2003; Williams et al. 2010) and land use (Patrick et al. 2014; Landry and Golden 2017). However, both groups have different believes about the effects of water quality and land use on SAV. Both groups believe that water quality in the Sound has declined and that affects SAV's abundance, which seems contradictory to the perceived SAV increased in the Sound. Note that he strength of their beliefs is not the same. Experts tend to have stronger beliefs about the negative effect of different activities on water quality and SAV. For example, experts believe that lumbering (Question 20) and septic tanks (Question 21) have a negative effect on water quality; while residents do not have strong beliefs in these areas. Areas where the strength of agreement is different could cause potential conflict between the users depending on the regulations that are used to manage natural resources. For example, if coastal residents do not believe that SAV are affected by development, but experts do; coastal residents will oppose regulations that limit development as a measure to protect SAV. As previously noted, I found that experts were more likely to agree that septic tanks could be affecting SAV; whereas, resident did not agree with this statement. I would expect coastal residents to think that they have little influence on SAV, as they are likely to oppose regulation that limits their activities.

Variation between the experts and coastal residents' beliefs and values could be explained by two factors. First, though experts and coastal residents are frequently in contact with the Sound, the expert group have more pressing economic, environmental, and political interests in the health of the aquatic environment, including SAV. The expert group are likely to have more uniform information about the Sound because either they are frequently in close proximity to the water, noticing changes in the environment over long time periods (in the case of fishers) or they are familiar with ongoing studies and monitoring of SAV (in the case of fishery managers). Second, although I did not ask respondents about their income, it may be that these two groups come from different socioeconomic backgrounds, with people living along the coast usually enjoying higher standards of living (due to high real estate value and property taxes) than either fishers or fishery managers (Bhat and Stamatiades, 2003). Johnson and Griffith (2010) and Griffith (2013) found that socioeconomic differences can lead to differences in beliefs in coastal social groups. The lack of consensus between social groups can lead to social conflicts, as regulation and policies are implemented to manage the resources (i.e., SAV). Finding areas of agreement can lay the ground for consensus building, something that is needed by managers to develop policies that will be effective and supported by different social groups.

SAV Maximum Extent Map

The LEK maximum extent map revealed that social science could potentially be a useful tool for looking into past natural resources distributions. This was especially evident when several respondents agreed that SAV were present, as there is evidence from biological data that SAV were present in similar locations. These results agreed with Schuegraf (2004), who also identified a high agreement between social surveys and biological samples of SAV. This study suggests that LEK could be useful in generating maps that extend beyond the time period covered by biological SAV survey data; suggested that LEK can go back as far as 100 years (Ambrose et al. 2014). Managers could use this information as a proxy for baseline distribution for SAV in the past. Nonetheless, it is important to caution managers that these LEK maps can only be considered as low-resolution maps. For example, the grid size respondents were asked to shade if they remembered the presence of SAV represented an area of 3 x 3 km, but SAV beds in the area are seldomly larger than 1 km (Chapter 1).

Success of using LEK

LEK was used in this study for two purposes: 1) to identify SAV stakeholders' values and beliefs; 2) to create a maximum extent SAV map based on LEK. LEK was used successfully to achieve both goals. This research revealed that both groups, experts and coastal residents find ecological value in SAV; however, there are differences between the groups, especially about the causes for change in SAV distribution and abundance. These results indicate that experts and coastal residents belong to different subcultures within the AS area, at least regarding their beliefs about SAV. These results are not different from what has been identified in other areas. For example, Grant and Miller (2004) used LEK to identify cultural groups in the Solomon Islands. Their results indicate than in fact there are two bodies of ecological knowledge within the area they sampled. Finding more than two cultures is common when studying coastal resources, as stakeholders often come from different socioeconomic backgrounds (Johnson and Pollnac 1989).

Summary and Conclusions

The experts and coastal residents in the sample have different values and beliefs about SAV; however, both groups agree, though to a different degree, that SAV are valuable habitat to fish and invertebrates. This important agreement between the two groups opens a great opportunity for dialog among managers and the two groups. Studying LEK identified several areas of agreement and disagreement between the two groups. Managers are encouraged to further study areas of agreement and disagreement between the groups, and to consider developing policies that address all stakeholders' concerns.

As future steps, managers should utilize other tools such as focus groups and workshops to develop policies that will help manage SAV. There is evidence that focus groups can help develop alternative policies that address the different stakeholders' concerns (Gregory and Keeney 1994; Prell et al. 2009). Gregory and Keeney (1994) suggest that managers can bring together stakeholders by first pointing out the areas of agreements. These areas of agreement can be identified through LEK research. Methods like the one discussed in this paper can be used by managers to obtain LEK information, which can be used for framing the decision-making process.

Regarding LEK and the historical distribution of SAV, managers and scientists should consider information from residents about the historical distribution of SAV as useful, especially when various respondents agree. Future studies should consider analyzing people's knowledge about the SAV distribution in the past 20, 30, 40, and 50 years. Other areas in the world and the Atlantic have experienced SAV loses (Orth and Moore 1983; Orth et al. 2006); however, NC has limited historical information in low-salinity regions. LEK research could be a way of addressing this information deficiency. Additionally, this methodology could be utilized not only in AS, but other areas that do not have historical information about SAV and other natural resources.

References

Ambrose, W.G., L.M. Clough, J.C. Johnson, M. Greenacre, D.C. Griffith, M.L. Carroll, and A. Whiting. 2014. Interpreting environmental change in coastal Alaska using traditional and scientific ecological knowledge. *Frontiers in Marine Science* 1: 1–15. doi:10.3389/fmars.2014.00040.

Bennett, N.J., R. Roth, S.C. Klain, K. Chan, P. Christie, D.A. Clark, G. Cullman, et al. 2017. Conservation social science: Understanding and integrating human dimensions to improve conservation. *Biological Conservation* 205. The Authors: 93–108. doi:10.1016/j.biocon.2016.10.006.

Berkes, F., J. Colding, and C. Folke. 2000. Rediscovery of traditional ecological knowledge as adaptive management. *Ecological applications* 10: 1251–1262.

Bernard, H.R. 2017. *Research methods in anthropology: Qualitative and quantitative approaches*. Rowman & Littlefield. doi:10.1525/aa.2000.102.1.183.

Bhat, M., and A. Stamatiades. 2003. Institutions, incentives, and resource use conflicts: The case of Biscayne Bay, Florida. *Population and Environment* 24: 485–509. doi:10.1023/A:1025026731145.

Borsuk, M., R. Clemen, L. Maguire, and K. Reckhow. 2001. Stakeholder values and scientific modeling in the Neuse River watershed. *Group Decision and Negotiation* 10: 355–373. doi:10.1023/A:1011231801266.

Bučas, M., A. Šaškov, A. Šiaulys, and Z. Sinkevičienė. 2016. Assessment of a simple hydroacoustic system for the mapping of macrophytes in extremely shallow and turbid lagoon. *Aquatic Botany* 134: 39–46. doi:10.1016/j.aquabot.2016.06.009.

Calheiros, D.F., A.F. Seidl, and C.J.A. Ferreira. 2000. Participatory research methods in environmental science: Local and scientific knowledge of a limnological phenomenon in the Pantanal wetland of Brazil. *Journal of Applied Ecology* 37: 684–696. doi:10.1046/j.1365-2664.2000.00524.x.

Costanza, R., R. D'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, et al. 1997. The value of the world's ecosystem services and natural capital. *Nature* 387: 253–260.

Davis, G.J., and M.M. Brinson. 1990. *A survey of submersed aquatic vegetation of the Currituck Sound and the western Albemarle-Pamlico estuarine system*. Greenville, North Carolina.

Dealteris, J.T., B.D. Kilpatrick, and R.B. Rheault. 2004. A comparative evaluation of the habitat value of shellfish aquaculture gear, submerged aquatic vegetation and a non-vegetated seabed. *Journal of Shellfish Research* 23: 867–874.

Deaton, A.S., W.S. Chappell, J. O'Neal, K. Hart, and B. Boutin. 2010. *North Carolina Coastal Habitat Protection Plan*. Morehead City, North Carolina.

Dennison, W.C., R.J. Orth, K.A. Moore, J.C. Stevenson, V. Carter, S. Kollar, P.W. Bergstrom, and R.A. Batiuk. 1993. Assessing water quality with submerged aquatic vegetation: Habitat requirements as barometers of Chesapeake Bay health. *BioScience* 43: 86–94.

doi:10.2307/1311969.

Dobson, J.E., E.A. Bright, R.L. Ferguson, D. Field, L.L. Wood, K.D. Haddad, H. Iredale III, et al. 1995. *NOAA Coastal Change Analysis Program (C-CAP): Guidance for regional implementation*. Vol. NOAA Techn.

Ferguson, R.L., and L.L. Wood. 1994. *Rooted vascular aquatic beds in the Albemarle-Pamlico estuarine system.* Beaufort, North Carolina: National Marne Fisheries, National Oceanic and Atmospheric Administration.

Flaherty-Walia, K.E., R.E.J. Matheson, and R. Paperno. 2015. Juvenile Spotted Seatrout (*Cynoscion nebulosus*) habitat use in an eastern Gulf of Mexico estuary: The effects of seagrass bed architecture, seagrass species composition, and varying degrees of freshwater influence. *Estuaries and Coasts* 38: 353–366.

Fonseca, M.S., W.J. Kenworthy, and G.W. Thayer. 1998. Guideline for the conservation and restoration of seagrasses in the United States and adjacent waters. NOAA Coastal Ocean Program Decision Analysis Series No. 12. *NOAA's Coastal Ocean Program* Decision A: 222.

Fourqurean, J.W., J.N. Boyer, M.J. Durako, L.N. Hefty, B.J. Peterson, L.E.E.N. Hefty, and B.J. Peterson. 2003. Forecasting responses of seagrass distributions to changing water quality using monitoring data. *Ecological Applications* 13: 474–489.

Fourqurean, J.W., C.M. Duarte, H. Kennedy, N. Marbà, M. Holmer, M.A. Mateo, E.T. Apostolaki, et al. 2012. Seagrass ecosystems as a globally significant carbon stock. *Nature Geoscience* 5: 1–5.

García-quijano, C.G. 2007. Fisher's knowledge of marine species assemblages: Bridging between scientific and local ecological knowledge in southeastern Puerto Rico. *American Anthropologist* 109: 529–536. doi:10.1525/AA.2007.109.3.529.530.

García-Quijano, C.G. 2009. Managing complexities: Ecological knowledge and success in Purto Rican small-scale fisheries. *Human Organization* 68: 1–17.

Giese, G.L., H.B. Wilder, and G.G.J. Parker. 1985. *Hydrology of major estuaries and sounds of North Carolina*. Alexandria, Virginia.

Grant, K.L., and M.L. Miller. 2004. A cultural consensus analysis of marine ecological knowledge in the Solomon Islands. *SPC Traditional Marine Resource Management and Knowledge Information Bulletin* 17: 3–13.

Gregory, R., and R.L. Keeney. 1994. Creating Policy Alternatives Using Stakeholder Values. *Management Science* 40: 1035–1048. doi:10.1287/mnsc.40.8.1035.

Griffith, D.C. 1999. *The estuary's gift: An Atlantic Coast cultural biography*. Penn State Press.

Griffith, D.C., C. García-Quijano, and M.V. Pizzini. 2013. A fresh defense: A cultural biography of quality in Puerto Rican fishing. *American Anthropologist* 115: 17–28. doi:10.1111/j.1548-1433.2012.01532.x.

Heck, K.L.J., and T.A. Thoman. 1984. The nursery role of seagrass meadows in the upper and lower reaches of the Chesapeake Bay. *Coastal and Estuarine Research Federation* 7: 70–92.

Van Holt, T. 2009. Influence of landscape change on nearshore fisheries in southern Chile. University of Florida. doi:10.1111/j.1365-2486.2012.02674.x.

Hunn, E.S., D.R. Johnson, P.N. Russell, and T.F. Thornton. 2003. Huna Tlingit traditional environmental knowledge, conservation, and the management of a "Wilderness" Park. *Current Anthropology* 44: 79–103.

Huntington, H.P. 2000. Using traditional ecological knowledge in science: Methods and applications. *Ecological applications* 10: 1270–1274.

IBM Corp. 2017. IBM SPSS Statistics for Windows. Armonk, NY: IBM Corp.

Jacobs, K., G. Garfin, and M. Lenart. 2005. More than just talk: Connecting science and decisionmaking. *Environment: Science and Policy for Sustainable Development* 47: 6–21. doi:10.3200/ENVT.47.9.6-21.

Johnson, D.R., and J.C. Creech. 1983. Ordinal measures in multiple indicator models: A simulation study of categorization error 48: 398–407.

Johnson, J.C., and D.C. Griffith. 2010. Finding common ground in the commons: Intracultural variation in users' conceptions of coastal fisheries issues. *Society and Natural Resources* 23. Taylor & Francis: 837–855.

Johnson, J.C., and R.B. Pollnac. 1989. Introduction to managing marine conflicts. *Ocean and Shoreline Management* 12: 191–198. doi:10.1016/0951-8312(89)90002-7.

Kantrud, H. 1990. Sago Pondweed (*Potamogeton pectinatus* L.): A Literature Review. *US Fish and Wildlifhe Service*: 1–98.

Keeney, R.L., D. von Winterfeldt, and T. Eppel. 1990. Eliciting public values for complex policy decisions. *Management Science* 36: 1011–1030. doi:10.1287/mnsc.36.9.1011.

Kenworthy, W.J., C.A. Buckel, D.E. Carpenter, D.B. Eggleson, D. Field, C.S. Krahforst, and J.J. Luczkovich. 2012. *Development of submerged aquatic vegetation monitoring protocols in North Carolina*. Morehead City, North Carolina.

Landry, J.B., and R.R. Golden. 2017. *In situ* effects of shoreline type and watershed land use on submerged aquatic vegetation habitat quality in the Chesapeake and Mid-Atlantic coastal bays. *Estuaries and Coasts*. Estuaries and Coasts: 1–13. doi:10.1007/s12237-017-0316-0.

Lemos, M.C., and B.J. Morehouse. 2005. The co-production of science and policy in integrated climate assessments. *Global Environmental Change* 15: 57–68. doi:10.1016/j.gloenvcha.2004.09.004.

Li, X., D.E. Weller, C.L. Gallegos, T.E. Jordant, and H.-C.C. Kim. 2007. Effects of watershed and estuarine characteristics on the abundance of submerged aquatic vegetation in Chesapeake Bay subestuaries. *Estuaries and Coasts* 30: 840–854. doi:10.1007/BF02841338.

Madsen, J.D., P.A. Chambers, W.F. James, E.W. Koch, and D.. Westlake. 2001. The interaction between water movement, sediment dynamics and submersed macrophytes. *Hydrobiologia* 444: 71–84. doi:10.1023/A.

Marshall, M.N. 1996. The key informant technique. *Family Practice* 13: 92–97.

Micheli, F., and C.H. Peterson. 1999. Estuarine vegetated habitats as corridors for predator movements. *Conservation Biology* 13: 869–881. doi:10.1046/j.1523-1739.1999.98233.x.

Miller, J.W. 2015. Utility of macrophyte habitat for juvenile fishes: contrasting use in turbid and clearwater conditions of Maumee Bay, Lake Erie. Bowling Green State University.

Nichols, S.A., and B.H. Shaw. 1986. Ecological life histories of the three aquatic nuisance plants, *Myriophyllum spicatum*, *Potamogeton crispus* and *Elodea canadensis*. *Hydrobiologia* 131: 3–21. doi:10.1007/BF00008319.

NCDEQ. 2016. *North Carolina Coastal Habitat Protection Plan Source Document*. Morehead City, North Carolina.

NCDMF. 2008. *Inventory of SAV maps and survey work in coastal North Carolina (1981-2008)*. Morehead City, North Carolina.

Oertli, H.J. 1964. The Venice System for the classification of marine waters according to salinity. *Pubblicazioni della Stazione Zoologioca di Napoli* 36: 346–347.

Olsson, P., and C. Folke. 2001. Local ecological knowledge and institutional dynamics for ecosystem management: A study of Lake Racken watershed, Sweden. *Ecosystems* 4: 85–104. doi:10.1007/s100210000061.

Orbach, M.K. 1989. Of mackerel and menhaden: A public policy perspective on fishery conflict. *Ocean and Shoreline Management* 12: 199–216. doi:10.1016/0951-8312(89)90003-9.

Orth, R.J., T.J.B. Carruthers, W.C. Dennison, C.M. Duarte, J.W. Fourqurean, K.L.J. Heck, A.R. Hughes, et al. 2006. A global crisis for seagrass ecosystems. *Bioscience* 56: 987–996.

Orth, R.J., W.C. Dennison, J.S. Lefcheck, C. Gurbisz, M. Hannam, J. Keisman, J.B. Landry, et al. 2017. Submersed aquatic vegetation in Chesapeake Bay: Sentinel species in a changing world. *BioScience* 67: 698–712. doi:10.1093/biosci/bix058.

Orth, R.J., and K.A. Moore. 1983. Chesapeake Bay: An unprecedented decline in submerged aquatic vegetation. *Science* 222: 51–53. doi:10.1126/science.222.4619.51.

Orth, R.J., M.R. Williams, S.R. Marion, D.J. Wilcox, T.J.B. Carruthers, K.A. Moore, W.M. Kemp, et al. 2010. Long-term trends in submersed aquatic vegetation (SAV) in Chesapeake Bay, USA, related to water quality. *Estuaries and Coasts* 33: 1144–1163. doi:10.1007/s12237-010-9311-4.

Patrick, C.J., and D.E. Weller. 2015. Interannual variation in submerged aquatic vegetation and its relationship to water quality in subestuaries of Chesapeake Bay. *Marine Ecology Progress Series* 537: 121–135. doi:10.3354/meps11412.

Patrick, C.J., D.E. Weller, X. Li, and M. Ryder. 2014. Effects of shoreline alteration and other stressors on submerged aquatic vegetation in subestuaries of Chesapeake Bay and the Mid-Atlantic coastal bays. *Estuaries and Coasts* 37: 1516–1531. doi:10.1007/s12237-014-9768-

7.

Poizat, G., and E. Baran. 1997. Fishermen's knowledge as background information in tropical fish ecology: a quantitative comparison with fish sampling results. *Environmental Biology of Fishes* 50: 435–449. doi:10.1023/A.

Pomeroy, R., J. Parks, R. Pollnac, T. Campson, E. Genio, C. Marlessy, E. Holle, et al. 2007. Fish wars: Conflict and collaboration in fisheries management in Southeast Asia. *Marine Policy* 31: 645–656. doi:10.1016/j.marpol.2007.03.012.

Prell, C., K. Hubacek, and M. Reed. 2009. Stakeholder analysis and social network analysis in natural resource management. *Society and Natural Resources2* 22: 501–518. doi:10.4324/9781315748771.

Quible and Associates. 2011. *A compensatory mitigation plan requierement for The Fund for Sandy Point North Carolina, LLC*. Kitty Wawk, North Carolina.

Rockloff, S.F., and S. Lockie. 2004. Participatory tools for coastal zone management: Use of stakeholder analysis and social mapping in Australia. *Journal of Coastal Conservation* 10: 81–92. doi:10.1652/1400-0350(2004)010[0081:PTFCZM]2.0.CO;2.

Romney, A.K., S.C. Weller, and W.H. Batchelder. 1986. Culture as Consensus : A Theory of Informant Accuracy. *American Anthropologist* 88: 313–338. doi:10.1525/aa.1986.88.2.02a00020.

Schuegraf, M.J. 2004. Establishment of seagrass decline and causative mechanisms in Pearl Lagoon, Nicaragua through use of traditional ecological knowledge, sediment coring and direct visual census. York University.

Sprecher, S.L., K.D. Getsinger, and A.B. Stewart. 1998. Selective effects of aquatic herbicides on Sago Pondweed. *Journal of Aquatic Plant Management* 36: 64–68.

Sullivan, G.M., and A.R. Artino. 2013. Analyzing and interpreting data from Likert-type scales. *Journal of Graduate Medical Education* 5: 541–542. doi:10.4300/JGME-5-4-18.

Thayer, G.W., K.A. Bjorndal, J.C. Ogden, S.L. Williams, and J.C. Zieman. 1984. Role of large herbivores in seagrass communities. *Estuaries* 7: 351–376.

Tomasini, S., and I. Theilade. 2019. Local ecological knowledge indicators for wild plant management: Autonomous local monitoring in Prespa, Albania. *Ecological Indicators* 101. Elsevier: 1064–1076. doi:10.1016/j.ecolind.2019.01.076.

Valdés-Pizzini, M. 1990. Fishermen associations in Puerto Rico: Praxis and discourse in the politics of fishing. *Human Organization* 49: 164–173. doi:10.17730/humo.49.2.bl24551243635627.

Williams, M.R., S. Filoso, B.J. Longstaff, and W.C. Dennison. 2010. Long-term trends of water quality and biotic metrics in Chesapeake Bay: 1986 to 2008. *Coastal and Estuarine Research Federation* 33: 1279–1299. doi:10.1007/sl.

Figures

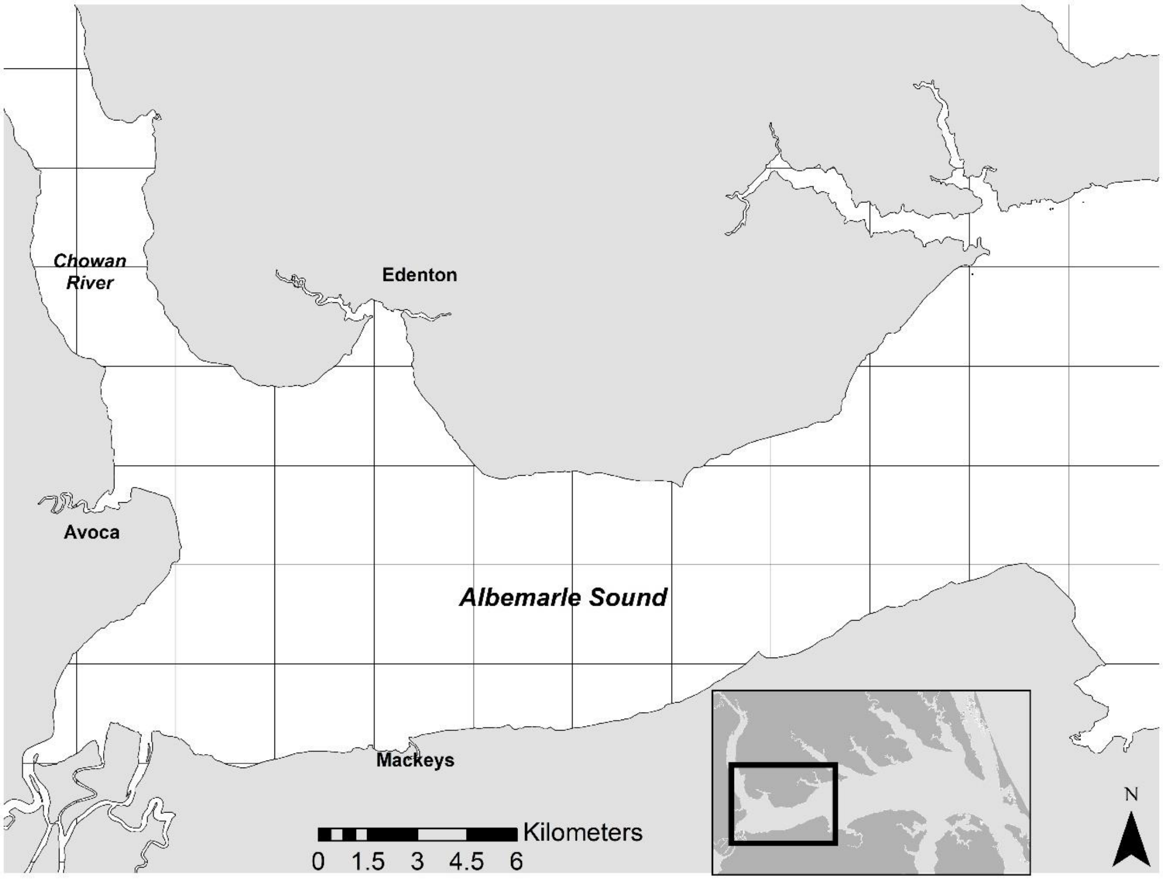


Figure 13. Western Albemarle Sound NC showing areas where respondents were asked about the presence of Submerged Aquatic Vegetation during the written survey. Each square in the grid represents areas of 3 x 3 km. Note that all the respondents are not likely to have visited each possible square.

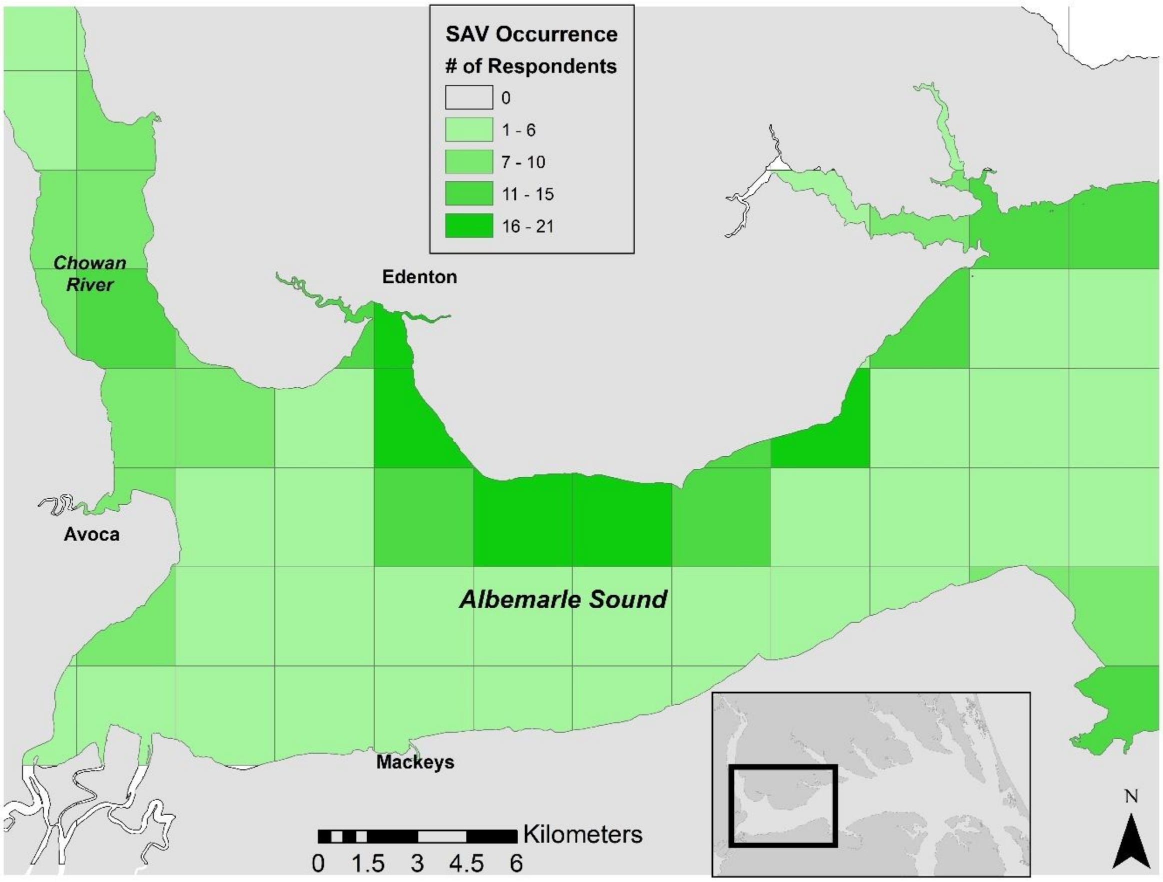


Figure 14. Maximum extent SAV map in the western Albemarle Sound NC based on LEK. The green color gradient represents number of respondents that reported SAV present at a grid on the LEK survey. A total of 41 people responded to the survey. 21 coastal residents and 20 experts. The green squares do not represent patch sizes. It was an approximate location for SAV beds.

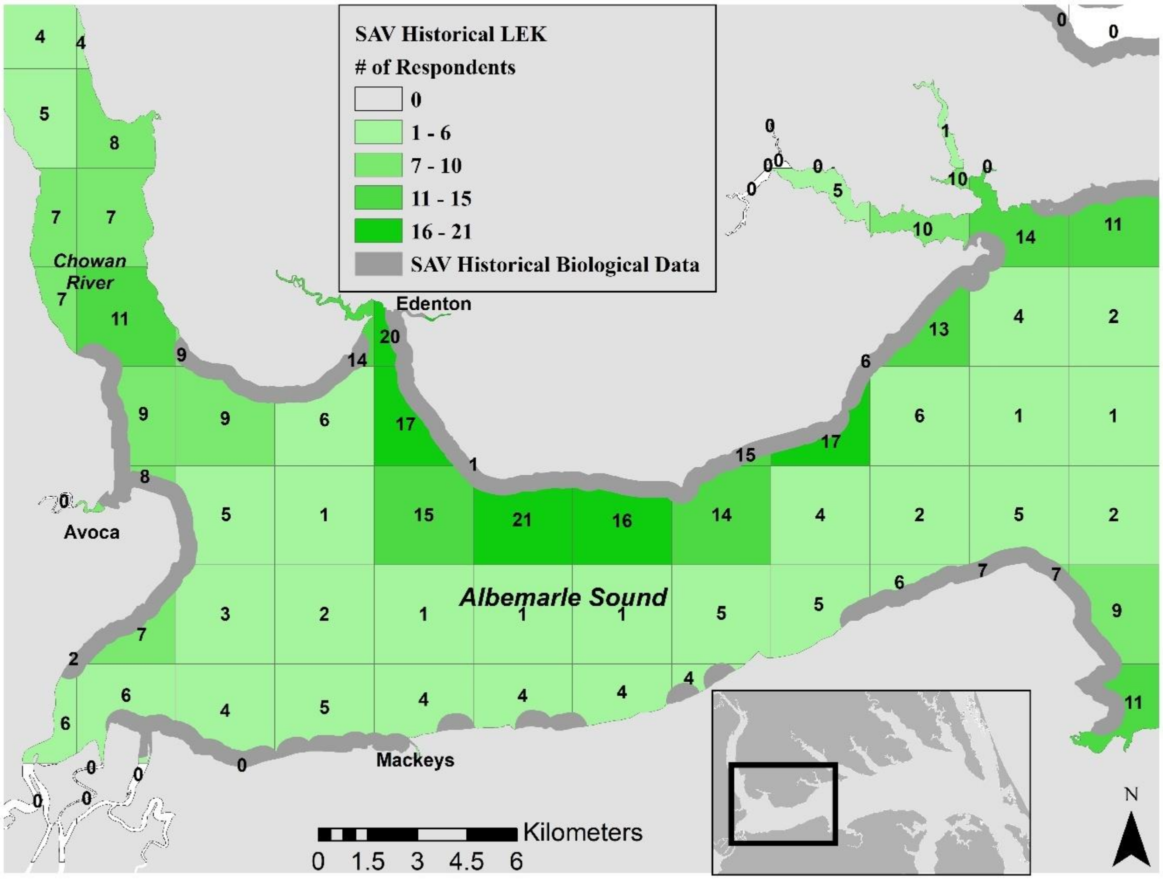


Figure 15. Maximum extent SAV map in the western Albemarle Sound NC based on LEK and SEK. The green color gradient represents number of respondents to a LEK survey. The numbers inside the grid are the number of respondents that confirmed SAV occurrence in that location. A total of 41 people responded the survey. 21 coastal residents and 20 experts. The squares do not represent patch sizes. It is an approximate location for SAV beds. The shaded areas represent areas with SAV on a maximum extent layer based on biological data. The NC Department of Environmental Quality (NCDEQ) created an SAV composite geographic layer (NCDMF 2008) that compiled SAV distribution data that were collected with various sampling methods between 1987 and 2008. In addition, it includes data collected by the East Carolina University SAV survey team in 2014.

Tables

Table 12 Mean and SD table for the Likert scale responses for each question in the written survey. The results were grouped by experts and coastal resident. The topic(s) classification for each question is also provided: SAV Value (Value), SAV Trend (Trend), Water Quality (WQ), Seasonality (Season), Development (D), Storms, (Storm). NA indicates that the question was not grouped into a chategory.

		Experts		Coastal Residents		
	Questions	**Mean**	**S.D.**	**Mean**	**S.D.**	**Topic class**
1	How long have you lived in the western Albemarle Sound (e.g., Edenton, Chowan River, Roanoke River, and Plymouth areas)?	2.55	0.58	2.33	0.61	NA
2	Overall SAV abundance has increased in the last 10 years	2.55	1.1	2	0.85	Trend
3	Overall SAV abundance has increased in the last 20 years	1.9	1.2	1.24	0.91	Trend
4	Overall there is not as much SAV as there used to be 50 years ago	1.5	1.03	1.1	1.25	Trend
5	SAV abundance changes all the time	2	1.03	1.76	0.87	Season
6	SAV distribution does not change from year to year	3.45	1.05	3.29	0.78	Season
7	Depending on the year, SAV is present in some areas and absent in other areas	1.75	0.97	1.62	0.92	Season
8	The invasive species, Eurasian watermilfoil, was common in the past, but improved water quality has caused a decline in its abundance	1.9	0.76	1.1	1.13	WQ
9	Improved water quality causes an increase in the abundance of Eurasian watermilfoil	2.15	0.75	0.81	1.17	WQ
10	During wet years, different SAV species are present in the sound than during dry years	2.15	1.04	0.95	0.47	WQ, Season
11	Extremely dry years are associated with an increase in algal blooms	2.15	1.1	1.76	1	WQ, Season
12	Algal blooms do not inhibit SAV growth	2.45	0.8	2.62	0.62	
13	Anything that inhibits water clarity inhibits SAV growth	1.65	0.92	1.48	0.64	WQ
14	Turbidity is the primary factor hindering SAV growth	2.2	0.96	1.48	0.67	WQ
15	Turbidity is primarily affected by wind and wave action	2.05	0.9	1.71	1.09	WQ

16	Turbidity is primarily affected by nutrient runoff	1.9	0.83	1.57	0.97	WQ
17	Overall, the water quality of the western Albemarle Region has declined in the last 10 years	1.9	0.91	1.9	0.86	WQ
18	Excess nutrients in the water (i.e., nutrient loading) caused by nutrient runoff from farms does not have a negative effect on SAV abundance	3.4	0.96	2.9	1.03	WQ
19	Poor water quality in the sound is primarily caused by agricultural runoff	2.1	0.85	2.14	0.96	WQ
20	Poor water quality in the sound is primarily caused by lumbering	3.05	0.92	2.52	1	WQ
21	Septic tanks are polluting the sound's water because they do not operate properly	2.25	1.02	1.9	0.61	WQ, D
22	Septic tanks do not have a negative effect on SAV abundance	2.95	1.05	2.19	1.1	WQ, D
23	SAV is an important habitat for juvenile and adult fish	1.3	0.47	1.43	0.84	Value
24	Excessive nutrients in the water do not cause algal blooms	2.8	0.8	3.52	0.57	WQ
25	Strong storms cannot uproot SAV	3.7	0.47	3	0.71	Storm
26	Northeast winds during the winter do more damage to the SAV than the summer winds	1.95	1.09	0.81	1.13	Storm
27	SAV abundance fluctuates because of hurricanes	1.8	0.94	2.05	0.8	Storm
28	Wake from boats uproots SAV	2.5	1.12	1.9	0.63	NA
29	SAV is not an important habitat for juvenile and adult crabs and other invertebrates	3.5	1	2.86	0.45	Value
30	Tremendous increase in SAV abundance is directly tied to larger crab catches	1.7	1.28	1.57	1.22	Value
31	Developed shorelines do not have a negative effect on SAV abundance	3.15	1.14	2.67	0.85	D
32	Development adversely affects SAV abundance	2.25	1.25	1.95	0.76	D
33	Sea Level Rise will cause SAV to decline	2.4	0.86	1.52	0.7	NA
34	Sea Level Rise has caused SAV to decline in the past decade	2.4	0.94	1.67	0.75	NA

Table 13 ANOVA's of SAV cultural knowledge by topic.

Topic	**F**	**df**	**p**
Overall Survey	11.59	1	0.001
General Statements	0.091	1	0.764
Specific Statements	0.288	1	0.595
SAV Value	0.604	1	0.0442
SAV Trend	0.463	1	0.463
Water Quality	9.036	1	0.0046
Seasonality	2.867	1	0.0984
Development	5.569	1	0.0234
Storms	1.085	1	0.304

CONCLUSION

Summary of Findings

The aim of this dissertation was to learn more about the temporal abundance and distribution of the SAV in AS by addressing two main questions: what is the distribution of SAV and what is its temporal variation in the AS? Furthermore, this study explored the use of social science through the implementation of LEK to understand stakeholder beliefs and knowledge about SAV and historical SAV distribution. The study intended to provide useful information to coastal resources managers, so they can make informed management decisions.

This dissertation met its objectives by carrying out three types of surveys, two biological surveys, and one social science survey. The biological surveys provided information about the abundance and distribution of SAV in AS and demonstrated that single-beam sonar is an adequate method for monitoring this resource; however, more work is needed to develop a sonar signal verification method. The social science survey provided information about historical SAV distribution and people's perception about this resource. Resources manages need both types of information (biological and social science) to make sound policy decisions.

After surveying approximately 60% of the entire AS shoreline, the Rapid Assessment Survey (RAS) identified several SAV beds in the AS. Most beds were patchy and ranged from (10 to 20% SAV occurrence). The beds were scattered throughout the sounds' larger tributaries, but three larger beds (>10 km) were located at the Edenton, Kitty Hawk, and East Lake areas. Further, the study confirmed that SAV are confined to a narrow band along the shore, as in the RA sampling more than 75% of SAV were concentrated in water shallower than 2 m. The RAS revealed that SAV have being a constant benthic feature in the AS for several years; however, its distribution and abundance has changed through time. Some areas seemed to consistently have beds; whereas, other areas had lost or gained SAV beds. SAV abundance and temporal fluctuations became more evident after the Sentinel Site (SS) survey.

After sampling 10 sites for two years (2014 and 2015) in the spring and the fall with sonar and in-water quadrat sampling, SAV beds at these sites were very dynamic, with temporal abundance and distribution changing through time and space. Further, I identified temporal trends at the site level, but because of the different temporal dynamics at each site, it was not possible to establish clear abundance and temporal patterns that could be generalized to the entire sound. However, these results are not unique to AS. In oligo- and meso-haline regions of the Chesapeake Bay, an estuary with similar characteristics as AS, researchers have also determined that SAV are highly dynamic (Orth et al. 2010; Patrick and Weller 2015).

Though SAV were highly dynamic, I was able to identify some generalities. Through these biological surveys, I detected that depth played a major role in SAV distribution. The sentinel site survey revealed that SAV were most abound at depths between ~ 0.5 and 2 m and most frequently found in areas closer to the shore (less than 300 m). SAV's proximity to the shore makes it especially susceptible to land use and population growth (Patrick et al. 2014; Gittman et al. 2016; Landry and Golden 2017).

The social science study revealed that fishers and managers (experts) perceived that SAV had increased in the last decades, which was different than the high variability in abundance I identified in the biological survey. Further, I identified that there were some agreements and disagreement between the two social groups. Coastal resources managers can utilize the areas of agreement between social groups as starting points for management; however, the areas of disagreement should be identified as potential areas of conflict, and managers need to develop strategies for minimizing them.

Implications for SAV Management

In NC, the human population in the AS water basin increased 19.0 % between 1990-2000 (Carpenter and Dubbs 2012). NC has an estimated population of 10.4 million with a 1.1 % annual growth rate since 2017, and likely to continue (Tippett 2018) leading to increased pollution from urbanization in recent years (Lin et al. 2007). The deterioration of these system's coastal waters is likely to have an effect on SAV abundance and distribution, as it has in the Chesapeake Bay, where SAV abundance has been impacted by nutrient and sediment loadings (Orth et al. 2010; Lefcheck et al. 2018). Considering increasing populations in NC, SAV will face new challenges. Hence, I urge resources managers to adopt the sentinel sites established in this dissertation. Currently, we are at the beginning stages of developing a monitoring program in low-salinity areas of NC that can identify SAV distribution and abundance changes; however, this monitoring program needs to mature towards differentiating between intrinsic variation and external variation. Understanding the factors that cause change in SAV should be the next priority, as it would help managers make evidence-based conservation and restoration decisions. Establishing water quality monitoring stations near the shore at the sentinel sites, not offshore or in channels, would immediately help address this need (Patrick and Weller 2015).

The effect of human population on the sound's water quality has been a problem for decades now (Moorman et al. 2017), so it is crucial to identify baseline SAV distributions as soon as possible, especially near the shore where coastal ecosystems are first impacted by coastal development. Though single-beam sonar is an excellent tool for monitoring SAV in AS at depths greater than 0.5 m., it is essential to implement SAV monitoring at shallower depths at the sentinel sites. A practical and cost-effective method would be to complement the sonar surveys with aerial imagery acquired by flying a low altitude (400 ft) drone parallel and inshore of the sonar track. Together, sonar and drone surveys could be used to efficiently and consistently to create accurate high-resolution SAV maps which can help delineate SAV beds in the Sound and detect changes overtime. Further, sonar and drone surveys can also help obtain information on SAV's depth preferences which can help develop maps for areas potentially available for SAV growth. Knowing SAV potential habitat can help create restoration targets (if restoration is necessary).

Historical information obtained apart from biological surveys can also assist in establishing conservation restoration targets, particularly when routine monitoring has not yet been established or it was recently established. McClenachan et al. 2012 suggested the use of archival documents, interviews with fishers and other resources' users, and zooarchaeological remains to estimate baseline distributions prior to biological surveys. In this dissertation, I identified that LEK has the potential to be a reliable source for past SAV distribution in AS. It is likely that future LEK SAV historical distribution studies in the area going further back in time (> 50 years) than the available biological data will yield greater SAV abundances; McClenachan et al. 2012 suggested that historical data tend further detail the effect of human activity on natural resources. Therefore, implementing LEK to study past SAV distributions may cause a shift in SAV baseline distributions.

The inclusion of stakeholders in natural resources management through LEK can also help managers minimize conflict, especially in a system that is going to experience increased stress due to increased populations. Increasing populations can lead to greater social conflict (Grimble and Wellard 1997), which can make natural resources management more complex and challenging. Larger populations tend to have more social groups, each with unique characteristics, interests, and perceptions. Resources managers are challenged to develop policies that are more in tune with a dynamic system and address the linkage between society and coastal systems (Olsson and Folke 2001).

Human activity and natural resources are interwoven; hence, there has been an increase in awareness to monitor natural resources in a multidisciplinary approach, which consider human dimensions (Rosenberg et al. 2015). Orth et al. (2017) described many useful steps to ensure the health, productivity, and endurance of the SAV community in the Chesapeake, a system that has been thoroughly studied for several decades, and it is a leading example for estuarine systems like AS. Hence, many of these steps can also be implemented to the AS, which is only at its infancy for routine SAV monitoring. Some of these steps include continued SAV monitoring and identification of the factors that affect its abundance and distribution, improved water quality monitoring programs, and addressing emerging issues, like climate change and sea level rise. However, it is also crucial to design research that can have a direct application to management policies. Social aspects of society, such as demographics, economics, land use, and cultural perspectives shape natural resources (Dale et al. 2000), as ecosystems do not exist in isolation. Therefore, natural resources managers require biological science along with other disciplines to develop adequate policies that can adapt to new information.

Future Research Suggestions

In face of rapid land use changes and the increasing population in NC, managing natural resources is challenging, with many possibilities for conflict. Natural resources managers are required to quickly learn about the natural environment and adapt to the human dimensions of natural resources; therefore, with a sense of urgency, I encourage resources managers to focus their research at the sentinel sites established in this study. Future work at the sentinel sites should focus on characterizing the potential stressors associated with these sites to ensure that these sites represent a wide range of conditions and are representative of the Sound. These studies can help assess if these sites should continue to be regularly monitored or if it is necessary to select different sites to ensure that a wide range of conditions across the Sound are being captured.

Advanced time series analysis, like the one carried out by Patrick and Weller (2015), can help further describe the complex SAV temporal patterns in the AS in conjunction with the effect of multiple environmental factors. Further, research is also necessary to improve the sonar's signal verification method (i.e., underwater video). Additionally, I recommend more intensive species composition sampling at the sentinel sites, as well as the application of other remote sensing methods in shallow areas, like drone surveys.

Finally, the reliable of LEK data could be evaluating by developing methods to assess confidence in the data. Other studies have linked biological data (e.g. zooarchaeological remain, mollusk biological data) to stakeholders' knowledge; hence, they were able to monitor change quantitatively using LEK (Schuegraf 2004; Ambrose et al. 2014).

References

Ambrose, W.G., L.M. Clough, J.C. Johnson, M. Greenacre, D.C. Griffith, M.L. Carroll, and A. Whiting. 2014. Interpreting environmental change in coastal Alaska using traditional and scientific ecological knowledge. *Frontiers in Marine Science* 1: 1–15. doi:10.3389/fmars.2014.00040.

Carpenter, D.E., and L. Dubbs. 2012. *2012 Albemarle-Pamlico ecosystem assessment, Albemarle-Pamlico National Estuary Partnership*. Raleigh, North Carolina.

Dale, V.H., S. Brown, R.A. Haeuber, N.T. Hobbs, N. Huntly, R.J. Naiman, M.G. Turner, and T.J. Valone. 2000. Ecological principles and guidelines for managing the use of land. *Ecological Applications2* 10: 639–670.

Gittman, R.K., S.B. Scyphers, C.S. Smith, I.P. Neylan, and J.H. Grabowski. 2016. Ecological consequences of shoreline hardening: a meta-analysis. *BioScience* 66: 763–773. doi:10.1093/biosci/biw091.

Grimble, R., and K. Wellard. 1997. Stakeholder methodologies in natural resource management: A review of principles, contexts, experiences and opportunities. *Agricultural Systems* 55: 173–193. doi:10.1016/S0308-521X(97)00006-1.

Landry, J.B., and R.R. Golden. 2017. *In situ* effects of shoreline type and watershed land use on submerged aquatic vegetation habitat quality in the Chesapeake and Mid-Atlantic coastal bays. *Estuaries and Coasts*. Estuaries and Coasts: 1–13. doi:10.1007/s12237-017-0316-0.

Lefcheck, J.S., R.J. Orth, W.C. Dennison, D.J. Wilcox, R.R. Murphy, J. Keisman, C. Gurbisz, et al. 2018. Long-term nutrient reductions lead to the unprecedented recovery of a temperate coastal region. *Proceedings of the National Academy of Sciences* 115: 3658–3662. doi:10.1073/pnas.1715798115.

Lin, J., L. Xie, L.J. Pietrafesa, J.S. Ramus, and H.W. Paerl. 2007. Water quality gradients across Albemarle-Pamlico estuarine system: seasonal variation and model application. *Journal of Coastal Research* 231: 213–229. doi:10.2112/05-0507.1.

McClenachan, L., F. Ferretti, and J.K. Baum. 2012. From archives to conservation: Why historical data are needed to set baselines for marine animals and ecosystems. *Conservation Letters* 5: 349–359. doi:10.1111/j.1755-263X.2012.00253.x.

Moorman, M.C., S.A. Fitzgerald, L.N. Gurley, A. Rhoni-Aref, and K.A. Loftin. 2017. *Water quality and bed sediment quality in the Albemarle Sound, North Carolina, 2012–14. Open-File Report 2016-1171*. Reston, Virginia. doi:10.3133/ofr20161171.

Olsson, P., and C. Folke. 2001. Local ecological knowledge and institutional dynamics for ecosystem management: A study of Lake Racken watershed, Sweden. *Ecosystems* 4: 85–104. doi:10.1007/s100210000061.

Orth, R.J., W.C. Dennison, J.S. Lefcheck, C. Gurbisz, M. Hannam, J. Keisman, J.B. Landry, et al. 2017. Submersed aquatic vegetation in Chesapeake Bay: Sentinel species in a changing world. *BioScience* 67: 698–712. doi:10.1093/biosci/bix058.

Orth, R.J., M.R. Williams, S.R. Marion, D.J. Wilcox, T.J.B. Carruthers, K.A. Moore, W.M. Kemp, et al. 2010. Long-term trends in submersed aquatic vegetation (SAV) in Chesapeake Bay, USA, related to water quality. *Estuaries and Coasts* 33: 1144–1163. doi:10.1007/s12237-010-9311-4.

Patrick, C.J., and D.E. Weller. 2015. Interannual variation in submerged aquatic vegetation and its relationship to water quality in subestuaries of Chesapeake Bay. *Marine Ecology Progress Series* 537: 121–135. doi:10.3354/meps11412.

Patrick, C.J., D.E. Weller, X. Li, and M. Ryder. 2014. Effects of shoreline alteration and other stressors on submerged aquatic vegetation in subestuaries of Chesapeake Bay and the Mid-Atlantic coastal bays. *Estuaries and Coasts* 37: 1516–1531. doi:10.1007/s12237-014-9768-7.

Rosenberg, A.A., W.J. Bolster, K.E. Alexander, W.B. Leavenworth, A.B. Cooper, and M.G. McKenzie. 2005. The history of ocean resources: Modeling cod biomass using historical records. *Frontiers in Ecology and the Environment* 3: 84–90. doi:10.2307/3868514.

Schuegraf, M.J. 2004. Establishment of seagrass decline and causative mechanisms in Pearl Lagoon, Nicaragua through use of traditional ecological knowledge, sediment coring and direct visual census. York University.

Tippett, R. 2018. 2018 marks third straight year of 100K+ population gains for NC. *Carolina Demography*.

APPENDIX A. IRB APPROVAL LETTER

EAST CAROLINA UNIVERSITY
University & Medical Center Institutional Review Board
4N-64 Brody Medical Sciences Building· Mail Stop 682
600 Moye Boulevard · Greenville, NC 27834
Office 252-744-2914 · Fax 252-744-2284 ·
www.ecu.edu/ORIC/irb

Notification of Initial Approval: Expedited

From: Social/Behavioral IRB
To: Hilde Speight
CC:
David Griffith
Hilde Speight
Date: 10/11/2017
Re: UMCIRB 17-001934
Submerged Aquatic Vegetation Cultural Consensus

I am pleased to inform you that your Expedited Application was approved. Approval of the study and any consent form(s) is for the period of 10/11/2017 to 10/10/2018. The research study is eligible for review under expedited category #6, 7. The Chairperson (or designee) deemed this study no more than minimal risk.

Changes to this approved research may not be initiated without UMCIRB review except when necessary to eliminate an apparent immediate hazard to the participant. All unanticipated problems involving risks to participants and others must be promptly reported to the UMCIRB. The investigator must submit a continuing review/closure application to the UMCIRB prior to the date of study expiration. The Investigator must adhere to all reporting requirements for this study.

Approved consent documents with the IRB approval date stamped on the document should be used to consent participants (consent documents with the IRB approval date stamp are found under the Documents tab in the study workspace).

The approval includes the following items:

Name	Description
Hilde's dissertation proposal	Study Protocol or Grant Application
Speight sample interview questions	Interview/Focus Group Scripts/Questions
Speight's sample survey	Surveys and Questionnaires
SURVEY Speight Cover Letter 10 7 14 (1).docx	Consent Forms

The Chairperson (or designee) does not have a potential for conflict of interest on this study.

IRB00000705 East Carolina U IRB #1 (Biomedical) IORG0000418
IRB00003781 East Carolina U IRB #2 (Behavioral/SS) IORG0000418

APPENDIX B. EVALUATING THE ACCURACY OF THE SINGLE-BEAM SONAR AS A MONITORING TOOL FOR SUBMERGED AQUATIC VEGETATION (SAV) IN A LOW-VISIBILITY ESTUARINE SYSTEM, THE ALBEMARLE SOUND, NC.

Introduction

Different methodologies have been used to monitor and map SAV in coastal habitats. Aerial remote sensing methods like aerial photography and satellite imagery are some of the most widely used methodologies to monitor SAV; however, their use is limited by water clarity and atmospheric conditions (Dobson et al. 1995; Moore et al. 2009; NCDEQ 2016), making these methodologies unsuitable for surveying SAV in turbid low-salinity estuaries. Low-salinity estuaries are characterized by large freshwater inputs that carry sediments, colored organic matter, tannins, and detritus, which severely affect water transparency. Sonar and underwater video have been suggested as alternative technologies to monitor these systems (Sabol et al. 2002; Valley et al. 2015; Christiaen et al. 2017); however, sonar is considered to be a more efficient method, as underwater video is more time consuming when trying to cover large areas in turbid waters.

Though, sonar has been successfully used to identify SAV, its accuracy has seldomly been thoroughly evaluated during large-scale surveys. In the past, accuracy evaluations of remote sensing data have been limited due to restricted financial and time resources (Goodman et al. 2013); however, accuracy assessments are necessary, as they expresses the degree of correctness of a map classification (Foody 2002), and it aids the user understand how well the remote sensing method depicts reality. According to Goodman et al. (2013), out of 80 peer-reviewed studies on benthic habitat mapping, only 38 included accuracy assessments, with overall accuracy, kappa, and tau being the most common measures. Further, the authors indicated that most studies had missing information on the sampling design and accuracy assessment, which can lead to accuracy misinterpretations. Hence, the authors suggested that studies that include remote sensing components, should incorporate detailed descriptions of the sampled area and the sampling design. Also, they advised that these studies should explain the reason for the chosen accuracy measures and validation methods.

In remote sensing methods, accuracy assessments should be common practice to evaluate signal interpretation (whether optic or acoustic) by comparing it to *in situ* samples; especially if the data generated is going to be used by resources managers to detect change and make policy decisions; otherwise, management decisions may not be appropriate (Green et al. 1996). To address the lack of accuracy assessments and to standardize sonar remote sensing accuracy reports for SAV identification utilizing single-beam sonar, this document was generated. This study focused on evaluating the accuracy of the Lowrance/Biobase single-beam sonar system along with underwater video as a signal verification method. The Biobase system is an automated cloud-based SAV signal detection method. To evaluate the sonar's accuracy, underwater video was obtained simultaneously with the sonar samples. This analysis is based on data collected during a monitoring project in Albemarle Sound (AS).

Sonar technology utilizes the characteristics of sound as it propagates through water to produce useful information. The application of sonar for SAV detection was first well documented by McCarthy (1997), where the author documented that the air bubbles and the tissue in the *Zostera marina* leaves had a unique acoustic return signal (echo). These findings were further affirmed by Wilson and Dunton (2009), where they confirmed the ability of the sonar to detect a unique acoustic signature from various SAV species. The use of sonar in SAV monitoring advanced further after Sabol et al. (1998) developed the first SAV automated sonar signal detection system (SAVEWS). Since this development, sonar has been used to map SAV beds in lakes and estuaries (Sabol et al. 1998; Sabol et al. 2002; Tseng 2009; Kenworthy et al. 2012; Barrell et al. 2015; Valley et al. 2015; Bučas et al. 2016; Howell and Richardson 2019).

There are different ways to directly or indirectly evaluate the accuracy of a method. Overall accuracy is a common accuracy analysis in remote sensing; it evaluates how often a map producer correctly classified a habitat, and it is often reported as a percentage. Though widely used, overall accuracy lacks information about potential sources of error, which are necessary to thoroughly evaluate a remote sensing technology (Congalton and Green 2008). A more refined accuracy analysis includes confusion or error matrices. Congalton (1991) suggested that error matrices should be a standard reporting convention for remotely sensed data. An error matrix is a square array which shows the sampling points assigned to a category (e.g., SAV present or SAV absent) as verified with *in situ* samples (Table 14). It also provides information about errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification. From the error matrix, it is possible to calculate producer’s and user’s accuracy.

The producer’s accuracy describes how well a category is classified. In the example from Table 14, the sonar algorithm was very effective at classifying SAV present (83.33%) but not very good as classifying SAV absent (60%). User’s accuracy or reliability indicates the probability that a classification represents an actual category on the ground. The producer’s and user’s accuracies are valuable for habitat maps, as they can help assess the accuracy of a method at classifying certain habitat types (i.e., SAV).

Other accuracy assessments have been proposed; for example, area under the curve (AUC), kappa coefficient (KHAT), and tau; however, these metrics have flaws. AUC is more commonly used for medical purposes to evaluate the accuracy of a diagnostic test and does not identify sources of error (Kumar and Indrayan 2011). The kappa coefficient (KHAT), developed by Cohen (1960), incorporates off-diagonal elements in an error matrix. Additionally, it tests whether the results in the error matrix are better than a random result. In other words, kappa accounts for correct classification due to chance (Rosenfield and Fitzpatrick-Lins 1986). However, research indicates that kappa may not completely reflect the reality of the data (Rodericks 2016), as kappa values and overall accuracy values tend to disagree when many zeroes are present in the data. In SAV sonar sampling, the data frequently has many zeros (i.e., SAV absent), so kappa would not be a good fit for SAV surveys. Additionally, Stehman (1997) caution the use of kappa, as it draws heavily on the margin proportions of the error matrix; rather, he suggested reporting the overall accuracy and the error matrix with user's and producer's accuracy as a standard. Tau accuracy, developed by Ma and Redmond (1995), is easier to interpret than kappa; however, Smits and Dellepiane (1999) suggested that this metric may not be very useful, as it is necessary to know sampling probabilities before analyzing the data. Based on this evidence, I concluded that overall accuracy, an error matrix, and user's and producer's accuracies were the most adequate accuracy assessment for this study.

The purpose of this study was to evaluate the accuracy of the Lowrance/Biobase single-beam sonar at detecting SAV in AS by calculating overall accuracies, error matrices, including producer's and user's accuracies. Further, I explored how accuracy could be affected by the distance between the sonar and video samples, and by SAV abundance. Finally, I evaluated the adequacy of the underwater video as a sonar verification method. This study was based on data collected at 10 sentinel sites in AS in two different seasons for two years (Chapter 2).

Materials and Methods

In the spring and fall of 2015 and 2016, I conduced SAV surveys at 10 established sentinel sites (SS) in AS (Appendix D). Chapters 1 and 2 in this dissertation addressed the importance and characteristics of the AS. The SS were monitored using sonar and video, as described in Chapter 2. Each of these SS were monitored with 40 transect lines, 25 m apart, perpendicular to the shore. The lines were selected *a priori* using the systematic approach described in (Kenworthy et al. 2012). One hundred randomly selected video points were chosen as a SAV sonar signal verification method.

The video data was classified as SAV present (1) or absent (0) and digitized in ArcGIS (ESRI 2011). Next, each video point was matched to the nearest sonar point; however, to assess whether the distance between the sonar and video points affected the sonar verification, I matched each video to sonar points at four different distance thresholds (1, 3, 6, and 10 m). If two or more sonar points with opposing SAV classifications were within a given distance threshold, only the closest sonar point to the video point was retained. Then, the SAV present verification percent (i.e., present user's accuracy) (Equation 6) and the SAV absent verification percent (i.e., absent user's accuracy) (Equation 7) were calculate for each of the distance thresholds for each sampling event (2 years and 2 season) at each SS. I chose the SAV present-absent verification percent to assess the effect of distance and percent occurrence on accuracy, as this measure can be used to identify potential sources of errors as opposed to overall accuracy.

$$\text{SAV present verification percent} = \frac{Total\ SAV\ present\ video\ points}{Total\ expected\ SAV\ present\ video\ points}\ X\ 100 \qquad (6)$$

$$\text{SAV absent verification percent} = \frac{Total\ SAV\ \text{absent}\ video\ points}{Total\ expected\ SAV\ \text{absent}\ video\ points}\ X\ 100 \tag{7}$$

I expected that SAV percent occurrence (bed density proxy) would affect accuracy; hence, I estimated percent occurrence at each sentinel site for each sampling event (Equation 8). I used Microsoft Excel to estimate the verification and occurrence percentages.

$$\text{SAV percent occurrence} = \frac{\text{Total sonar positive points}}{\text{Total sonar points}}\ X\ 100 \tag{8}$$

I selected the linear regression function in SPSS (IBM 2012) to examine the effect that distance and percent occurrence had on SAV present-absent varication percentages (present-absent user's accuracy).

The overall percent accuracy was estimated by Equation 9:

$$Accuracy\ \% = \frac{True\ Positive\ Points + True\ Negative\ Points}{Video\ Points} \times 100 \tag{9}$$

True positive points were points where both, the sonar signal and the video, agreed on the presence of SAV, and true negative points were where both, the sonar signal and the video, agreed on SAV absence. Total video points were, the total *in situ* points taken.

The overall accuracy was calculated utilizing the 'caret' package for R (Kuhn 2016). Error matrixes like the example in Table 14 were created partially with information obtained from the 'caret' package for R (Kuhn 2016), but user's and producer's (Equations 10 and 11) accuracies were calculated in Excel spreadsheets. For all accuracy metrics, I chose to compare the sonar to video at the 10-m threshold, as the distance between video and sonar was not significant ($p > 0.05$), and the 10-m threshold would allow me to include the most sampling points.

$$Producer's\ accuracy\ (SAV\ present) = \frac{True\ Positive\ Points}{\text{False Positive } Points}\ x\ 100 \quad (10)$$

$$Producer's\ accuracy\ (SAV\ absent) = \frac{True\ Absent\ Points}{\text{False } Absent\ Points}\ x\ 100 \quad (11)$$

Results

A total of 3,749 video-verification samples were taken at the 10 SS during the 2015 and 2016 spring and fall samplings. Though, distance between the video and sonar did not have a significant effect ($p > 0.05$) on SAV present-absent verification percent, SAV present verification percent increased with increasing SAV presence ($B=1.36$, $DF=1$, $p<0.05$; Figure 16). Almost a mirror-image with a negative slope, SAV absent percent verification decreased with increasing percent occurrence ($B=-0.78$, $DF=1$, $p<0.05$; Figure 17). The total SAV present verification percentage was 38.51%; whereas, the total SAV absent verification percentage was 92.59% at the 10-m distance threshold.

The overall accuracy was 85.62% (Table 15). The user's accuracy was very high for SAV absent with 91.06% of the data correctly classified as absent; however, only 43.46% was correctly classified as SAV present. A complete error matrix and producer's and user's accuracy matrices for each site and each sampling event is provided in Appendix G.

Discussion

Single-beam sonar has been successfully used to monitor SAV in low-visibility regions, where optical (satellite and aerial photography) survey methods are not feasible. The ability of the sonar to detect SAV has been clearly established in lab settings (McCarthy 1997; Wilson and Dunton 2009) and field surveys (Valley and Drake 2005; Winfield et al. 2007; Tseng 2009; Kenworthy et al. 2012; Bučas et al. 2016; Helminen et al. 2019), but rigorous accuracy assessments for sonar SAV surveys are seldomly reported; yet, accuracy reporting is essential in any remote sensing project (Congalton 1991). In this study, I compared sonar SAV signal interpretation to underwater video from data collected at 10 SS. As expected, overall accuracy was high (85.62%); however, this accuracy measure failed to provide a true picture about the accuracy of the sonar, and the video's ability to works as the sonar's verification method.

Accuracy measurements were highly affected by bed density. This was first evident in the strong relationship between SAV occurrence and absent-present verification percentages. Further, SAV present verification percent (present producer's accuracy) was only 38.51% and SAV present user's accuracy was 43.46%; whereas, areas with no SAV tended to have higher accuracy: SAV absent verification percent (absent producer's accuracy) was 92.59%, and absent user's accuracy was 91.06%. Due to the vast literature that has clearly established the sonar's ability to detect SAV in various fresh and saltwater habitats (McCarthy 1997; Sabol et al. 2002; Valley and Drake 2005; Winfield et al. 2007), the low accuracy dependence on bed density is likely due to a methodological issue rather than the sonar's misclassification. These classification errors can potentially be attributed to a combination of three factors; 1) a co-location error, 2) different sampling rates between the sonar and the camera, and 3) differences in instrument footprint.

Re-acquiring a waypoint for SAV presence determined from the sonar was imprecise. The WAAS-GPS used in this survey had an accuracy ± 3.0 m, making it very difficult to return to the exact position of the sonar detection point, especially in windy conditions. Theoretically, the two positions could be as much as 6 m apart. The survey frequently encountered discontinuous and patchy SAV distribution, so small deviations between the positions of the sonar and the camera drop can lead to a preponderance of "false negative" classifications where SAV presence is expected based on the sonar, but not detected in the video. However, co-location is likely not a major issue, as the analysis revealed that the distance between the sonar and video did not significantly affect verification percentages. Therefore, the difference in sampling rates may play a more significant role. The sonar's higher sampling rate (~every 2 m) makes it more likely to detect small SAV patches that may be difficult to relocate precisely with a single drop of the camera. This argument was supported by the decreased verification in SAV presence as percent occurrence decreased (i.e., patchier sites). On the other hand, false negative detections were much less of a problem when SAV coverage was low, hence there was better agreement between the sonar and the camera in detecting the absence of SAV. Other studies have encountered similar issues, Stevens et al. (2008) compared sonar to video agreement in the Puget Sound, and they also found high agreement between the sonar and video in bare (91.6%) and dense SAV beds areas (76.4%), but the agreement was very low in patchy areas (43.5%).

Although, video and sonar disagreements were likely overestimated due to methodology errors; these low accuracies can be concerning, as it's difficult to have a clear understanding about the sonar's detection true margin of error. Knowing margins of error is especially important when these surveys are intended to identify changes in inter- and intra-annual SAV distribution and make policy decisions. Kenworthy et al. (2012) initially developed the NC SAV monitoring protocol, which was the guideline I used for these surveys, with the objective of detecting at least 10% inter-annual change. However, if the margin of error is larger than 10%, I cannot confidently determine if SAV abundance changes are due to true changes or due to methodological errors. Schultz (2008) indicated that resources managers need precise quantification of SAV losses before the losses become too large. Therefore, uncertainty about SAV presence classification complicates the ability of the surveys to detect change.

Possible solutions to the "verification" dilemma include, one or some of the following options; 1) improving the accuracy of positioning by incorporating real time kinematic GPS (RTK-GPS) into the survey equipment, 2) modifying the camera drop method to intensify the sampling frequency either by increasing number of drops or deploying the camera in a series of drift transects around the sonar point, 3) in-water samples directly on the sonar's footprint. The first two modifications to the verification method could possibly improve the agreement between the sonar and video. However, these will be accompanied by increasing costs and longer survey time, thus reducing the overall efficiency and benefits of the sonar method as a viable SAV survey and monitoring option. Additionally, I am not confident that the first two options would greatly increase SAV presence-absence verification, as this study indicated that distance between the sonar and video did not significantly improved verification. A more robust, yet more time consuming option, would be to take in-water signal verification samples directly in the sonar's foot print (area covered by the sonar's acoustic cone), similar to the method described by McCarthy (1997) and Valley (2005). The latter option is likely to yield higher agreement between the sonar and this verification method but add both time and cost.

Conclusions and Recommendations

With any remote sensing methodology, it is important to verify the signal interpretation, so the data collected, and the method can have scientific credibility. The sonar remote sensing community has not been effective at reporting detailed verification assessments or determining a standardized accuracy reporting. Hence, I carried out this sonar signal accuracy study for the sentinel sites at AS. After searching the literature for sonar accuracy and its reliability in detecting SAV, it is clear that sonar is effective at detecting SAV under various environmental conditions; however, this study unearthed low SAV-presence accuracy values. After taking a closer look to the data, it is evident that the low values are likely due to a methodological issue, rather than true sonar misclassifications; nonetheless, these low values may raise a flag in the sonar's ability to reliably detect change. The sonar's reliability is of importance, especially as these data may be used by state and federal agencies to make management policy decisions. Hence, it is of utmost importance to reassure state and federal agencies about the reliability of the sonar at detecting SAV through rigorous sonar accuracy assessments in low-salinity regions in NC.

It is possible to immediately improve sonar accuracy reporting and signal evaluation at the sentinel sites through some minor modifications to the methodology described in this study. If the objective at the sentinel sites is to assess SAV abundance and trends, accuracy verification efforts should be focused on areas with SAV, rather than bare areas. Based on the data reported in this dissertation, we now have a better understanding of SAV beds distribution at the sentinel sites, so stratified random sampling with a special focus on SAV beds should be possible. Stehman and Czaplewski (1998) recommended stratified random sampling over random or systematic sampling for verification sampling in remote sensing, as this approach would increase verification sampling at the feature of interest (i.e., SAV) and increase accuracy.

Other improvements to sonar accuracy reporting and signal evaluation will take more effort and require additional studies; however, these studies are necessary to reassure agencies about the sonar's reliability. Laboratory and field experiments evaluating the sonar's system (i.e.

Lowrance-Biobase system) should be conducted. Field experiments should directly sample within the sonar’s footprint. Similar studies have been conducted in other coastal habitats (McCarthy 1997) and lake (Valley and Drake 2005). These studies will likely yield increased sonar accuracy, which will help more accurately detect change in NC low-salinity regions.

References

Barrell, J., J. Grant, A. Hanson, and M. Mahoney. 2015. Evaluating the complementarity of acoustic and satellite remote sensing for seagrass landscape mapping. *International Journal of Remote Sensing* 36: 4069–4094. doi:10.1080/01431161.2015.1076208.

Bučas, M., A. Šaškov, A. Šiaulys, and Z. Sinkevičienė. 2016. Assessment of a simple hydroacoustic system for the mapping of macrophytes in extremely shallow and turbid lagoon. *Aquatic Botany* 134: 39–46. doi:10.1016/j.aquabot.2016.06.009.

Christiaen, B., L. Ferrier, P. Dowty, J. Gaecle, and H. Berry. 2017. *Puget Sound seagrass monitoring report monitoring year 2015*. Olympia, Washington.

Cohen, J. 1960. A coefficient of agreement for nomical scales. *Educational and Psychological Measurement* XX: 37–46.

Congalton, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment* 37: 35–46.

Congalton, R.G., and K. Green. 2008. *Assessing the accuracy of remotely sensed data: principles and practices*. CRC press.

Dobson, J.E., E.A. Bright, R.L. Ferguson, D. Field, L.L. Wood, K.D. Haddad, H. Iredale III, et al. 1995. *NOAA Coastal Change Analysis Program (C-CAP): Guidance for regional implementation*. Vol. NOAA Techn.

ESRI. 2011. ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

Foody, G.M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80: 185–201. doi:10.1016/S0034-4257(01)00295-4.

Goodman, J.A., S.J. Purkins, and S.R. Phinn. 2013. Coral reef remote sensing. *A guide for mapping, monitoring and management. 436p*. Springer.

Green, E.P., P.J. Mumby, A.J. Edwards, and C.D. Clark. 1996. A review of remote sensing for the assessment and management of tropical coastal resources. *Coastal Management* 24: 1–40. doi:10.1080/08920759609362279.

Helminen, J., T. Linnansaari, M. Bruce, R. Dolson-Edge, and R.A. Curry. 2019. Accuracy and precision of low-cost echosounder and automated data processing software for habitat mapping in a large river. *Diversity* 11: 1–18. doi:10.3390/d11070116.

Howell, A.W., and R.J. Richardson. 2019. Correlation of consumer grade hydroacoustic signature to submersed plant biomass. *Aquatic Botany* 155. Elsevier: 45–51. doi:10.1016/j.aquabot.2019.02.001.

IBM. 2012. IBM SPSS Advanced Statistics 23. *IBM Corporation*: 1–111. doi:10.1080/02331889108802322.

Kenworthy, W.J., C.A. Buckel, D.E. Carpenter, D.B. Eggleson, D. Field, C.S. Krahforst, and J.J. Luczkovich. 2012. *Development of submerged aquatic vegetation monitoring protocols in*

North Carolina. Morehead City, North Carolina.

Kuhn, M. 2016. Caret: Classification and Regression Training. R package version 6.0-71.

Kumar, R., and A. Indrayan. 2011. Receiver Operating Characteristic (ROC) curve for medical researchers. *Indian pediatrics* 48: 277–287. doi:10.1007/s13312-011-0055-4.

Ma, Z., and R.L. Redmond. 1995. Tau coefficient for accuracy assessment of classification of remote sensing data. *Photogrametric engineering and remote sensing society* 61: 435–439.

McCarthy, E.M. 1997. Acoustic characterization of submerged aquatic vegetation. In *SACLANTCEN Proceedings Series CP-45, High Frequency Acoustics in Shallow Water*, ed. N. G. Pouliquen, E. Bergem, and A. P. Lyons, 362–369. Lerici, Italy: NATO SACLANT Undersea Research Centre.

Moore, K.A., R.J. Orth, and D.J. Wilcox. 2009. Assessment of the abundance of submersed aquatic vegetation (SAV) communities in the Chesapeake Bay and its use in SAV management. In *Remote sensing and geospatial technologies for coastal ecosystem assessment and management, lecture notes in geoinformation and cartography*, ed. X. Jang, 233–257. Berlin: Springer-Verlang. doi:10.1007/978-3-540-88183-4.

NCDEQ. 2016. *North Carolina Coastal Habitat Protection Plan Source Document*. Morehead City, North Carolina.

Rodericks, I.K. 2016. A comparison of qualitative and quantitative data collection techniques to assess mapping accuracy in the Florida Keys. Nova Southeastern University.

Rosenfield, G.H., and K. Fitzpatrick-Lins. 1986. A coefficient of agreement as a measure of thematic classification accuracy. *American Society for Photogrammetry and Remote Sensing* 52: 223–227.

Sabol, B.M., R.E.J. Melton, R. Chamberlain, P. Doering, and K. Haunert. 2002. Evaluation of a digital echosounder system for detection of submersed aquatic vegetation. *Estuaries* 25: 133–141. doi:10.1007/BF02696057.

Sabol, B.M., R.E. Meltona, and R.. Kasul. 1998. Method and apparatus for hydroacoustic detection of submersed aquatic vegetation. Washington, District of Columbia: U.S. Patent Office.

Schultz, S.T. 2008. Seagrass monitoring by underwater videography: Disturbance regimes, sampling design, and statistical power. *Aquatic Botany* 88: 228–238. doi:10.1016/j.aquabot.2007.10.009.

Smits, P.C., and S.G. Dellepiane. 1999. Quality assessment of image classification algorithms for land-cover mapping: A review and a proposal for a cost-based approach. *International Journal of Remote Sensing* 20: 1461–1486. doi:10.1080/014311699212560.

Stehman, S. V. 1997. Selecting and interpreting measures of thematic classification accuracy. *Remote Sensing of Environment* 62: 77–89. doi:10.1016/S0034-4257(97)00083-7.

Stehman, S. V., and R.L. Czaplewski. 1998. Design and analysis for thematic map accuracy assessment: fundamental principles. *Remote Sensing of Environment* 64: 331–344.

doi:10.1016/S0034-4257(98)00010-8.

Stevens, A.W., J.R. Lacy, D.P. Finlayson, and G. Gelfenbaum. 2008. *Evaluation of a single-beam sonar system to map seagrass at two sites in northern Puget Sound, Washington*. *Scientific investigations report 2008-5009*. Reston, Virginia.

Tseng, Y.-T. 2009. Recognition and assessment of seafloor vegetation using a single beam echosounder. Curtin University of Technology.

Valley, R.D., and M.T. Drake. 2005. *Accuracy and precision of hydroacoustics estimates of aquatic vegetation and the repeatability of whole-lake surveys: Field tests with a commercial echosounder*. *Minnesota Department of Natural Resources Investigational Report*.

Valley, R.D., M.B. Johnson, D.L. Dustin, K.D. Jones, M.R. Lauenstein, and J. Nawrocki. 2015. Combining hydroacoustic and point-intercept survey methods to assess aquatic plant species abundance patterns and community dominance. *Journal of Aquatic Plant Management* 53: 121–129.

Wilson, P.S., and K.H. Dunton. 2009. Laboratory investigation of the acoustic response of seagrass tissue in the frequency band 0.5–2.5 kHz. *The Journal of the Acoustical Society of America* 125: 1951–1959. doi:10.1121/1.3086272.

Winfield, I.J., C. Onoufriou, M.J. O'Connell, M. Godlewska, R.M. Ward, A.F. Brown, and M.L. Yallop. 2007. Assessment in two shallow lakes of a hydroacoustic system for surveying aquatic macrophytes. *Hydrobiologia* 584: 111–119. doi:10.1007/s10750-007-0612-y.

Figures

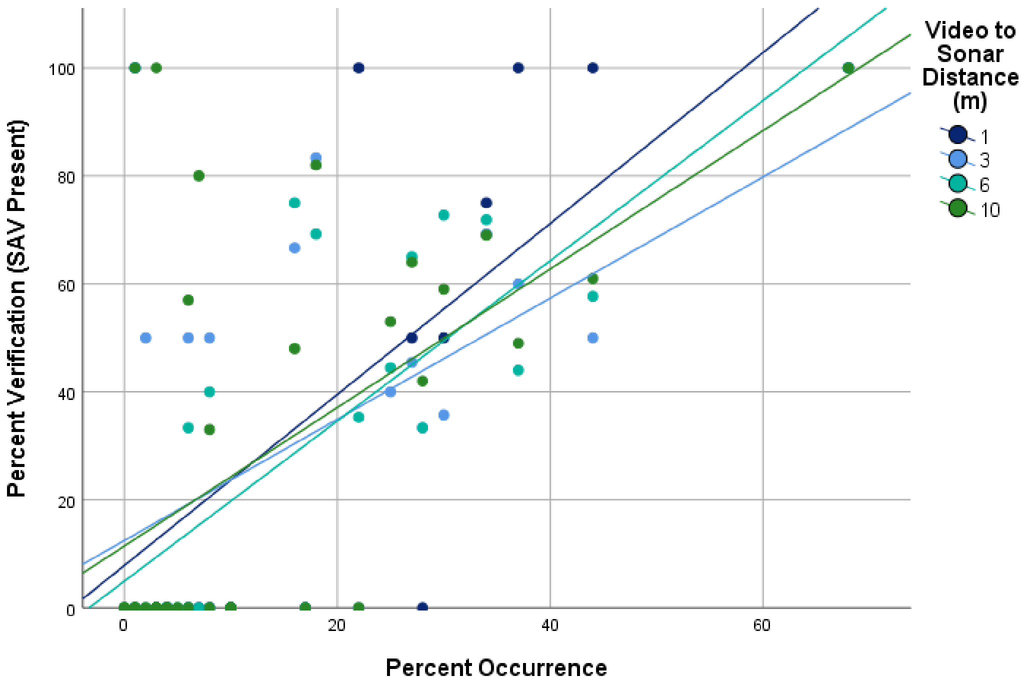


Figure 16. Percent SAV occurrence and SAV present percent verification at the 10 sentinel sites, in the 2015 and 2016 spring and fall with video to sonar distance as a factor. Raw data available in Appendix I.

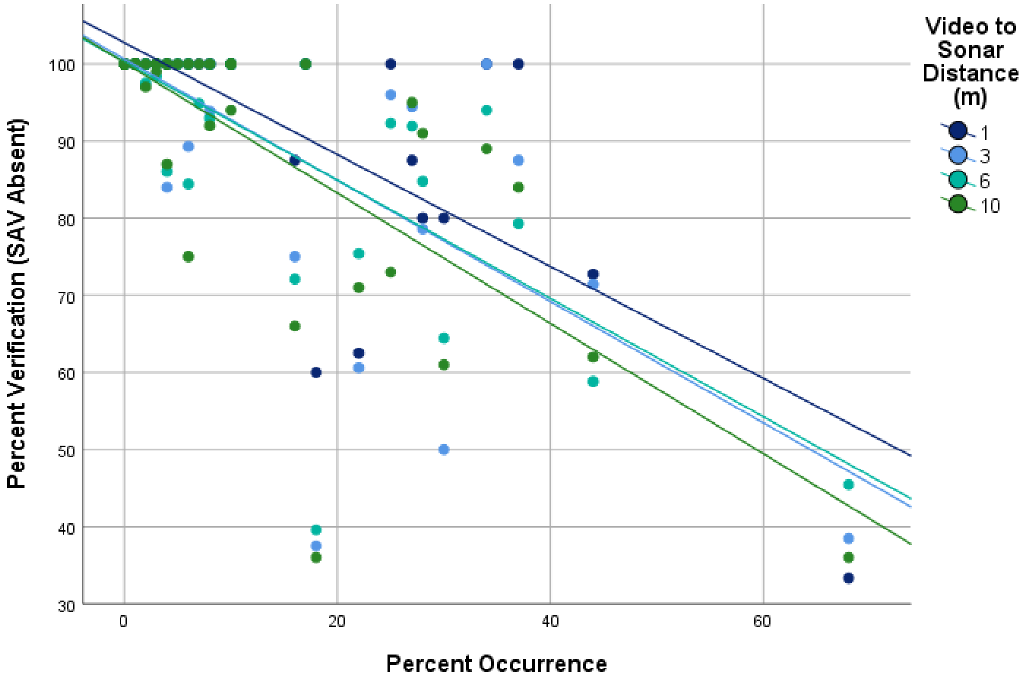


Figure 17. Percent SAV occurrence and SAV absent percent verification at the 10 sentinel sites, in the 2015 and 2016 spring and fall with video to sonar distance as a factor. Raw data available in Appendix H.

Tables

Table 14. Example of an error matrix. Biobase algorithm classification for sonar data and verified by underwater video..

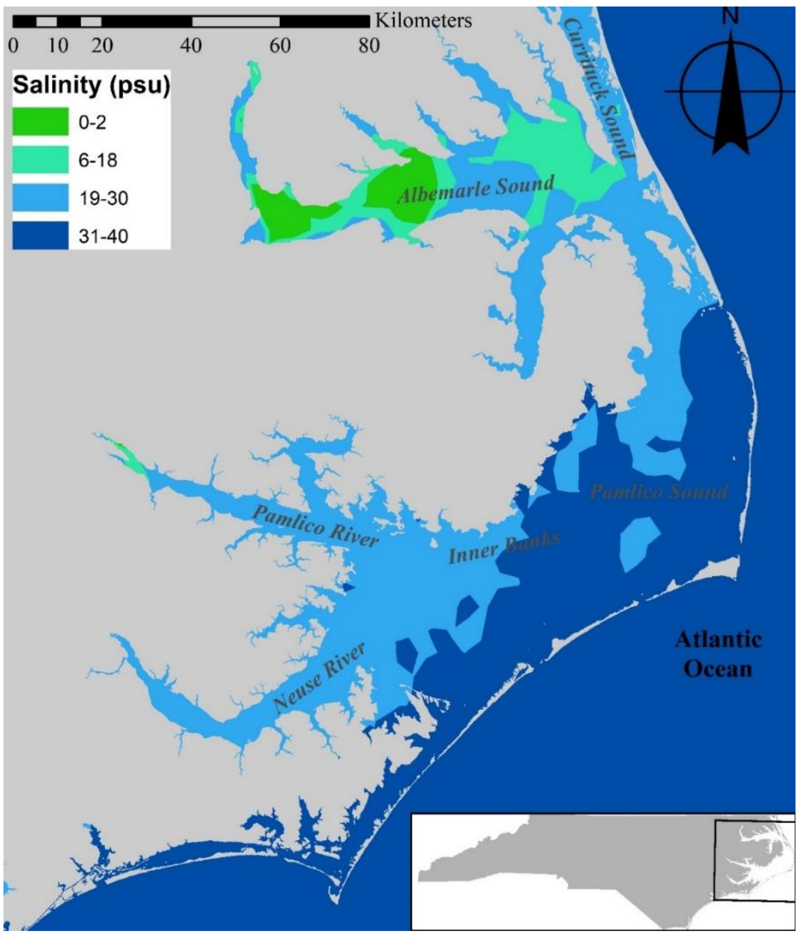
	Verification Data (underwater video data)			
Sonar Classification	**SAV Absent**	**SAV Present**	**Row Total**	**User's Accuracy**
SAV Absent	**3**	1	4	**75**
SAV Present	2	**5**	7	**71.43**
Column Total	5	6		
Producer's Accuracy	**60.00**	**83.33**		
Overall Accuracy	**72.73**			

Table 15. Error matrix with overall accuracy and user's and producer's accuracies for all the data collected during the ten sentinel sites in the spring and fall of 2015 and 2016 in the Albemarle Sound, NC. Biobase algorithm classification for sonar data.

	Verification Data (underwater video data)			
Classification	SAV Absent	SAV Present	Row Total	User's Accuracy
SAV Absent	**3024.00**	297.00	3321.00	**91.06**
SAV Present	242.00	**186.00**	428.00	**43.46**
Column Total	3266.00	483.00		
Producer's Accuracy	**92.59**	**38.51**		
Overall Accuracy	**85.62**			

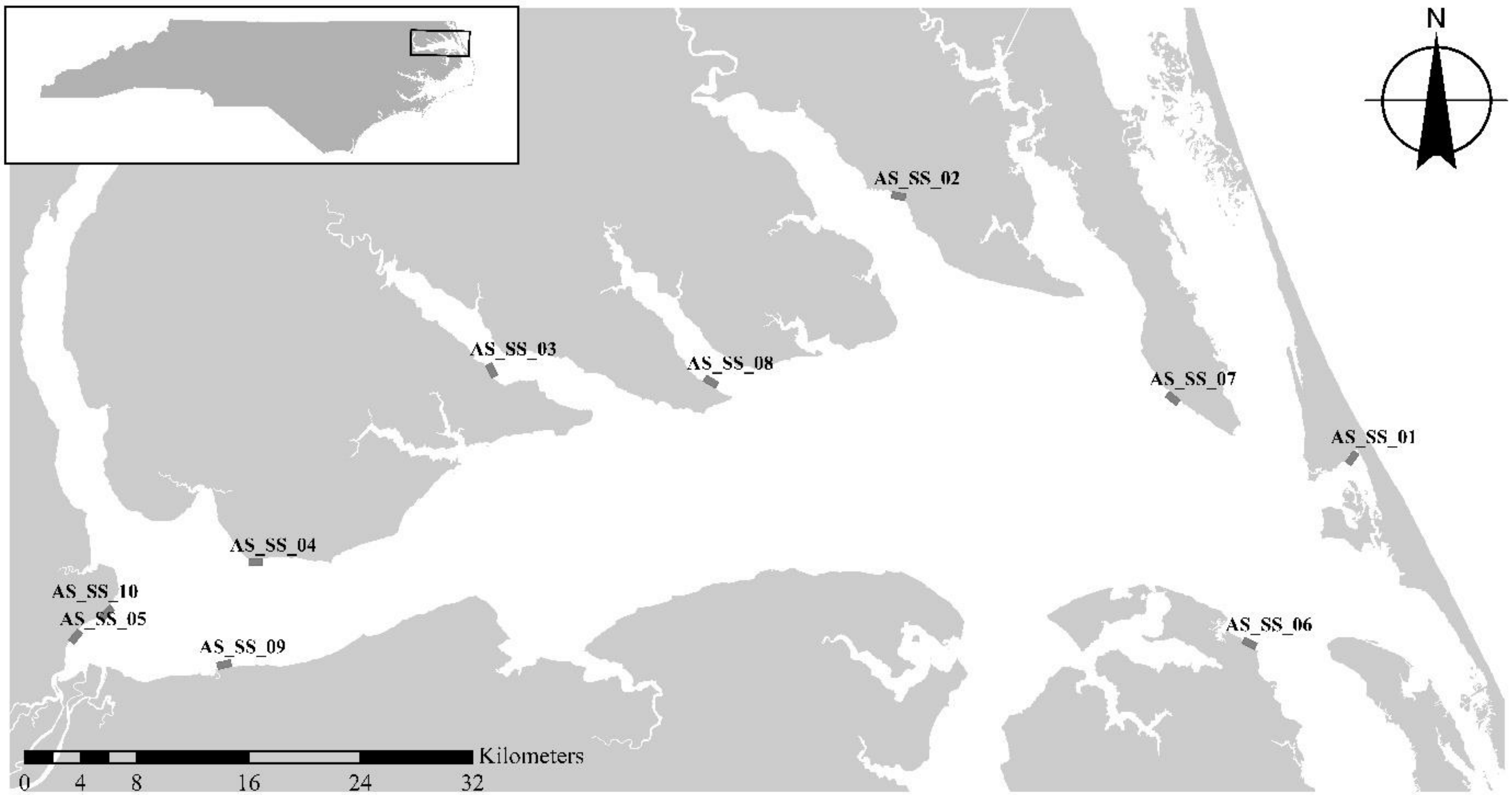
APPENDIX C. NORTH CAROLINA COASTAL REGION WITH SALINITY CONTOURS

Contour lines for salinity zones obtained from the Salwise salinity data for North Carolina. Salwise is a database developed by a UNC-IMS team (N. Lindquist, S. Fegley, and R. Guajardo) with support from the NC Division of Marine Fisheries Coastal Recreational Fishing License grant program (Lindquist and Fegley 2016). Also, the proposed NC low-salinity coastal region classification strata: 1) Currituck Sound, 2) Albemarle Sound, 3) Inner Banks of Western Pamlico Sound, 4) Pamlico River and 5) Neuse River per (Kenworthy et al. 2012).



APPENDIX D. ALBEMARLE SOUND SENTINEL SITES LOCATION AND CODE NAMES

Map of the Sentinel Sites in the Albemarle Sound, along with the coordinates for the Albemarle Sound SAV sentinel sites along with their code names. Coordinate system: NAD 1983 HARN State Plane North Carolina FIPS 3200.



Site #	Site Code	Site Name	Vertix X1	Vertix Y1	Vertix X2	Vertix Y2	Vertix X3	Vertix Y3	Vertix X4	Vertix Y4
1	AS_SS_01	Kitty Hawk	906569.48	260058.4	906161.89	260348.01	906741.12	261163.18	907148.71	260873.56
2	AS_SS_02	Pasquotank	873726.42	279167.97	873821.62	279658.82	874803.33	279468.41	874708.12	278977.56
3	AS_SS_03	Perquimans	845643.9	266551.25	845643.9	266551.25	845198.22	266324.62	844744.95	267215.99
4	AS_SS_04	Edenton	827834.15	252933.25	827837.8	253433.23	828837.77	253425.95	828834.13	252925.96
5	AS_SS_05	Batchelor's Bay South	815994.47	248087.88	815365.84	247310.18	814976.99	247624.49	815605.61	248402.2
6	AS_SS_06	Mann's Harbor	899884.52	247376.4	899655.41	246931.98	898766.57	247390.22	898995.69	247834.63
7	AS_SS_07	North River	893288.95	264977.79	893597.4	265371.3	894384.43	264754.38	894075.97	264360.87
8	AS_SS_08	Little River	861418.48	266026.62	861166.67	265594.66	860302.75	266098.28	860554.56	266530.24
9	AS_SS_09	Mackey's Landing	825546.43	245998.51	826520.6	246224.33	826633.51	245737.25	825659.34	245511.43
10	AS_SS_10	Batchelor's Bay North	817546.68	249054.49	817200.18	249414.96	817921.12	250107.96	818267.62	249747.49

APPENDIX E. DEPTH UNIVARIATE STATISTICS BY SAV OCCURRENCE

Depth univariate statistics by SAV Occurrence: SAV absent (0) and SAV present (1) for the Albemarle Sound Sentinel Sites based on sonar reports.

Site	Year	Season	SAV	Median	Mean	SD	Min.	Max.
AS_SS_01	**2015**	**Spring**	0	1.84	1.85	0.27	0.87	2.5
			1	1.44	1.41	0.3	0.79	1.83
			Total	1.75	1.67	0.35	0.79	2.5
		Fall	0	1.84	1.86	0.24	1	2.41
			1	1.37	1.37	0.23	0.83	2.14
			Total	1.79	1.75	0.32	0.83	2.41
	2016	**Spring**	0	1.9	1.92	0.25	0.86	2.53
			1	1.54	1.48	0.3	0.79	1.97
			Total	1.84	1.81	0.32	0.79	2.53
		Fall	0	2.22	2.23	0.26	0.92	2.83
			1	1.77	1.74	0.4	0.82	2.73
			Total	2.15	2.06	0.39	0.82	2.83
AS_SS_02	**2015**	**Spring**	0	1.91	1.86	0.55	0.79	3.15
			1	0.93	0.99	0.15	0.8	1.75
			Total	1.89	1.82	0.57	0.79	3.15
		Fall	0	2.29	2.27	0.7	1.09	4.07
			1	1.68	1.97	0.76	1.11	3.81
			Total	2.25	2.22	0.72	1.09	4.07
	2016	**Spring**	0	1.95	1.93	0.59	0.82	3.23
			1	1.29	1.34	0.31	0.82	2.43
			Total	1.9	1.88	0.59	0.82	3.23
		Fall	0	2.03	1.98	0.7	1.03	3.49
			1	1.23	1.28	0.22	1.03	3.12
			Total	1.99	1.95	0.7	1.03	3.49
AS_SS_03	**2015**	**Spring**	0	2.63	2.35	0.74	0.79	4.17
			1	1.13	1.16	0.28	0.79	2.73
			Total	2.59	2.3	0.76	0.79	4.17
		Fall	0	2.89	2.67	0.8	1.1	4.73
			1	1.2	1.25	0.21	1.03	1.75
			Total	2.88	2.65	0.81	1.03	4.73
	2016	**Spring**	0	2.67	2.42	0.67	0.85	4.23
			1	1.37	1.42	0.37	0.82	2.91
			Total	2.62	2.36	0.7	0.82	4.23
		Fall	0	2.67	2.44	0.64	0.96	4.23

			1	1.33	1.37	0.25	0.97	2.71
			Total	2.63	2.38	0.67	0.96	4.23
AS_SS_04	**2015**	**Spring**	0	1.61	2.51	1.31	0.83	4.7
			1	1.33	1.3	0.18	0.79	1.71
			Total	1.37	1.71	0.96	0.79	4.7
		Fall	0	1.93	2.14	0.79	1.08	5.19
			1	1.82	1.77	0.26	1.09	2.98
			Total	1.91	2.08	0.74	1.08	5.19
	2016	**Spring**	0	1.87	2.16	0.87	0.85	5.15
			1	1.71	1.71	0.48	0.87	4.96
			Total	1.82	2.03	0.81	0.85	5.15
		Fall	0	1.89	2.13	0.85	1.04	5.15
			1	1.9	1.9	0.27	1.05	4.29
			Total	1.89	2.08	0.76	1.04	5.15
AS_SS_05	**2015**	**Spring**	0	2.4	2.27	0.48	1.04	3.08
			1	2.22	2.12	0.49	1.05	2.79
			Total	2.4	2.26	0.48	1.04	3.08
		Fall	0	2.49	2.38	0.41	0.96	2.95
			1	1.3	1.29	0.11	1.11	1.5
			Total	2.49	2.38	0.42	0.96	2.95
	2016	**Spring**	0	2.41	2.28	0.44	0.84	2.9
			1	1.18	1.21	0.18	0.79	1.63
			Total	2.4	2.26	0.46	0.79	2.9
		Fall	0	2.78	2.68	0.36	1.43	3.23
			Total	2.78	2.68	0.36	1.43	3.23
AS_SS_06	**2015**	**Spring**	0	2.62	2.51	0.69	1.08	3.77
			1	2.59	2.48	0.5	1.08	3.15
			Total	2.62	2.51	0.68	1.08	3.77
		Fall	0	2.76	2.66	0.61	0.86	3.79
			1	1.18	1.19	0.16	0.87	1.59
			Total	2.75	2.64	0.62	0.86	3.79
	2016	**Spring**	0	2.84	2.76	0.64	1.15	3.97
			1	1.5	1.5	0.15	1.22	1.81
			Total	2.84	2.75	0.65	1.15	3.97
		Fall	0	3.27	3.19	0.65	1.06	4.38
			1	1.99	2.16	0.55	1.09	3.9
			Total	3.25	3.17	0.67	1.06	4.38
AS_SS_07	**2015**	**Spring**	0	1.61	1.59	0.2	0.82	2
			1	1.32	1.31	0.25	0.79	1.81
			Total	1.59	1.56	0.22	0.79	2

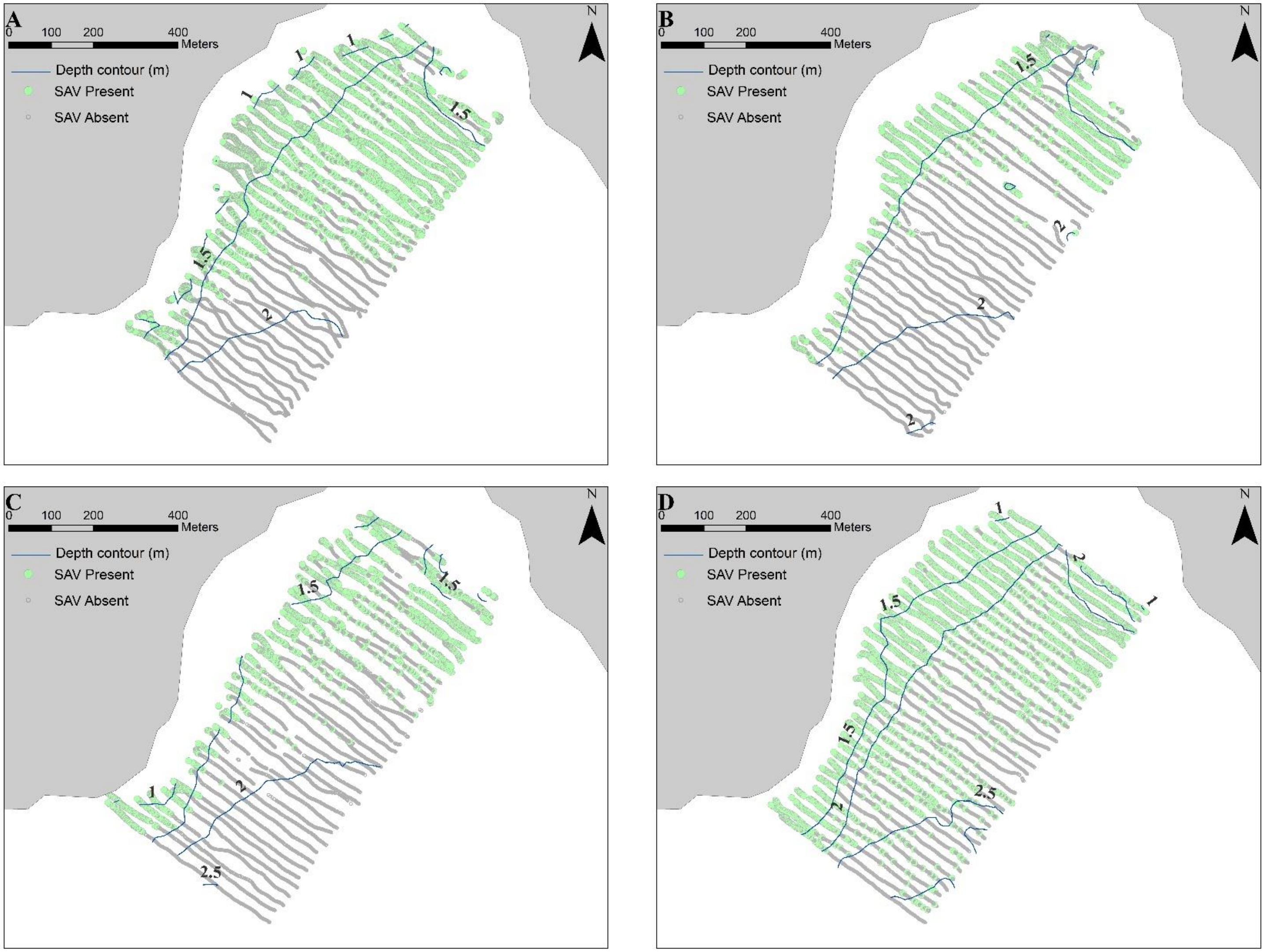
		Fall	0	1.56	1.55	0.18	1.08	1.92
			1	1.3	1.31	0.15	1.08	1.81
			Total	1.55	1.54	0.18	1.08	1.92
	2016	**Spring**	0	1.53	1.54	0.18	0.8	1.91
			1	1.32	1.31	0.13	0.96	1.67
			Total	1.52	1.53	0.19	0.8	1.91
		Fall	0	1.91	1.9	0.18	1.04	2.27
			1	1.76	1.72	0.18	1.12	2.07
			Total	1.9	1.88	0.19	1.04	2.27
AS_SS_08	**2015**	**Spring**	0	1.67	1.7	0.36	0.88	2.46
			1	1.15	1.2	0.19	0.82	1.96
			Total	1.59	1.62	0.38	0.82	2.46
		Fall	0	2	2.03	0.35	1.12	2.98
			1	1.71	1.77	0.38	1.12	2.93
			Total	1.92	1.93	0.38	1.12	2.98
	2016	**Spring**	0	1.73	1.78	0.25	1.19	2.47
			1	1.36	1.36	0.11	1.1	2.01
			Total	1.69	1.74	0.27	1.1	2.47
		Fall	0	1.9	1.91	0.35	1.09	2.73
			1	1.62	1.63	0.31	1.11	2.44
			Total	1.85	1.83	0.36	1.09	2.73
AS_SS_09	**2015**	**Spring**	0	1.51	1.5	0.18	1.04	2.03
			1	1.41	1.42	0.15	1.11	1.81
			Total	1.51	1.5	0.18	1.04	2.03
		Fall	0	1.67	1.66	0.19	1.09	2.11
			1	1.61	1.56	0.19	1.1	1.85
			Total	1.66	1.65	0.19	1.09	2.11
	2016	**Spring**	0	1.86	1.86	0.15	1.07	2.28
			1	1.76	1.74	0.16	1.09	2.18
			Total	1.85	1.85	0.15	1.07	2.28
		Fall	0	1.99	1.99	0.16	1.34	2.58
			1	2.05	2.06	0.03	2	2.11
			Total	1.99	1.99	0.16	1.34	2.58
AS_SS_10	**2015**	**Spring**	0	1.47	1.84	0.85	0.79	3.24
			1	1.13	1.28	0.42	0.8	2.37
			Total	1.47	1.84	0.85	0.79	3.24
		Fall	0	2.69	2.38	0.71	0.85	3.34
			1	0.91	1.27	0.64	0.9	2.7

		Total	2.69	2.38	0.71	0.85	3.34
2016	**Spring**	0	2.49	2.22	0.8	1.03	3.31
		1	1.23	1.27	0.16	1.04	1.68
		Total	2.42	2.19	0.81	1.03	3.31
	Fall	0	2.75	2.46	0.78	1.04	3.47
		1	1.35	1.37	0.17	1.09	1.78
		Total	2.71	2.43	0.79	1.04	3.47
Total		0	1.98	2.14	0.69	0.79	5.19
		1	1.50	1.57	0.42	0.79	4.96
		Total	1.91	2.07	0.69	0.79	5.19

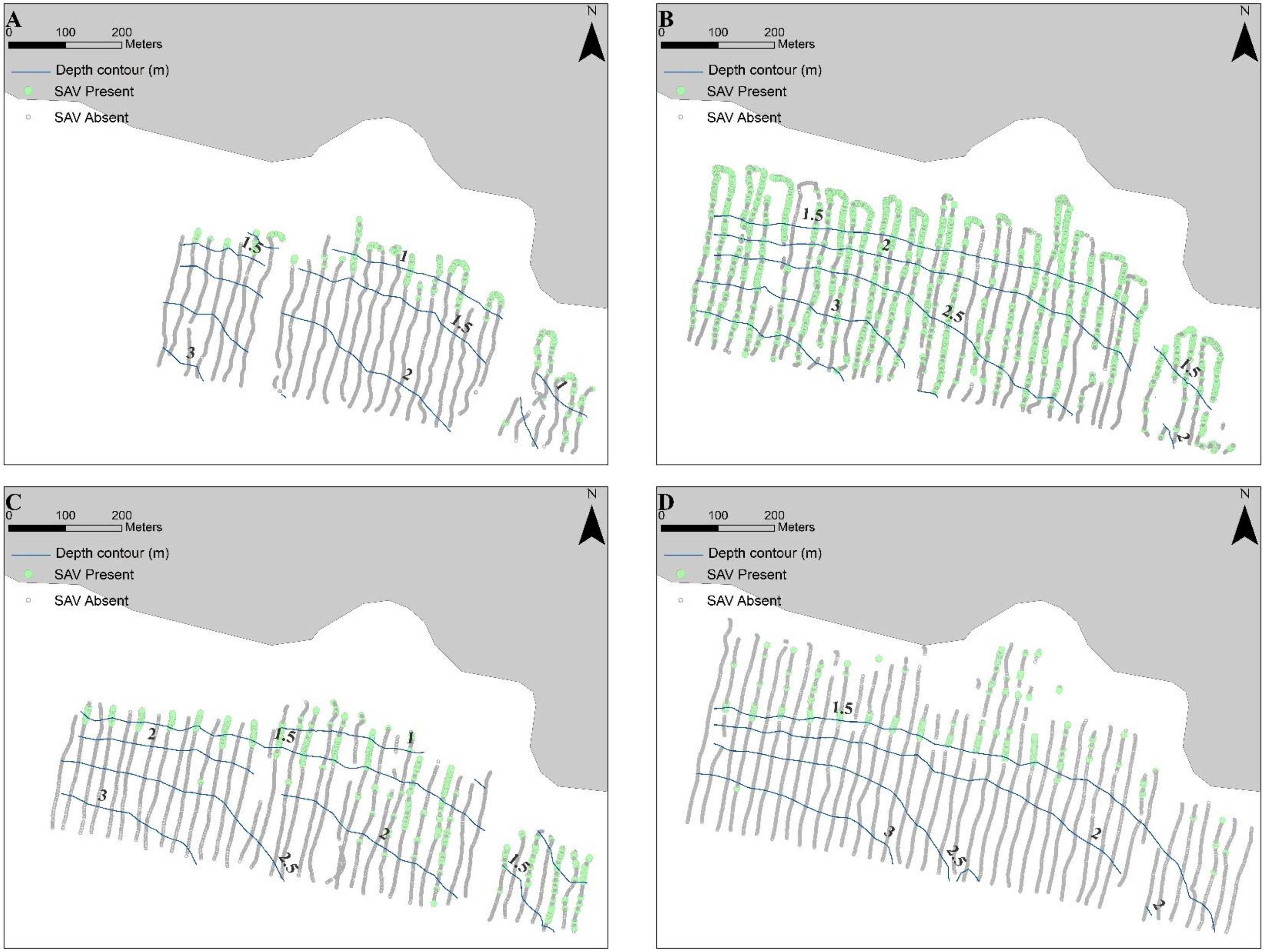
APPENDIX F. SONAR REPORT FROM BIOBASE ANALYSIS FOR ALL SENTINEL SITES

Sonar reports from the Biobase analysis for all sentinel sites. The larger green points represent the sonar SAV present reports; whereas, the smaller black points represent sonar SAV absent reports. Depth contours are also displayed. spring 2015 (A), fall 2015 (B), spring 2016 (C), and fall 2016 (D).

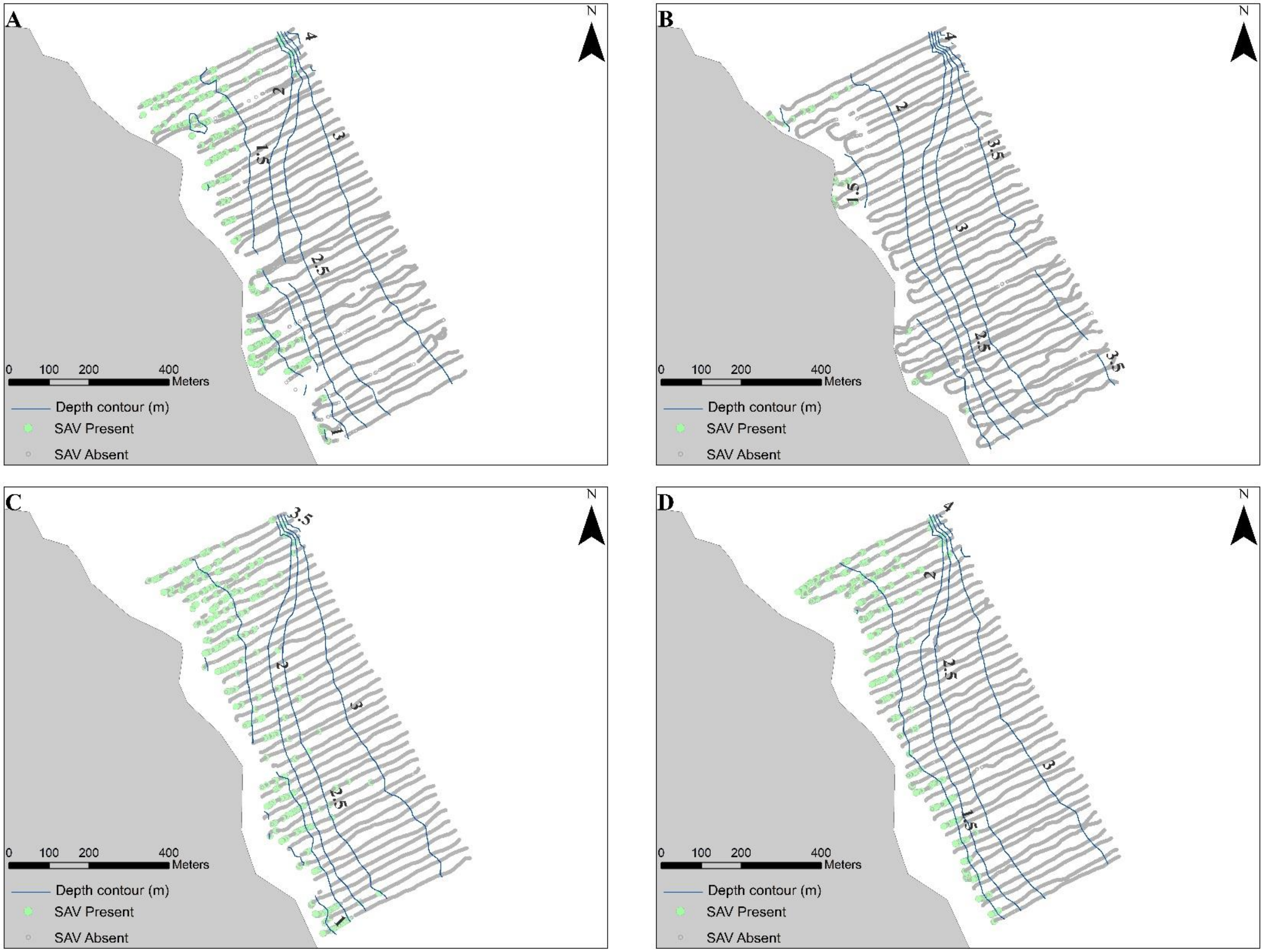
Site 1


A
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
N
1
1
1
1.5
1.5
2
B
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
N
1.5
2
2
2
C
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
N
1.5
1.5
1
2
2.5
D
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
N
1
2
1
1.5
1.5
2
2.5

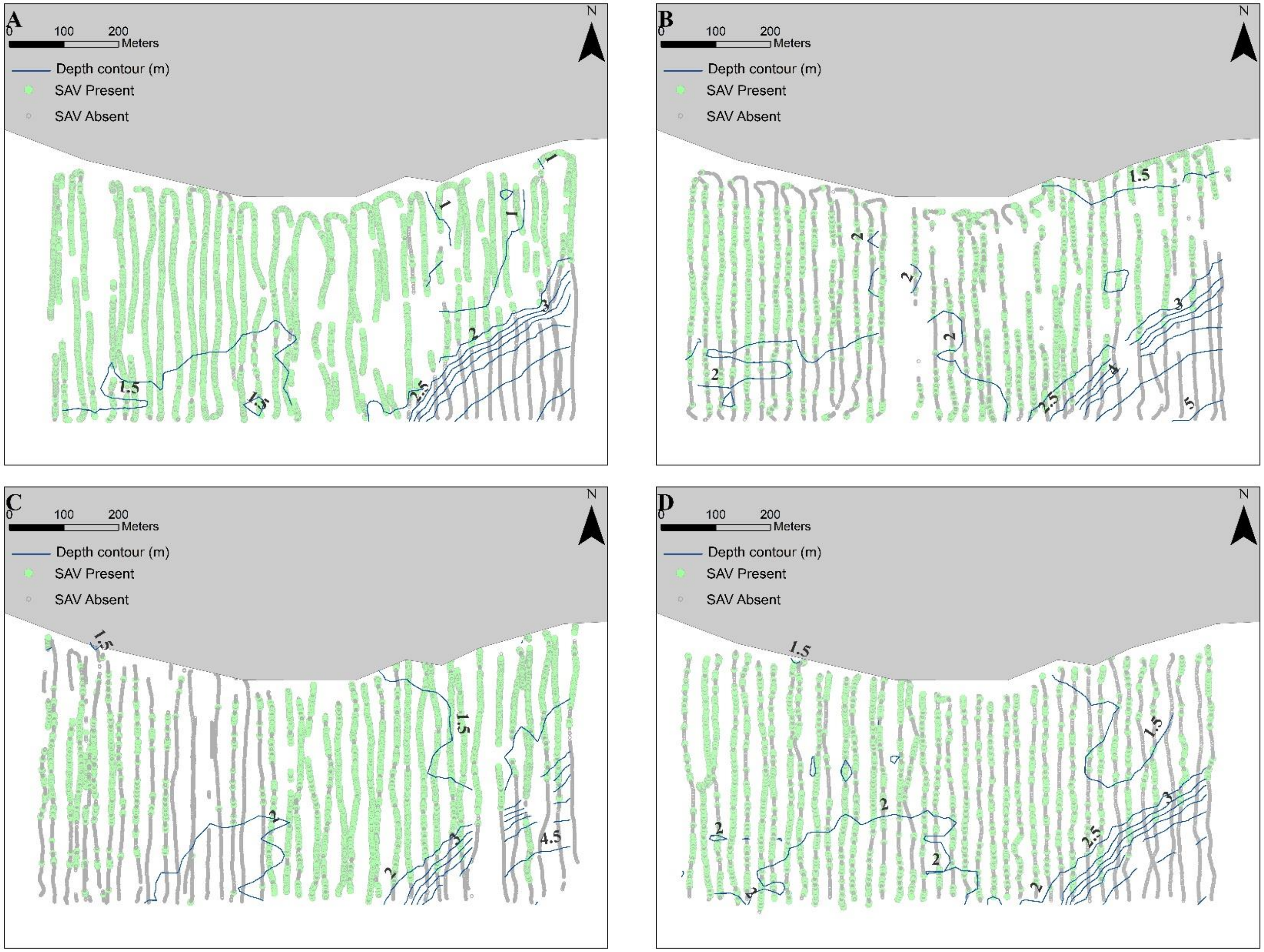
Site 2


A
B
C
D
0
100
200
Meters
N
Depth contour (m)
SAV Present
SAV Absent
1
1.5
2
2.5
3

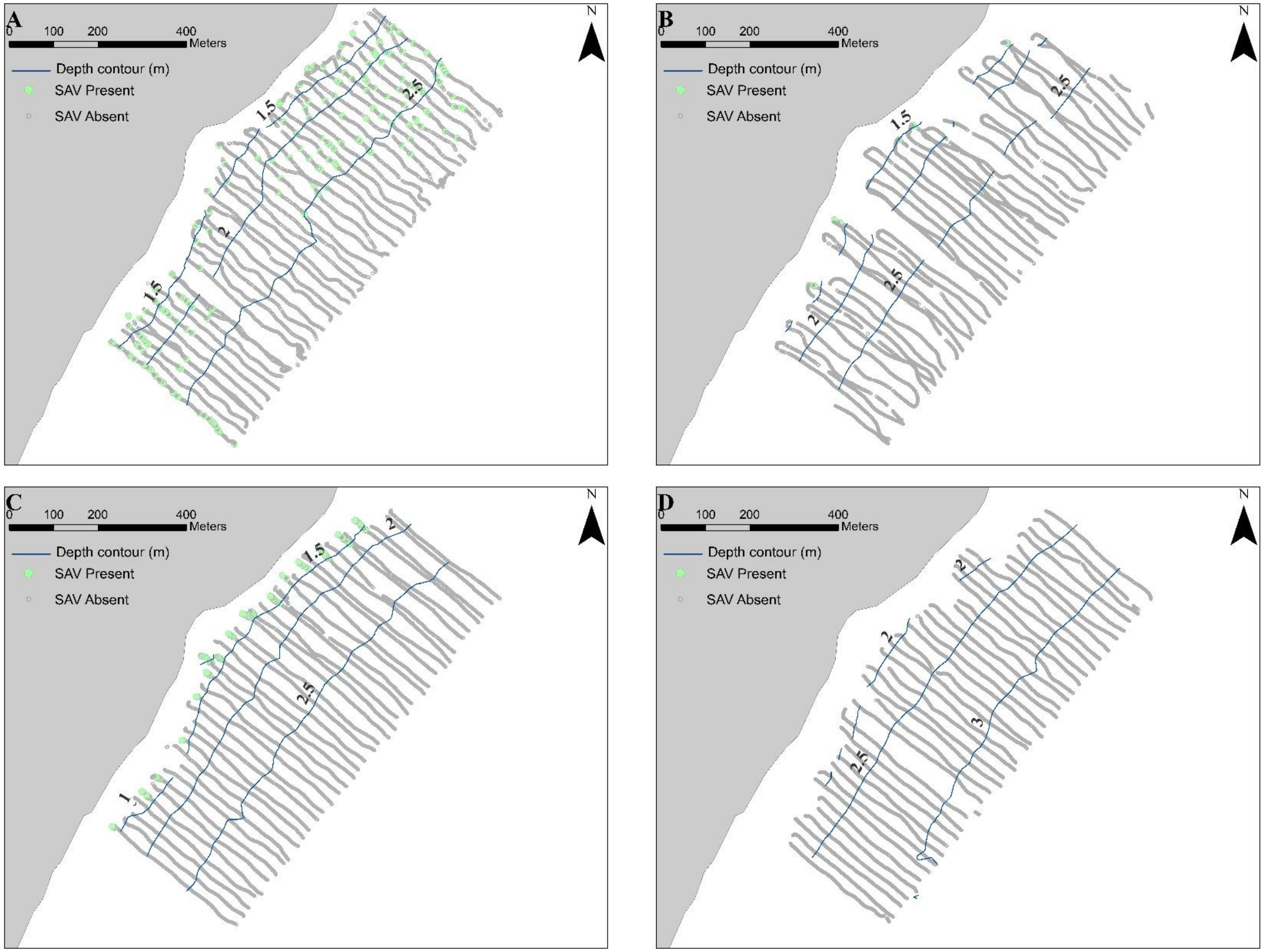
Site 3


A
N
4
2
1.5
3
2.5
1
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
B
N
4
2
3.5
1.5
3
2.5
3.5
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
C
N
3.5
2
3
2.5
1
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
D
N
4
2
2.5
3
1.5
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent

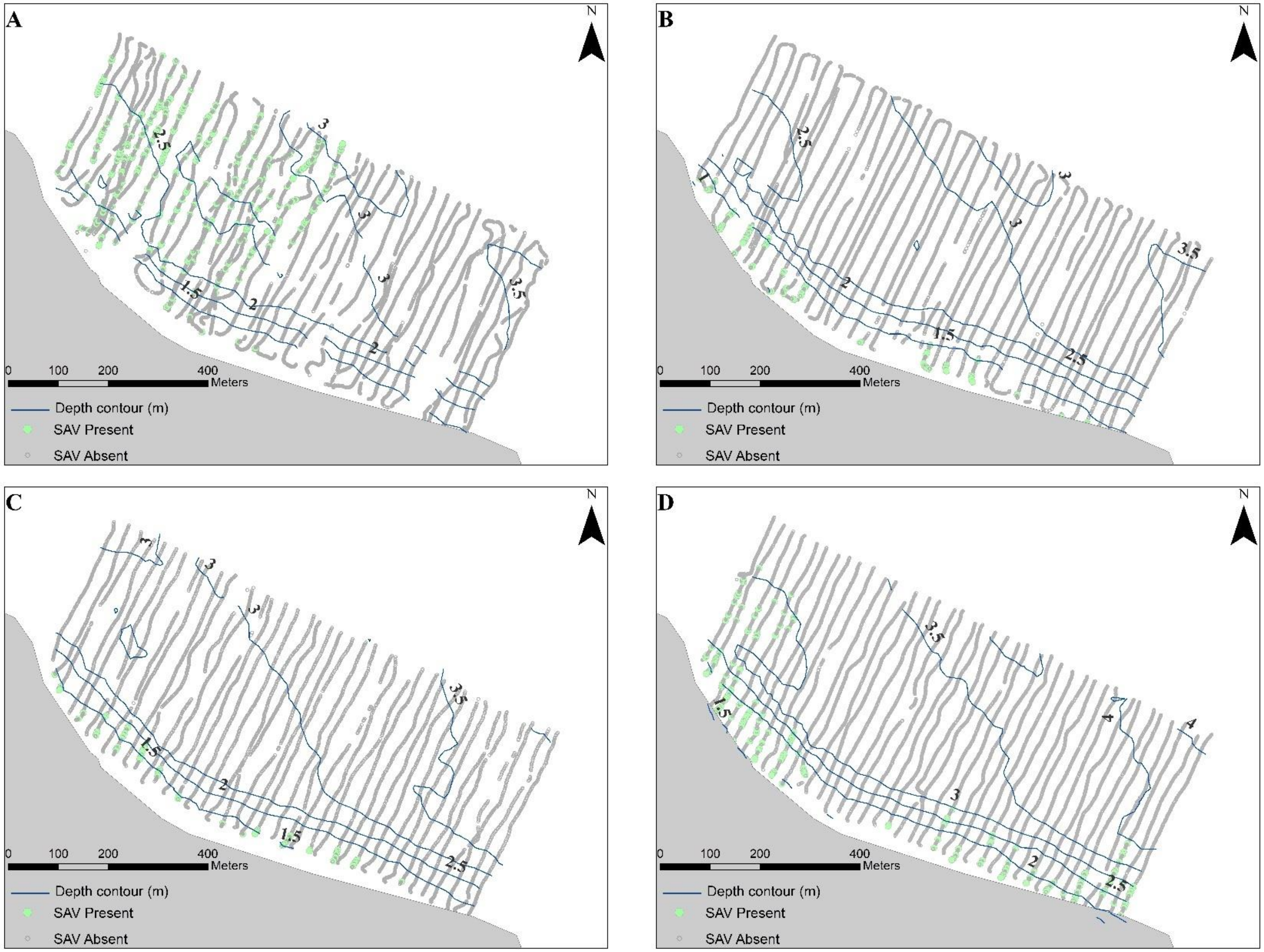
Site 4


A
B
C
D
0 100 200 Meters
N
Depth contour (m)
SAV Present
SAV Absent
1
1.5
2
2.5
3
4
4.5
5

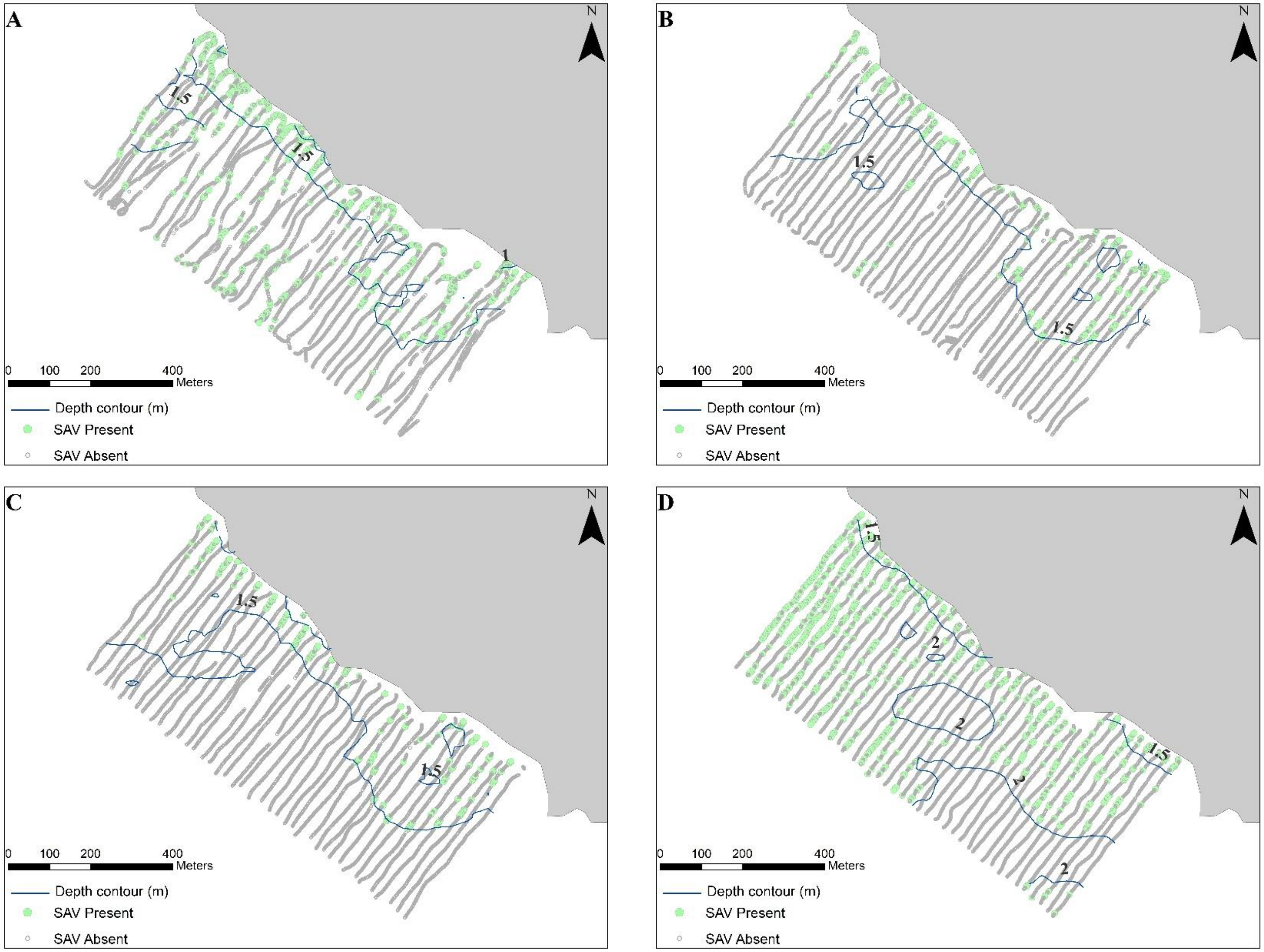
Site 5


A
B
C
D
0 100 200 400 Meters
N
Depth contour (m)
SAV Present
SAV Absent
1
1.5
2
2.5
3

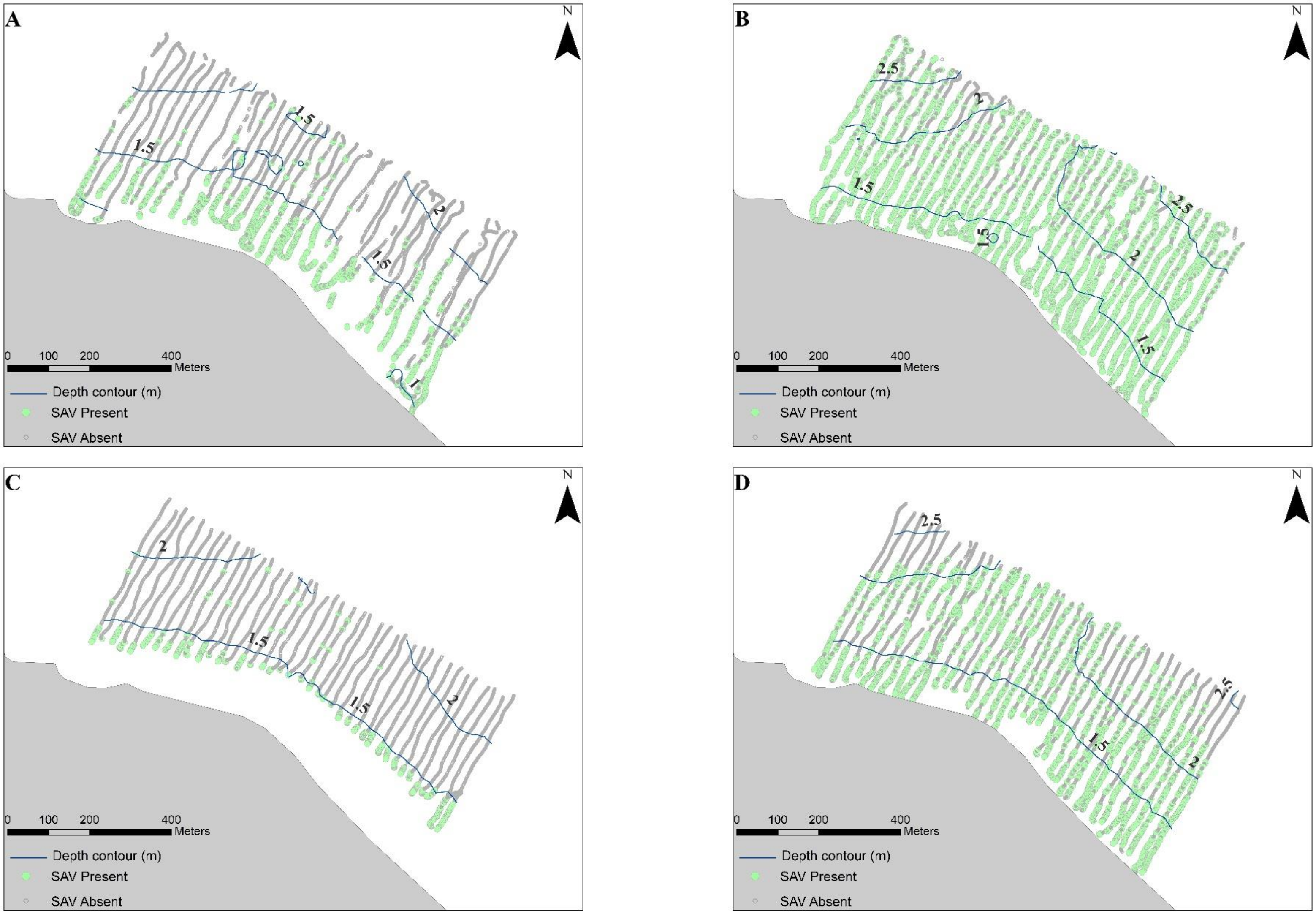
Site 6


A
B
C
D
N
0
100
200
400
Meters
Depth contour (m)
SAV Present
SAV Absent
1
1.5
2
2.5
3
3.5
4

Site 7

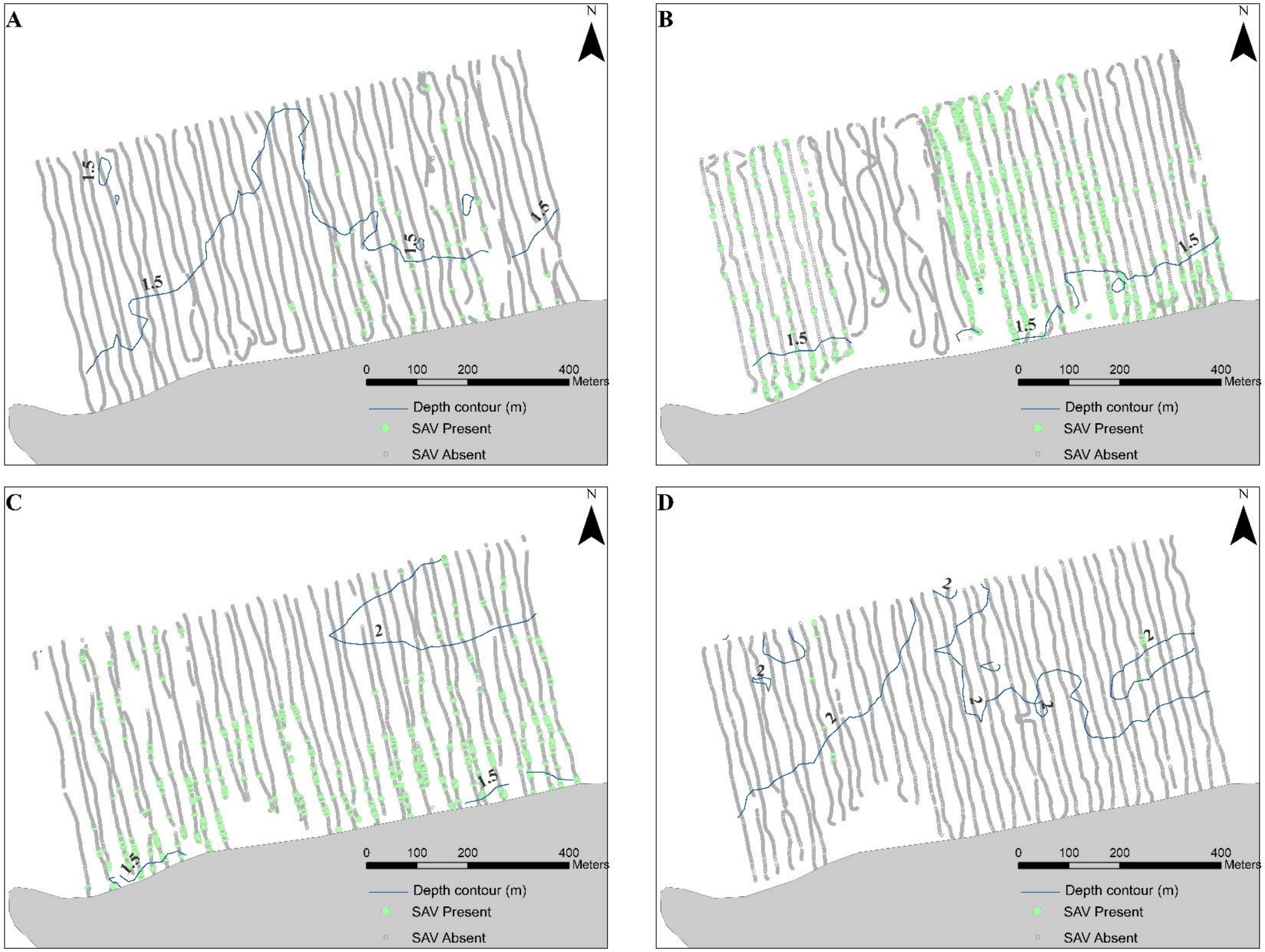

A
N
1.5
1.5
1
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
B
N
1.5
1.5
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
C
N
1.5
1.5
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent
D
N
1.5
2
2
2
1.5
2
0 100 200 400
Meters
Depth contour (m)
SAV Present
SAV Absent

Site 8



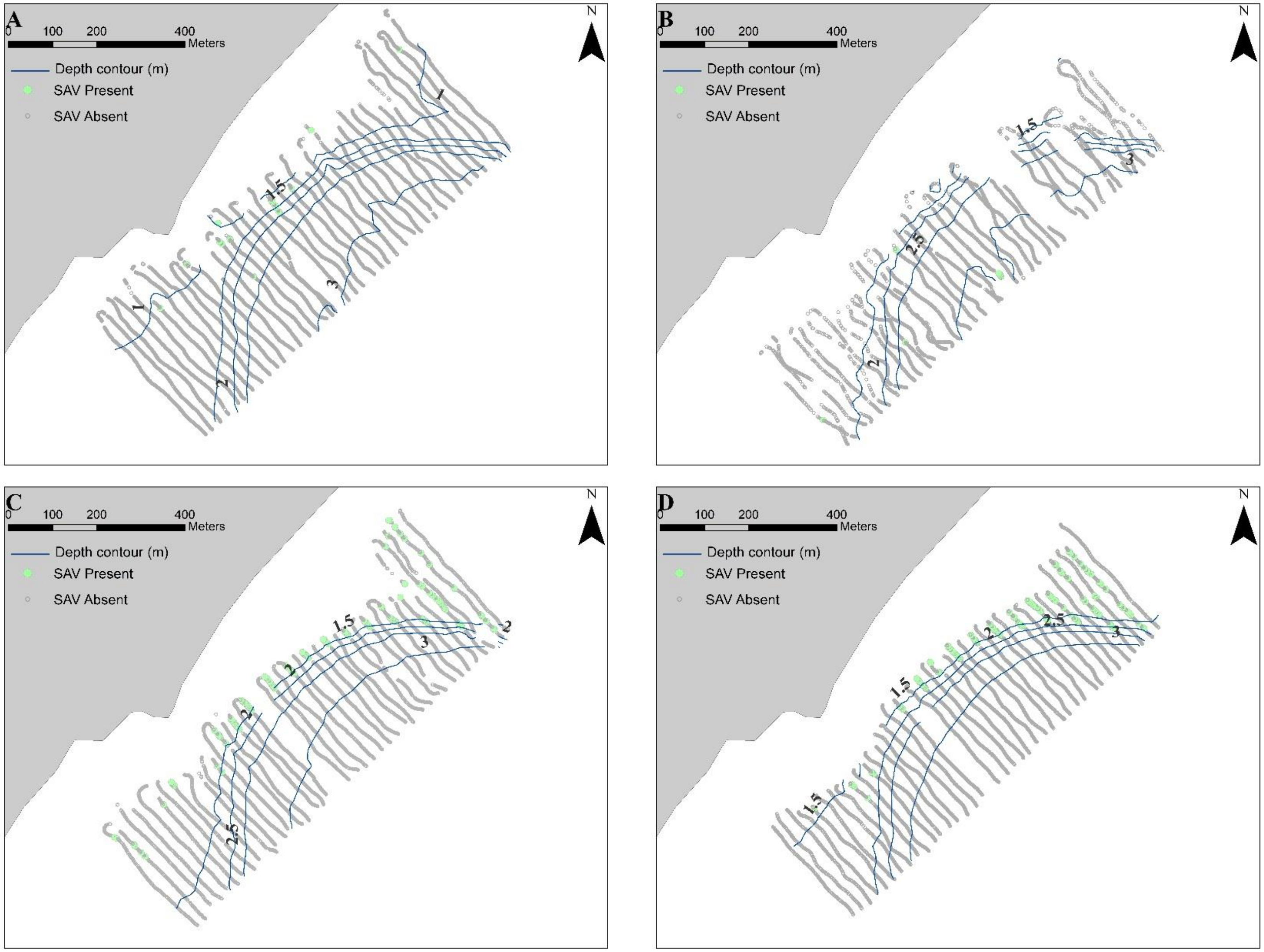
A
B
C
D
N
0 100 200 400 Meters
Depth contour (m)
SAV Present
SAV Absent
1.5
2
2.5
1

Site 9



A
N
1.5
0
100
200
400
Meters
Depth contour (m)
SAV Present
SAV Absent
B
N
1.5
0
100
200
400
Meters
Depth contour (m)
SAV Present
SAV Absent
C
N
2
1.5
0
100
200
400
Meters
Depth contour (m)
SAV Present
SAV Absent
D
N
2
0
100
200
400
Meters
Depth contour (m)
SAV Present
SAV Absent

Site 10


A
0 100 200 400 Meters
Depth contour (m)
SAV Present
SAV Absent
N
1
1.5
2
3
B
0 100 200 400 Meters
Depth contour (m)
SAV Present
SAV Absent
N
1.5
2
2.5
3
C
0 100 200 400 Meters
Depth contour (m)
SAV Present
SAV Absent
N
1.5
2
2.5
3
D
0 100 200 400 Meters
Depth contour (m)
SAV Present
SAV Absent
N
1.5
2
2.5
3

APPENDIX G. ERROR MATRICES WITH OVERALL ACCURACY AND USER'S AND PRODUCER'S ACCURACIES FOR EACH SENTINEL SITE

Site: AS_SS_01_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**43.00**	26.00	69.00	**62.32**
Present	12.00	**19.00**	31.00	**61.29**
Column Total	55.00	45.00		
Producer's Accuracy	**78.18**	**42.22**		
Overall Accuracy	**62.00**			

Site: AS_SS_01_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**63.00**	3.00	66.00	**95.45**
Present	9.00	**16.00**	25.00	**64.00**
Column Total	72.00	19.00		
Producer's Accuracy	**87.50**	**84.21**		
Overall Accuracy	**86.81**			

Site: AS_SS_01_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**62.00**	23.00	85.00	**72.94**
Present	7.00	**8.00**	15.00	**53.33**
Column Total	69.00	31.00		
Producer's Accuracy	**89.86**	**25.81**		
Overall Accuracy	**70.00**			

Site: AS_SS_01_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**57.00**	7.00	64.00	**89.06**
Present	11.00	**25.00**	36.00	**69.44**
Column Total	68.00	32.00		
Producer's Accuracy	**83.82**	**78.13**		
Overall Accuracy	**82.00**			

Site: AS_SS_02_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**90.00**	0.00	90.00	**100.00**
Present	2.00	**8.00**	10.00	**80.00**
Column Total	92.00	8.00		
Producer's Accuracy	**97.83**	**100.00**		
Overall Accuracy	**98.00**			

Site: AS_SS_02_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**54.00**	0.00	54.00	**100.00**
Present	11.00	**0.00**	11.00	**0.00**
Column Total	65.00	0.00		
Producer's Accuracy	**83.08**	**#DIV/0!**		
Overall Accuracy	**83.08**			

Site: AS_SS_02_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**92.00**	0.00	92.00	**100.00**
Present	8.00	**0.00**	8.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**92.00**	**#DIV/0!**		
Overall Accuracy	**92.00**			

Site: AS_SS_02_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**88.00**	0.00	88.00	**100.00**
Present	12.00	**0.00**	12.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**88.00**	**#DIV/0!**		
Overall Accuracy	**88.00**			

Site: AS_SS_03_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**80.00**	12.00	92.00	**86.96**
Present	8.00	**0.00**	8.00	**0.00**
Column Total	88.00	12.00		
Producer's Accuracy	**90.91**	**0.00**		
Overall Accuracy	**80.00**			

Site: AS_SS_03_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**79.00**	0.00	79.00	**100.00**
Present	0.00	**1.00**	1.00	**100.00**
Column Total	79.00	1.00		
Producer's Accuracy	**100.00**	**100.00**		
Overall Accuracy	**100.00**			

Site: AS_SS_03_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**70.00**	23.00	93.00	**75.27**
Present	3.00	**4.00**	7.00	**57.14**
Column Total	73.00	27.00		
Producer's Accuracy	**95.89**	**14.81**		
Overall Accuracy	**74.00**			

Site: AS_SS_03_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**93.00**		93.00	**100.00**
Present	7.00	**0.00**	7.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**93.00**	**#DIV/0!**		
Overall Accuracy	**93.00**			

Site: AS_SS_04_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**24.00**	43.00	67.00	**35.82**
Present	0.00	**33.00**	33.00	**100.00**
Column Total	24.00	76.00		
Producer's Accuracy	**100.00**	**43.42**		
Overall Accuracy	**57.00**			

Site: AS_SS_04_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**28.00**	50.00	78.00	**35.90**
Present	2.00	**9.00**	11.00	**81.82**
Column Total	30.00	59.00		
Producer's Accuracy	**93.33**	**15.25**		
Overall Accuracy	**41.57**			

Site: AS_SS_04_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**46.00**	30.00	76.00	**60.53**
Present	13.00	**19.00**	32.00	**59.38**
Column Total	59.00	49.00		
Producer's Accuracy	**77.97**	**38.78**		
Overall Accuracy	**60.19**			

Site: AS_SS_04_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**61.00**	25.00	86.00	**70.93**
Present	14.00	**0.00**	14.00	**0.00**
Column Total	75.00	25.00		
Producer's Accuracy	**81.33**	**0.00**		
Overall Accuracy	**61.00**			

Site: AS_SS_05_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**99.00**	1.00	100.00	**99.00**
Present	0.00	**1.00**	1.00	**100.00**
Column Total	99.00	2.00		
Producer's Accuracy	**100.00**	**50.00**		
Overall Accuracy	**99.01**			

Site: AS_SS_05_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**79.00**	0.00	79.00	**100.00**
Present	2.00	**0.00**	2.00	**0.00**
Column Total	81.00	0.00		
Producer's Accuracy	**97.53**	**#DIV/0!**		
Overall Accuracy	**97.53**			

Site: AS_SS_05_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**100.00**	0.00	100.00	**100.00**
Present	0.00	**0.00**	0.00	**#DIV/0!**
Column Total	100.00	0.00		
Producer's Accuracy	**100.00**	**#DIV/0!**		
Overall Accuracy	**100.00**			

Site: AS_SS_05_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**100.00**	0.00	100.00	**100.00**
Present	0.00	**0.00**	0.00	**#DIV/0!**
Column Total	100.00	0.00		
Producer's Accuracy	**100.00**	**#DIV/0!**		
Overall Accuracy	**100.00**			

Site: AS_SS_06_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**94.00**	3.00	97.00	**96.91**
Present	2.00	**0.00**	2.00	**0.00**
Column Total	96.00	3.00		
Producer's Accuracy	**97.92**	**0.00**		
Overall Accuracy	**94.95**			

Site: AS_SS_06_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**76.00**	0.00	76.00	**100.00**
Present	3.00	**0.00**	3.00	**0.00**
Column Total	79.00	0.00		
Producer's Accuracy	**96.20**	**#DIV/0!**		
Overall Accuracy	**96.20**			

Site: AS_SS_06_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**100.00**	0.00	100.00	**100.00**
Present	0.00	**0.00**	0.00	**#DIV/0!**
Column Total	100.00	0.00		
Producer's Accuracy	**100.00**	**#DIV/0!**		
Overall Accuracy	**100.00**			

Site: AS_SS_06_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**98.00**	0.00	98.00	**100.00**
Present	2.00	**0.00**	2.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**98.00**	**#DIV/0!**		
Overall Accuracy	**98.00**			

Site: AS_SS_07_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**48.00**	3.00	51.00	**94.12**
Present	7.00	**0.00**	7.00	**0.00**
Column Total	55.00	3.00		
Producer's Accuracy	**87.27**	**0.00**		
Overall Accuracy	**82.76**			

Site: AS_SS_07_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**85.00**	0.00	85.00	**100.00**
Present	4.00	**0.00**	4.00	**0.00**
Column Total	89.00	0.00		
Producer's Accuracy	**95.51**	**#DIV/0!**		
Overall Accuracy	**95.51**			

Site: AS_SS_07_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**100.00**	0.00	100.00	**100.00**
Present	0.00	**0.00**	0.00	**#DIV/0!**
Column Total	100.00	0.00		
Producer's Accuracy	**100.00**	**#DIV/0!**		
Overall Accuracy	**100.00**			

Site: AS_SS_07_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**94.00**	0.00	94.00	**100.00**
Present	6.00	**0.00**	6.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**94.00**	**#DIV/0!**		
Overall Accuracy	**94.00**			

Site: AS_SS_08_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**38.00**	20.00	58.00	**65.52**
Present	22.00	**20.00**	42.00	**47.62**
Column Total	60.00	40.00		
Producer's Accuracy	**63.33**	**50.00**		
Overall Accuracy	**58.00**			

Site: AS_SS_08_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**36.00**	7.00	43.00	**83.72**
Present	19.00	**18.00**	37.00	**48.65**
Column Total	55.00	25.00		
Producer's Accuracy	**65.45**	**72.00**		
Overall Accuracy	**67.50**			

Site: AS_SS_08_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**89.00**	8.00	97.00	**91.75**
Present	2.00	**1.00**	3.00	**33.33**
Column Total	91.00	9.00		
Producer's Accuracy	**97.80**	**11.11**		
Overall Accuracy	**90.00**			

Site: AS_SS_08_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**69.00**	7.00	76.00	**90.79**
Present	14.00	**10.00**	24.00	**41.67**
Column Total	83.00	17.00		
Producer's Accuracy	**83.13**	**58.82**		
Overall Accuracy	**79.00**			

Site: AS_SS_09_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**92.00**		92.00	**100.00**
Present	8.00		8.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**92.00**	**#DIV/0!**		
Overall Accuracy	**92.00**			

Site: AS_SS_09_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**70.00**	0.00	70.00	**100.00**
Present	9.00	**0.00**	9.00	**0.00**
Column Total	79.00	0.00		
Producer's Accuracy	**88.61**	**#DIV/0!**		
Overall Accuracy	**88.61**			

Site: AS_SS_09_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**92.00**	0.00	92.00	**100.00**
Present	8.00	**0.00**	8.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**92.00**	**#DIV/0!**		
Overall Accuracy	**92.00**			

Site: AS_SS_09_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**100.00**	0.00	100.00	**100.00**
Present	0.00	**0.00**	0.00	**#DIV/0!**
Column Total	100.00	0.00		
Producer's Accuracy	**100.00**	**#DIV/0!**		
Overall Accuracy	**100.00**			

Site: AS_SS_10_Spring2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**97.00**	0.00	97.00	**100.00**
Present	3.00	**0.00**	3.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**97.00**	**#DIV/0!**		
Overall Accuracy	**97.00**			

Site: AS_SS_10_Fall2015

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**50.00**	0.00	50.00	**100.00**
Present	0.00	**0.00**	0.00	**#DIV/0!**
Column Total	50.00	0.00		
Producer's Accuracy	**100.00**	**#DIV/0!**		
Overall Accuracy	**100.00**			

Site: AS_SS_10_Spring2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**97.00**	0.00	97.00	**100.00**
Present	3.00	**0.00**	3.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**97.00**	**#DIV/0!**		
Overall Accuracy	**97.00**			

Site: AS_SS_10_Fall2016

	Verification Data (underwater video data)			
Classification	Absent	Present	Row Total	User's Accuracy
Absent	**97.00**	0.00	97.00	**100.00**
Present	3.00	**0.00**	3.00	**0.00**
Column Total	100.00	0.00		
Producer's Accuracy	**97.00**	**#DIV/0!**		
Overall Accuracy	**97.00**			

APPENDIX H. SAV PRESENT-ABSENT VERIFICATION PERCENT AT EACH SENTINEL SITE SAMPLING

Site	Year	Season	% Occurrence	% Verification	Verification Type	Video to Sonar distance (m)
AS_SS_01	2015	Spring	44	72.73	Absent	1
AS_SS_01	2015	Spring	44	100	Present	1
AS_SS_01	2015	Spring	44	71.43	Absent	3
AS_SS_01	2015	Spring	44	50	Present	3
AS_SS_01	2015	Spring	44	58.82	Absent	6
AS_SS_01	2015	Spring	44	57.69	Present	6
AS_SS_01	2015	Spring	44	62	Absent	10
AS_SS_01	2015	Spring	44	61	Present	10
AS_SS_01	2015	Fall	27	87.5	Absent	1
AS_SS_01	2015	Fall	27	50	Present	1
AS_SS_01	2015	Fall	27	94.44	Absent	3
AS_SS_01	2015	Fall	27	45.45	Present	3
AS_SS_01	2015	Fall	27	91.94	Absent	6
AS_SS_01	2015	Fall	27	65	Present	6
AS_SS_01	2015	Fall	27	95	Absent	10
AS_SS_01	2015	Fall	27	64	Present	10
AS_SS_01	2016	Spring	25	100	Absent	1
AS_SS_01	2016	Spring	25		Present	1
AS_SS_01	2016	Spring	25	96	Absent	3
AS_SS_01	2016	Spring	25	40	Present	3
AS_SS_01	2016	Spring	25	92.31	Absent	6
AS_SS_01	2016	Spring	25	44.44	Present	6
AS_SS_01	2016	Spring	25	73	Absent	10
AS_SS_01	2016	Spring	25	53	Present	10
AS_SS_01	2016	Fall	34	100	Absent	1
AS_SS_01	2016	Fall	34	75	Present	1
AS_SS_01	2016	Fall	34	100	Absent	3
AS_SS_01	2016	Fall	34	69.23	Present	3
AS_SS_01	2016	Fall	34	94	Absent	6
AS_SS_01	2016	Fall	34	71.88	Present	6
AS_SS_01	2016	Fall	34	89	Absent	10
AS_SS_01	2016	Fall	34	69	Present	10
AS_SS_02	2015	Spring	7	100	Absent	1
AS_SS_02	2015	Spring	7	0	Present	1
AS_SS_02	2015	Spring	7	100	Absent	3

AS_SS_02	2015	Spring	7		Present	3
AS_SS_02	2015	Spring	7	94.87	Absent	6
AS_SS_02	2015	Spring	7	0	Present	6
AS_SS_02	2015	Spring	7	100	Absent	10
AS_SS_02	2015	Spring	7	80	Present	10
AS_SS_02	2015	Fall	17	100	Absent	1
AS_SS_02	2015	Fall	17	0	Present	1
AS_SS_02	2015	Fall	17	100	Absent	3
AS_SS_02	2015	Fall	17	0	Present	3
AS_SS_02	2015	Fall	17	100	Absent	6
AS_SS_02	2015	Fall	17	0	Present	6
AS_SS_02	2015	Fall	17	100	Absent	10
AS_SS_02	2015	Fall	17	0	Present	10
AS_SS_02	2016	Spring	8	100	Absent	1
AS_SS_02	2016	Spring	8	0	Present	1
AS_SS_02	2016	Spring	8	100	Absent	3
AS_SS_02	2016	Spring	8	0	Present	3
AS_SS_02	2016	Spring	8	100	Absent	6
AS_SS_02	2016	Spring	8	0	Present	6
AS_SS_02	2016	Spring	8	100	Absent	10
AS_SS_02	2016	Spring	8	0	Present	10
AS_SS_02	2016	Fall	3	100	Absent	1
AS_SS_02	2016	Fall	3		Present	1
AS_SS_02	2016	Fall	3	100	Absent	3
AS_SS_02	2016	Fall	3	0	Present	3
AS_SS_02	2016	Fall	3	100	Absent	6
AS_SS_02	2016	Fall	3	0	Present	6
AS_SS_02	2016	Fall	3	100	Absent	10
AS_SS_02	2016	Fall	3	0	Present	10
AS_SS_03	2015	Spring	4	100	Absent	1
AS_SS_03	2015	Spring	4	0	Present	1
AS_SS_03	2015	Spring	4	84	Absent	3
AS_SS_03	2015	Spring	4	0	Present	3
AS_SS_03	2015	Spring	4	86.05	Absent	6
AS_SS_03	2015	Spring	4	0	Present	6
AS_SS_03	2015	Spring	4	87	Absent	10
AS_SS_03	2015	Spring	4	0	Present	10
AS_SS_03	2015	Fall	1	100	Absent	1
AS_SS_03	2015	Fall	1	100	Present	1
AS_SS_03	2015	Fall	1	100	Absent	3
AS_SS_03	2015	Fall	1	100	Present	3
AS_SS_03	2015	Fall	1	100	Absent	6
AS_SS_03	2015	Fall	1	100	Present	6

AS_SS_03	2015	Fall	1	100	Absent	10
AS_SS_03	2015	Fall	1	100	Present	10
AS_SS_03	2016	Spring	6	100	Absent	1
AS_SS_03	2016	Spring	6		Present	1
AS_SS_03	2016	Spring	6	89.29	Absent	3
AS_SS_03	2016	Spring	6	50	Present	3
AS_SS_03	2016	Spring	6	84.44	Absent	6
AS_SS_03	2016	Spring	6	33.33	Present	6
AS_SS_03	2016	Spring	6	75	Absent	10
AS_SS_03	2016	Spring	6	57	Present	10
AS_SS_03	2016	Fall	6	100	Absent	1
AS_SS_03	2016	Fall	6	0	Present	1
AS_SS_03	2016	Fall	6	100	Absent	3
AS_SS_03	2016	Fall	6	0	Present	3
AS_SS_03	2016	Fall	6	100	Absent	6
AS_SS_03	2016	Fall	6	0	Present	6
AS_SS_03	2016	Fall	6	100	Absent	10
AS_SS_03	2016	Fall	6	0	Present	10
AS_SS_04	2015	Spring	68	33.33	Absent	1
AS_SS_04	2015	Spring	68	100	Present	1
AS_SS_04	2015	Spring	68	38.46	Absent	3
AS_SS_04	2015	Spring	68	100	Present	3
AS_SS_04	2015	Spring	68	45.45	Absent	6
AS_SS_04	2015	Spring	68	100	Present	6
AS_SS_04	2015	Spring	68	36	Absent	10
AS_SS_04	2015	Spring	68	100	Present	10
AS_SS_04	2015	Fall	18	60	Absent	1
AS_SS_04	2015	Fall	18		Present	1
AS_SS_04	2015	Fall	18	37.5	Absent	3
AS_SS_04	2015	Fall	18	83.33	Present	3
AS_SS_04	2015	Fall	18	39.58	Absent	6
AS_SS_04	2015	Fall	18	69.23	Present	6
AS_SS_04	2015	Fall	18	36	Absent	10
AS_SS_04	2015	Fall	18	82	Present	10
AS_SS_04	2016	Spring	30	80	Absent	1
AS_SS_04	2016	Spring	30	50	Present	1
AS_SS_04	2016	Spring	30	50	Absent	3
AS_SS_04	2016	Spring	30	35.71	Present	3
AS_SS_04	2016	Spring	30	64.44	Absent	6
AS_SS_04	2016	Spring	30	72.73	Present	6
AS_SS_04	2016	Spring	30	61	Absent	10
AS_SS_04	2016	Spring	30	59	Present	10
AS_SS_04	2016	Fall	22	62.5	Absent	1

AS_SS_04	2016	Fall	22	100	Present	1
AS_SS_04	2016	Fall	22	60.61	Absent	3
AS_SS_04	2016	Fall	22	0	Present	3
AS_SS_04	2016	Fall	22	75.41	Absent	6
AS_SS_04	2016	Fall	22	35.29	Present	6
AS_SS_04	2016	Fall	22	71	Absent	10
AS_SS_04	2016	Fall	22	0	Present	10
AS_SS_05	2015	Spring	3	100	Absent	1
AS_SS_05	2015	Spring	3		Present	1
AS_SS_05	2015	Spring	3	100	Absent	3
AS_SS_05	2015	Spring	3		Present	3
AS_SS_05	2015	Spring	3	98.36	Absent	6
AS_SS_05	2015	Spring	3	0	Present	6
AS_SS_05	2015	Spring	3	99	Absent	10
AS_SS_05	2015	Spring	3	100	Present	10
AS_SS_05	2015	Fall	0	100	Absent	1
AS_SS_05	2015	Fall	0		Present	1
AS_SS_05	2015	Fall	0	100	Absent	3
AS_SS_05	2015	Fall	0		Present	3
AS_SS_05	2015	Fall	0	100	Absent	6
AS_SS_05	2015	Fall	0	0	Present	6
AS_SS_05	2015	Fall	0	100	Absent	10
AS_SS_05	2015	Fall	0	0	Present	10
AS_SS_05	2016	Spring	2	100	Absent	1
AS_SS_05	2016	Spring	2		Present	1
AS_SS_05	2016	Spring	2	100	Absent	3
AS_SS_05	2016	Spring	2		Present	3
AS_SS_05	2016	Spring	2	100	Absent	6
AS_SS_05	2016	Spring	2		Present	6
AS_SS_05	2016	Spring	2	100	Absent	10
AS_SS_05	2016	Spring	2		Present	10
AS_SS_05	2016	Fall	0	100	Absent	1
AS_SS_05	2016	Fall	0		Present	1
AS_SS_05	2016	Fall	0	100	Absent	3
AS_SS_05	2016	Fall	0		Present	3
AS_SS_05	2016	Fall	0	100	Absent	6
AS_SS_05	2016	Fall	0		Present	6
AS_SS_05	2016	Fall	0	100	Absent	10
AS_SS_05	2016	Fall	0		Present	10
AS_SS_06	2015	Spring	2	100	Absent	1
AS_SS_06	2015	Spring	2		Present	1
AS_SS_06	2015	Spring	2	100	Absent	3
AS_SS_06	2015	Spring	2	50	Present	3

AS_SS_06	2015	Spring	2	97.5	Absent	6
AS_SS_06	2015	Spring	2	0	Present	6
AS_SS_06	2015	Spring	2	97	Absent	10
AS_SS_06	2015	Spring	2	0	Present	10
AS_SS_06	2015	Fall	1		Absent	1
AS_SS_06	2015	Fall	1		Present	1
AS_SS_06	2015	Fall	1		Absent	3
AS_SS_06	2015	Fall	1		Present	3
AS_SS_06	2015	Fall	1		Absent	6
AS_SS_06	2015	Fall	1		Present	6
AS_SS_06	2015	Fall	1	100	Absent	10
AS_SS_06	2015	Fall	1	0	Present	10
AS_SS_06	2016	Spring	1	100	Absent	1
AS_SS_06	2016	Spring	1		Present	1
AS_SS_06	2016	Spring	1	100	Absent	3
AS_SS_06	2016	Spring	1	0	Present	3
AS_SS_06	2016	Spring	1	100	Absent	6
AS_SS_06	2016	Spring	1	0	Present	6
AS_SS_06	2016	Spring	1	100	Absent	10
AS_SS_06	2016	Spring	1	0	Present	10
AS_SS_06	2016	Fall	3	100	Absent	1
AS_SS_06	2016	Fall	3		Present	1
AS_SS_06	2016	Fall	3	100	Absent	3
AS_SS_06	2016	Fall	3		Present	3
AS_SS_06	2016	Fall	3	100	Absent	6
AS_SS_06	2016	Fall	3	0	Present	6
AS_SS_06	2016	Fall	3	100	Absent	10
AS_SS_06	2016	Fall	3	0	Present	10
AS_SS_07	2015	Spring	10	100	Absent	1
AS_SS_07	2015	Spring	10		Present	1
AS_SS_07	2015	Spring	10	100	Absent	3
AS_SS_07	2015	Spring	10	0	Present	3
AS_SS_07	2015	Spring	10	100	Absent	6
AS_SS_07	2015	Spring	10	0	Present	6
AS_SS_07	2015	Spring	10	94	Absent	10
AS_SS_07	2015	Spring	10	0	Present	10
AS_SS_07	2015	Fall	4	100	Absent	1
AS_SS_07	2015	Fall	4	0	Present	1
AS_SS_07	2015	Fall	4	100	Absent	3
AS_SS_07	2015	Fall	4	0	Present	3
AS_SS_07	2015	Fall	4	100	Absent	6
AS_SS_07	2015	Fall	4	0	Present	6
AS_SS_07	2015	Fall	4	100	Absent	10

AS_SS_07	2015	Fall	4	0	Present	10
AS_SS_07	2016	Spring	4		Absent	1
AS_SS_07	2016	Spring	4		Present	1
AS_SS_07	2016	Spring	4		Absent	3
AS_SS_07	2016	Spring	4		Present	3
AS_SS_07	2016	Spring	4		Absent	6
AS_SS_07	2016	Spring	4		Present	6
AS_SS_07	2016	Spring	4	100	Absent	10
AS_SS_07	2016	Spring	4		Present	10
AS_SS_07	2016	Fall	10	100	Absent	1
AS_SS_07	2016	Fall	10	0	Present	1
AS_SS_07	2016	Fall	10	100	Absent	3
AS_SS_07	2016	Fall	10	0	Present	3
AS_SS_07	2016	Fall	10	100	Absent	6
AS_SS_07	2016	Fall	10	0	Present	6
AS_SS_07	2016	Fall	10	100	Absent	10
AS_SS_07	2016	Fall	10	0	Present	10
AS_SS_08	2015	Spring	16	87.5	Absent	1
AS_SS_08	2015	Spring	16		Present	1
AS_SS_08	2015	Spring	16	75	Absent	3
AS_SS_08	2015	Spring	16	66.67	Present	3
AS_SS_08	2015	Spring	16	72.09	Absent	6
AS_SS_08	2015	Spring	16	75	Present	6
AS_SS_08	2015	Spring	16	66	Absent	10
AS_SS_08	2015	Spring	16	48	Present	10
AS_SS_08	2015	Fall	37	100	Absent	1
AS_SS_08	2015	Fall	37	100	Present	1
AS_SS_08	2015	Fall	37	87.5	Absent	3
AS_SS_08	2015	Fall	37	60	Present	3
AS_SS_08	2015	Fall	37	79.31	Absent	6
AS_SS_08	2015	Fall	37	44	Present	6
AS_SS_08	2015	Fall	37	84	Absent	10
AS_SS_08	2015	Fall	37	49	Present	10
AS_SS_08	2016	Spring	8	100	Absent	1
AS_SS_08	2016	Spring	8		Present	1
AS_SS_08	2016	Spring	8	93.88	Absent	3
AS_SS_08	2016	Spring	8	50	Present	3
AS_SS_08	2016	Spring	8	92.96	Absent	6
AS_SS_08	2016	Spring	8	40	Present	6
AS_SS_08	2016	Spring	8	92	Absent	10
AS_SS_08	2016	Spring	8	33	Present	10
AS_SS_08	2016	Fall	28	80	Absent	1
AS_SS_08	2016	Fall	28	0	Present	1

AS_SS_08	2016	Fall	28	78.57	Absent	3
AS_SS_08	2016	Fall	28	33.33	Present	3
AS_SS_08	2016	Fall	28	84.78	Absent	6
AS_SS_08	2016	Fall	28	33.33	Present	6
AS_SS_08	2016	Fall	28	91	Absent	10
AS_SS_08	2016	Fall	28	42	Present	10
AS_SS_09	2015	Spring	1	100	Absent	1
AS_SS_09	2015	Spring	1		Present	1
AS_SS_09	2015	Spring	1	100	Absent	3
AS_SS_09	2015	Spring	1	0	Present	3
AS_SS_09	2015	Spring	1	100	Absent	6
AS_SS_09	2015	Spring	1	0	Present	6
AS_SS_09	2015	Spring	1	100	Absent	10
AS_SS_09	2015	Spring	1	0	Present	10
AS_SS_09	2015	Fall	10	100	Absent	1
AS_SS_09	2015	Fall	10		Present	1
AS_SS_09	2015	Fall	10	100	Absent	3
AS_SS_09	2015	Fall	10	0	Present	3
AS_SS_09	2015	Fall	10	100	Absent	6
AS_SS_09	2015	Fall	10	0	Present	6
AS_SS_09	2015	Fall	10	100	Absent	10
AS_SS_09	2015	Fall	10	0	Present	10
AS_SS_09	2016	Spring	5	100	Absent	1
AS_SS_09	2016	Spring	5		Present	1
AS_SS_09	2016	Spring	5	100	Absent	3
AS_SS_09	2016	Spring	5		Present	3
AS_SS_09	2016	Spring	5	100	Absent	6
AS_SS_09	2016	Spring	5	0	Present	6
AS_SS_09	2016	Spring	5	100	Absent	10
AS_SS_09	2016	Spring	5	0	Present	10
AS_SS_09	2016	Fall	0	100	Absent	1
AS_SS_09	2016	Fall	0		Present	1
AS_SS_09	2016	Fall	0	100	Absent	3
AS_SS_09	2016	Fall	0		Present	3
AS_SS_09	2016	Fall	0	100	Absent	6
AS_SS_09	2016	Fall	0		Present	6
AS_SS_09	2016	Fall	0	100	Absent	10
AS_SS_09	2016	Fall	0		Present	10
AS_SS_10	2015	Spring	0		Absent	1
AS_SS_10	2015	Spring	0		Present	1
AS_SS_10	2015	Spring	0		Absent	3
AS_SS_10	2015	Spring	0		Present	3
AS_SS_10	2015	Spring	0		Absent	6

AS_SS_10	2015	Spring	0		Present	6
AS_SS_10	2015	Spring	0	100	Absent	10
AS_SS_10	2015	Spring	0	0	Present	10
AS_SS_10	2015	Fall	0	100	Absent	1
AS_SS_10	2015	Fall	0		Present	1
AS_SS_10	2015	Fall	0	100	Absent	3
AS_SS_10	2015	Fall	0		Present	3
AS_SS_10	2015	Fall	0	100	Absent	6
AS_SS_10	2015	Fall	0		Present	6
AS_SS_10	2015	Fall	0	100	Absent	10
AS_SS_10	2015	Fall	0		Present	10
AS_SS_10	2016	Spring	3	100	Absent	1
AS_SS_10	2016	Spring	3		Present	1
AS_SS_10	2016	Spring	3	100	Absent	3
AS_SS_10	2016	Spring	3		Present	3
AS_SS_10	2016	Spring	3	100	Absent	6
AS_SS_10	2016	Spring	3		Present	6
AS_SS_10	2016	Spring	3	100	Absent	10
AS_SS_10	2016	Spring	3	0	Present	10
AS_SS_10	2016	Fall	3	100	Absent	1
AS_SS_10	2016	Fall	3		Present	1
AS_SS_10	2016	Fall	3	100	Absent	3
AS_SS_10	2016	Fall	3	0	Present	3
AS_SS_10	2016	Fall	3	100	Absent	6
AS_SS_10	2016	Fall	3	0	Present	6
AS_SS_10	2016	Fall	3	100	Absent	10
AS_SS_10	2016	Fall	3	0	Present	10