The Use of Remote Sensing to Assess Salt Marsh Dieback

by

Nathan Reetz

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Accepted:

____
Eric R. Annis, Ph.D.
Project Advisor

____
Susan L. Carney, Ph.D.
Director, Environmental Biology Program

____
April M. Boulton, Ph.D.
Dean of the Graduate School

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Abstract

Salt marshes are invaluable to coastal communities, providing carbon sequestration, habitat, and mitigation from storms. All along the Eastern Atlantic seaboard, salt marsh vegetation has been experiencing diebacks. While the cause of these diebacks is presently unknown, studies have made links to climate change-related factors, such as temperature increase, drought, and sea level rise. This study used remote sensing techniques to access the relationships between vegetation loss within the Blackwater National Wildlife Refuge and several climate-related variables. The reflectance of the vegetation was isolated using a normalized difference vegetation index (NDVI) and square kilometers of vegetation cover were measured for each year from 2003 to 2018. Image transformations allowed the subtraction of one year's vegetation cover from another, providing a change in vegetation over time with a total percent loss of vegetation of 0.32%. There was a positive correlation between vegetation loss and time ($r(15) = 0.547$, $p = 0.014$). Additionally, there was a positive correlation between vegetation loss and river discharge when lag time was added to vegetation loss ($r(14) = 0.494$, $p = 0.031$). No other significant relationships were found between marsh loss and the following variables: air temperature, surface water temperature, sea level, and elevation.

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Introduction

A significant challenge in assessing the extent and causes of salt marsh dieback is a paucity of baseline information necessary to establish historical trends and variability (Alber et al., 2008). Low-resolution satellite imagery is readily available for establishing baselines but has been criticized for lacking the necessary accuracy to assess changes in salt marsh vegetation (Campbell et al., 2017). Miller et al. (2017) have recently challenged this assumption by demonstrating that analysis using LANDSAT satellites can achieve ground truthing accuracy approaching 80%. Low-resolution remote sensing not only has sufficient accuracy, but a large catalog of historical images is freely and publicly available (USGS, 2018). It has the potential to provide baseline data for this important ecosystem.

Salt marshes perform several important functions within coastal communities. Along the coast of North America, saltmarshes are dominated by their foundational species, *Spartina alterniflora,* or smooth cordgrass. *S. alterniflora* builds elevation using two mechanisms. In sediment-heavy regions, dense above-ground biomass traps this sediment. In areas of low sediment, peat is accumulated by below ground biomass of *S. alterniflora*, which acts to sequester carbon (Crosby et al., 2017). From a hydrological perspective, upstream and tidal waters are slowed due to this biomass, allowing for further sediment deposition. Coastlines benefit from this slowing as sea action and storm waters are mediated (Marani et al., 2006).

Thick biomass of *S. alterniflora* also provides habitat to numerous species. Juvenile fish and invertebrates use salt marshes as protection from predation (Oliver et al., 2012). Along the Atlantic coasts alone, salt marshes provide temporary or permanent habitat to more than 70 species of birds. These birds use salt marshes for breeding, roosting, and feeding (Erwin et al., 2004). The loss of salt marshes would not only threaten the organisms that utilize them but due to the numerous other ecological benefits, their loss would have a profound impact on the entire region.

Salt marsh diebacks have been reported all along the US Gulf and Atlantic coasts. A survey of 9 states where dieback has been reported found that *S. alterniflora* was the dominant species at all 9 locations (Alber et al., 2008). There is debate on the causes of salt marsh dieback, with theories including trophic cascade, soil chemistry, fungal pathogens, and climate change. Silliman and Bertness (2012) discovered a trophic cascade from overfishing of snail predators such as blue crabs. Within 8 months of the removal of top-down predation pressure, overgrazing by snails completely stripped several square kilometers of salt marsh (Silliman and Bertness, 2002). McKee et al. (2004) explored a possible mechanism for drought-related soil chemistry changes. In Louisiana, soils were oxidizing without rain and converting metal sulfides present in the soil into sulfuric acid (McKee et al., 2004). Elmer and Marra (2011) found that the fungal pathogen *Fusarium spp.* might play an indirect role in *S. alterniflora* dieback events.

Most of the research on salt marsh dieback has been devoted to abiotic factors related to climate change. Drought conditions not only stress the plants themselves, but they also have the potential to change soil chemistry (Hughes et al., 2012; McKee et al., 2004). Through transplant experiments, *S. alterniflora* has been shown to have some degree of plasticity in its temperature tolerance. Unfortunately, this only seems to apply when transplanted from warm climates to cold and not from cold to warm climates (Crosby et al., 2017). This has dire implications considering global temperature trends.

Sea level rise is another climate-change-related threat to salt marshes. Due to its ability to accumulate sediment and increase the elevation of the marsh, *S. alterniflora* can tolerate a slow rate of sea level rise (Smith et al., 2017; Kolker et al., 2009). Salt marshes typically increase elevation at a rate of 1.40 mm per year (Raposa et al., 2017). During the 15 years of a New England salt marsh study, sea levels rose at a rate of 5.26 mm per year, outpacing the rate at which salt marshes can accrue sediment and resulting in the loss of salt marsh area (Raposa et al., 2017). Miller et al. (2017) found positive correlations between lower elevations and loss of marsh vegetation. While each of these climate-change-related studies has shown a positive correlation between abiotic factors and vegetation loss, it is difficult to uncouple these factors and point to just one cause.

Remote sensing is becoming an invaluable tool for studying salt marsh dieback. The amount and rate of dieback are now possible to quantify. High-resolution imagery is able to produce accurate, detailed images (Campbell et al., 2017; Tuxen et al., 2011; Kolker et al., 2009). These images have helped researchers in determining diversity and community structure (Tuxen et al., 2011), the impact of Hurricane Sandy on marsh restoration efforts (Campbell et al., 2017), and the effects of sea-level rise on marshes (Kolker et al., 2009). The need to charter a satellite for imaging is prohibitively expensive, and the lack of access to historical images makes long term studies impossible. There are free, publicly available alternatives, but these tend to be low resolution, which is defined as 250 m to 1 m for remote sensing. The European Union's Sentinel satellites offer up to 10 m resolution, but they launched in 2015 providing no prior data (ESA, 2015). LANDSAT, a joint venture between the USGS and NASA, offers 30 m resolution and a database of images that extends to the mission's inception in 1972 (USGS, 2018).

Campbell et al. (2017) discouraged the use of low-resolution imagery for salt marsh research while offering a detailed analysis of the impacts of Hurricane Sandy. According to Campbell et al. (2017), low accuracy at the water-marsh interface should limit the usage of LANDSAT for the study of salt marshes. However, there has been successful usage of

LANDSAT in studying salt marshes. Miller et al. (2017) conducted a 5-year analysis of the salt marshes of South Carolina and found a negative correlation between increased dieback and higher elevation. They achieved a ground truthing accuracy of 76.2%. This raises doubt over previous assumption that using low-resolution imagery to assess salt marshes is not a viable approach.

This study used LANDSAT data to assess marsh dieback in a long-term study of Blackwater National Wildlife Refuge (BNWR) in Maryland from 2003 to 2018 to test the hypothesis that the Blackwater National Wildlife Refuge has experienced a loss of vegetation that is positively correlated to both sea-level rise and temperature increase over the past 16 years. BWNR is unique for a study in its documented levels of subsidence (Eggleston and Pope, 2013). Subsidence should have a reinforcing effect on sea level rise within the study area, resulting in a clearer relationship. By comparing the satellite imagery through the study period, it was possible to quantifiably determine the amount of vegetation loss or gain. Vegetation flux and air temperature data, sea-level rise data, and river discharge rates from BNWR were used to determine relationships through correlation analysis. River discharge rates were used as a proxy for precipitation. Correlation between climate-change-driven variables, whether directly through gradual warming or indirectly through sea-level rise, and salt marsh dieback has the potential to help us understand the factors causing this relationship.

Materials and Methods

Data

Several data sets were acquired for this analysis including LANDSAT images, Blackwater air temperature data, Solomons Island surface water temperature, Solomons Island sea level measurements, Chicamacomico River water flow rate, the BNWR shapefile, and BNWR elevation data (Table 1). LANDSAT images were obtained from the United States Geological Survey (USGS) via the EarthExplorer interface. LANDSAT 7 launched on April 15, 1999, and LANDSAT 8 launched on February 11, 2013. Daily air temperature data from the BNWR weather station were available since November 2002 from NOAA's National Centers for Environmental Information in CSV format. These data were used to generate monthly means for the month of May. May was midway through the growing season for *S. alterniflora*, right after the spring active growth phase and right before the summer pre-flowering phase (Mendelssohn, 1979). It was during this time vegetation should be at its yearly maximum. From NOAA's Center for Operational Oceanographic Products and Services: Tide and Currents, continuous monthly relative sea-level data were available since 1979. This was obtained for Solomons Island. The Solomons Island weather station was also able to provide surface water temperatures. Discharge rates for the Chicamacomico River were obtained from the USGS National Water Information System. Elevation data were obtained from NOAA's National Geodetic Survey, specifically the North American Vertical Datum of 1988 (NAVD88). Since no temperature data were available prior to 2002, I limited the study to the time frame of May 2003-2018. LANDSAT data were weather dependent. Images with the least amount of cloud cover during the month of May for each year during this time frame were selected and downloaded. Due to a Scan Line Corrector error that occurred to the LANDSAT 7 satellite in 2003 that affects approximately 22% of the data, LANDSAT 8 images were chosen preferentially when available. The BNWR shapefile was downloaded from the US Fish and Wildlife Service's Spatial Data Library. BNWR itself is discontiguous, consisting of two main areas and several small areas. The smaller areas and the inland main area were excluded from the study using the CROP function within the RASTER toolbox in ArcMap, leaving a contiguous main study area of 306.11 km^2. The smaller areas did not always consist of marshland, and the excluded main area was inland, containing no marshland.

Data	Source	Website
LANDSAT imagery	USGS EarthExplorer	https://earthexplorer.usgs.gov/
BNWR air temperature	National Centers for Environmental Information	https://www.ncdc.noaa.gov/cdo-web/datatools/findstation
Solomons Island surface water temperature	Center for Operational Oceanographic Products and Services: Tide and Currents	https://tidesandcurrents.noaa.gov/stationhome.html?id=8577330
Solomons Island relative sea level	Center for Operational Oceanographic Products and Services: Tide and Currents	https://tidesandcurrents.noaa.gov/stationhome.html?id=8577330
Chicamacomico River discharge rate	National Water Information System	https://waterdata.usgs.gov/nwis/inventory?agency_code=USGS&site_no=01490000
BNWR shapefile	Spatial Data Library	https://www.fws.gov/northeast/gis/metadata.html#Maryland
BNWR elevation	NAVD88 Data Explorer	https://www.ngs.noaa.gov/NGSDataExplorer/

Table 1 – Table including all data obtained for this study, the source of the data, and a direct link to the website from which data were obtained.

Image Manipulation

Once selected, the LANDSAT images were processed in the Idrisi TerraSet software package (Clark Labs, Worchester, Massachusetts) and ArcMap 10.3.1 (ESRI, Redlands, California). All LANDSAT images were downloaded as previously atmospherically corrected.

The red and near-infrared bands of these images were further transformed into normalized difference vegetation index (NDVI) in Idrisi using the VEGINDEX function (Figure 1). NDVI is a standardized index used to study vegetation obtained through the following equation:

$$NDVI = \frac{(Near\ Infrared\ band - Red\ band)}{(Near\ Infrared\ Band + Red\ Band)}$$

The IMAGE CALCULATOR allows the manipulation of images using various programming languages. Setting all vegetation pixels to values greater than zero using the SQL code of "[NDVI image] > 0", every pixel not identified by reflectance as vegetation was assigned a value of zero. The resulting image, MASK, was then used to mask all but vegetation in the finished image using the MASK image multiplied by the NDVI image with the OVERLAY function.

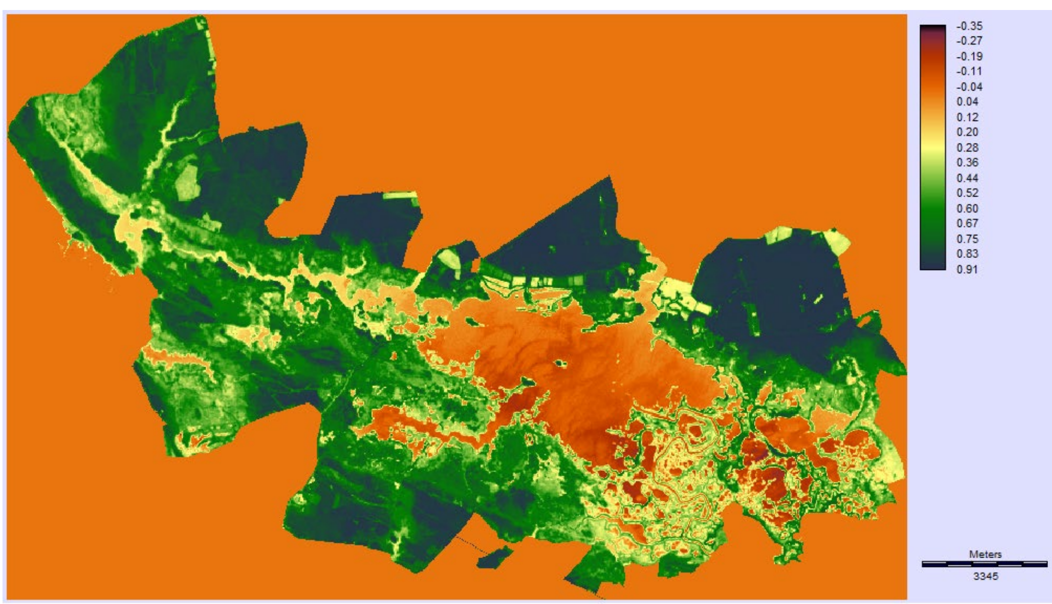

Figure 1 – NDVI transformation using imagery obtained from the LANDSAT 8 satellite. The image has been cropped to the BNWR shapefile allowing just the study area to be displayed and analyzed.

Spatial Analysis

Time series differences were calculated in Idrisi using initial masked NDVI image (2003) minus each subsequent year's masked NDVI image ($NDVI_i - NDVI_n$) within the OVERLAY function. For images with scan line error, the OVERLAY function includes an option to overwrite zero values with existing data. This replaced zero values resulting from errors with historic values reducing data loss. Once the difference was calculated at each time step, the AREA function provided the vegetation loss (< 0) or gain (> 0) in square kilometers. These numbers were subtracted to generate the net change in vegetation for that time step.

Tides

LANDSAT 8 images were obtained of the marsh-heavy region of the eastern Maryland peninsula. With only 2 to 3 images per month, the closest interval between opposing tide cycles was 3 months: June 15th, 2018 for high tide and September 19th, 2018 for low tide (Figure 2).

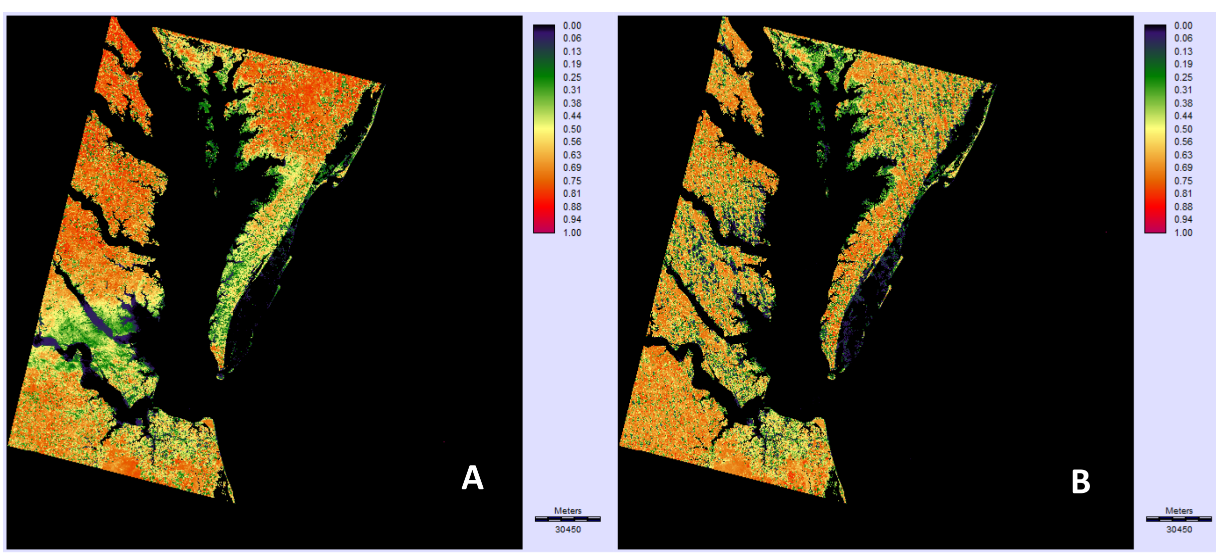

Figure 2 – A. Masked NDVI transformation of the eastern peninsula of Maryland on 15 June 2018 (High Tide). B. Masked NDVI transformation of the eastern peninsula of Maryland on 19 September 2018 (Low Tide). Both images had all non-vegetation masked so that only vegetation is displayed and analyzed.

Elevation

Miller et al.'s (2017) elevation analysis was recreated using BNWR data. As an example of successful LANDSAT usage to evaluate salt marsh vegetation, it was important to determine whether a change in location altered the results of a static elevation analysis. Much of the imagery needed for the elevation analysis was already generated from the spatial analysis. The 2003 – 2018 NDVI difference image was imported into ArcMap. Within the study area, 24 elevation points were selected from NAVD88 (Figure 3). Elevation data points were placed onto the map according to latitude and longitude provided from NAVD88. Corresponding values on the map represented the vegetation difference at those points.

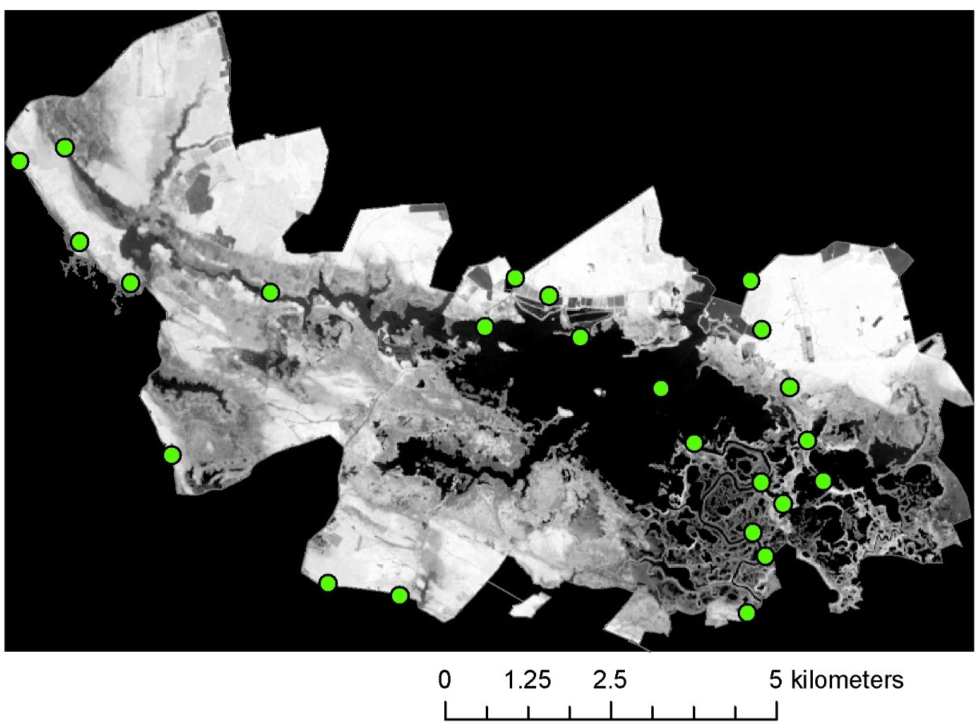

Figure 3 – Map of BNWR study area with locations of NAVD88 elevation data points marked in green.

Statistical Analysis

The average air temperatures for May of each year for the duration of the study were compiled in a Microsoft Excel file along with relative sea level from Cambridge, Maryland, and the net vegetation loss for those same time periods. Using SPSS (IBM, Armonk, New York), these values were statistically compared using bivariate correlation with air temperature, surface water temperature, sea-level rise, stream flow, and vegetation loss as variables. The resulting coefficients demonstrate the relationships between vegetation loss and its five possible climate-change-related causes. The 24 NAVD88 elevations and the corresponding vegetation values were compared using bivariate correlation.

Results

Tides

Due to the amount of time between the images, a change in vegetation was expected as a result of tide cycles. The comparison indicated that tides had minimal impact on the assessment of vegetation coverage because considerable vegetation change occurred inland as expected due to seasonality, but very little change occurred at the coastline (Figure 4). Light penetration was sufficient to detect vegetation even at high tides.

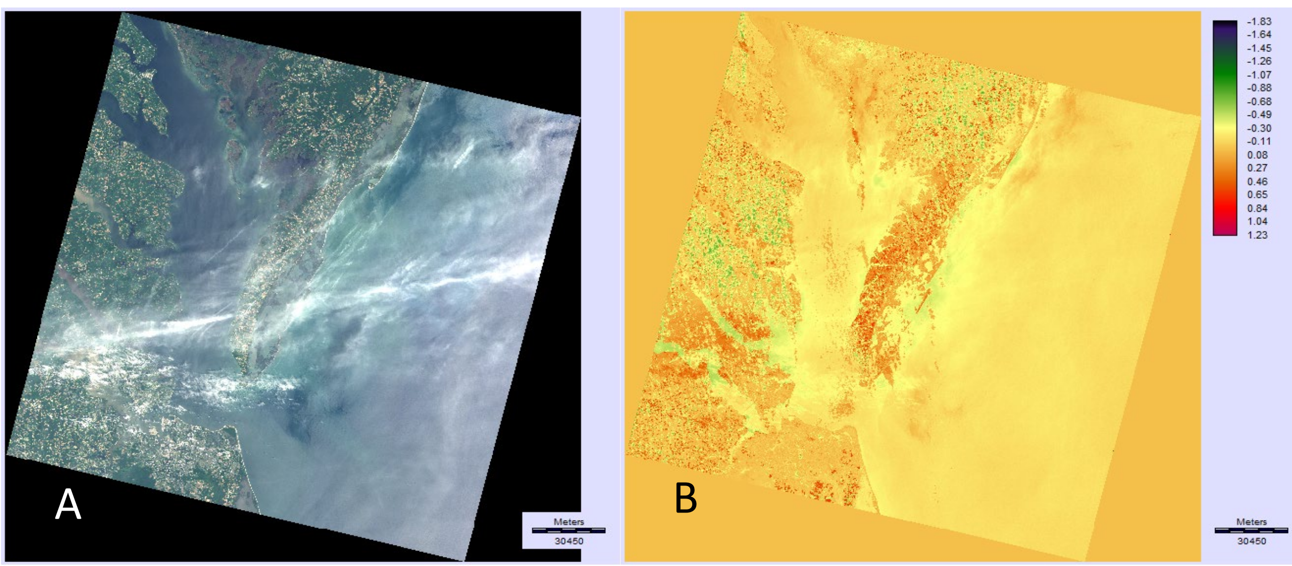

Figure 4 – A. True color composite of the BNWR study area using bands 2, 3 and 4 from an image acquired in June 2018. B. An OVERLAY difference between NDVI processed images from September and June 2018.

Climate-Related Variables

The data for net vegetation loss (NVL) and mean May air temperature (AT) at BNWR, relative sea level rise (RSL) and mean May surface water temperature (SWT) at Solomons Island, and discharge rates of the Chicamacomico River provided two significant relationships (Figure 5). NVL showed a strong positive trend over time that was confirmed with a strong positive correlation ($r(15) = 0.547$, $p = 0.014$). The other variables showed no correlation with time (Table 2).

There was no significant correlation between NVL and the other variables. The only other relationship found was between air temperature and water temperature. When vegetation loss was offset by one year, such that vegetation loss was correlated with environmental variables for the previous year, the discharge rate of the Chicamacomico River was positively correlated with vegetation loss ($r(14) = 0.494$, $p = 0.031$; Table 3).

Elevation

Between 2003 and 2018, BNWR lost 0.270 km^2 of vegetation cover for a total percent loss of 0.32%. Despite this loss of vegetation over time, there was no correlation between this vegetation change and static recorded elevation ($p = 0.338$; Table 4).

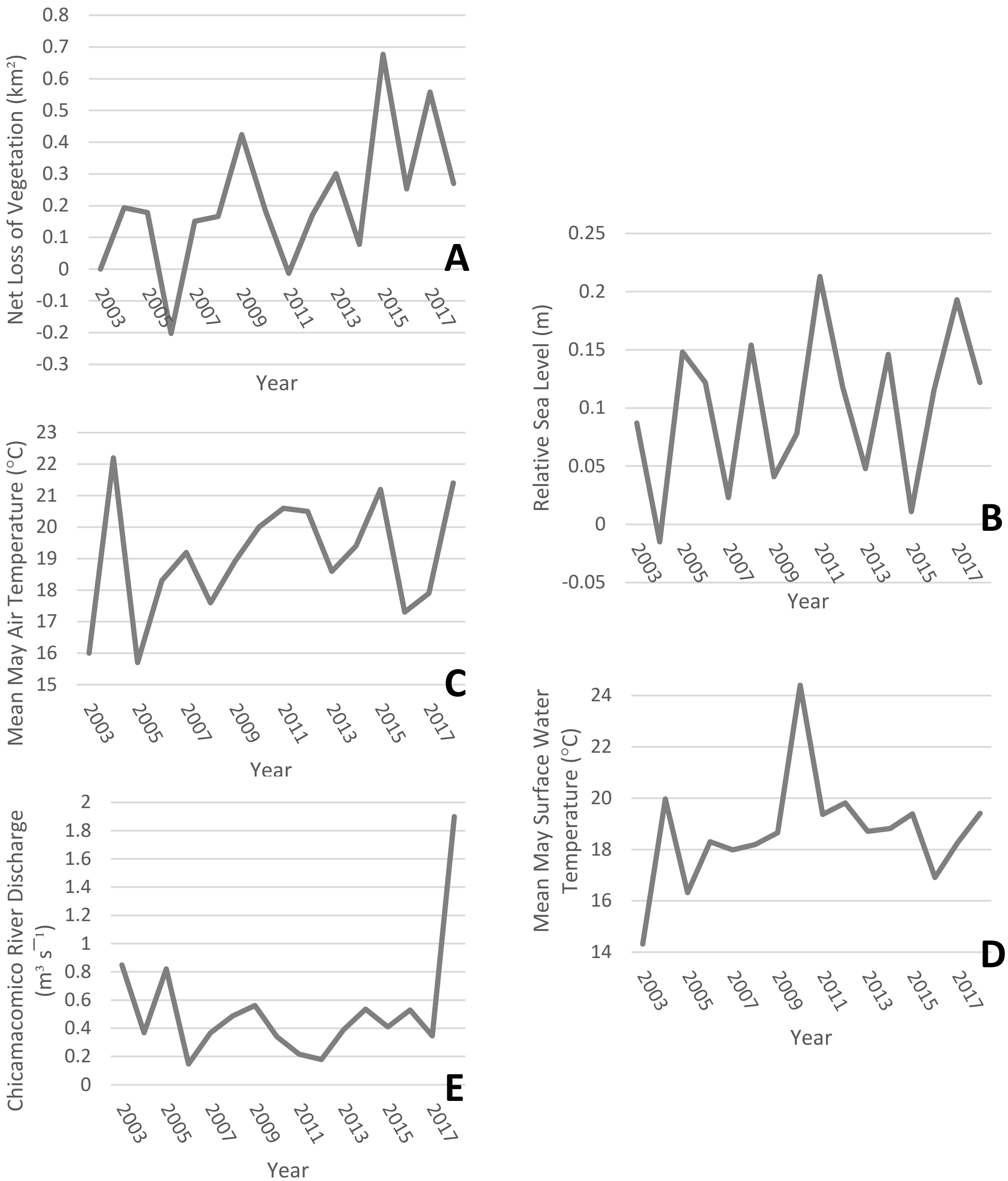

Figure 5 –Time series of the variables of interest during the duration of the study at BNWR. Shown are charts for net vegetation loss (A), relative sea level (B), mean May air temperature (C), mean May surface water temperature (D), and discharge rate of the Chicamacomico River (E).

		Year	NVL	AT	RSL	SWT	Discharge
Year	Pearson Correlation	1.000					
	Sig.	-					
NVL	Pearson Correlation	**0.547**	1.000				
	Sig.	**0.014**	-				
AT	Pearson Correlation	0.302	0.194	1.000			
	Sig.	0.128	0.236	-			
RSL	Pearson Correlation	0.276	-0.284	-0.335	1.000		
	Sig.	0.151	0.143	0.102	-		
SWT	Pearson Correlation	0.259	0.145	**0.693**	-0.156	1.000	
	Sig.	0.167	0.296	**0.001**	0.282	-	
Discharge	Pearson Correlation	0.237	0.105	-0.001	0.053	-0.208	1.000
	Sig.	0.189	0.350	0.498	0.422	0.219	-

Table 2 – Results of bivariate correlation between the variables: net vegetation loss (NVL), mean May air temperature (AT), relative sea level (RSL), mean May surface water temperature (SWT), and discharge rate of the Chicamacomico River. Significant correlations indicated in bold.

		Offset	AT	RSL	SWT	Discharge
Offset	Pearson Correlation	1.000				
	Sig.	-				
AT	Pearson Correlation	-0.181	1.000			
	Sig.	0.259	-			
RSL	Pearson Correlation	0.379	-0.407	1.000		
	Sig.	0.082	0.066	-		
SWT	Pearson Correlation	0.070	0.605	-0.224	1.000	
	Sig.	0.403	0.008	0.211	-	
Discharge	Pearson Correlation	**0.494**	0.093	0.066	-0.115	1.000
	Sig.	**0.031**	0.370	0.407	0.341	-

Table 3 - Results of bivariate correlation between the variables: net vegetation loss offset by one year (Offset), mean May air temperature (AT), relative sea level (RSL), mean May surface water temperature (SWT), and discharge rate of the Chicamacomico River. Significant correlations indicated in bold.

		VegChng
Elevation	Pearson Correlation	-0.204
	Sig.	0.338

Table 4 – Results of bivariate correlation between the NAVD88 elevations of 24 stations within the BNWR and the difference in vegetation between the LANDSAT images of 2003 and 2018.

Discussion

Climate-Related Variables

The literature is clear that a loss of salt marsh vegetation over time is occurring throughout the Mid-Atlantic and Gulf Coast regions (Alber et al., 2008; Crosby et al., 2017; Hughes et al., 2012; Mckee et al., 2004; Miller et al., 2017). Supporting this consensus, my analysis revealed that the area of vegetation cover is decreasing over time within the BNWR. This is indicated by the positive correlation between the area of net vegetation loss reported and time. Of the climate-related variables studied, only the Chicamacomico River discharge rate showed a correlation with vegetation loss. No other relationships were identified with the available data.

Alber et al. (2008) suggest that there is evidence that drought might be associated with marsh dieback in the Gulf Coast region but could not find evidence in the Atlantic region. McKee et al. (2004) drew the conclusion that while some soil chemistry in the Mississippi River delta support drought-related dieback, sea-level rise and multiple stressors were more likely causes. Using river discharge as a proxy for precipitation, I found that in the BNWR dieback was associated with higher amounts of precipitation and not the lower precipitation levels typical of drought conditions. This agrees with Alber et al.'s (2008) findings of no relationship between drought and vegetation loss in the Atlantic region.

The relationship between river discharge and dieback was only present when the analysis was time lagged. The growing season for *S. alterniflora* extends from February to October (Mendelssohn, 1979). While May would represent a mid-point in the growing season and a period of maximum growth, the growth found in May would be influenced by more than just the conditions present in May. Offsetting the vegetation data sequentially by one year would address some of these issues. This shift would mean the data recorded in 2009 would affect vegetation loss in 2010, therefore the 2010 image was offset for analysis with the 2009 data.

What is unclear is how exactly higher precipitation would be linked with marsh dieback. The saturation of marshes with this extra water should show up in the sea-level data as well as discharge rates. Raposa et al. (2017) reported that Rhode Island salt marsh's accretion rates were insufficient to keep up with rising sea levels, leaving the marshes vulnerable to dieback due to both short term and long-term sea-level rise. Crosby et al. (2017) suggested that temperature changes could affect belowground peat accumulation, further slowing accretion rates. Kolker et al. (2009) suggest this accretion rate, coupled with the rate of sea-level rise, determines how marsh can respond to climate change. This literature all suggests a strong link between sea-level rise and salt marsh dieback. My analysis did not support this conclusion. However, the data suggest a link. The bivariate correlation of the lagged vegetation data and sea-level rise resulted in a positive correlation that was just outside of significance ($r(14) = 0.379$, $p = 0.082$).

BNWR is in an area known to be experiencing subsidence (Eggleston and Pope, 2013). This should have had a reinforcing effect on the correlation between dieback and sea-level rise if such a relationship exists. However, there was no sea-level data available within the study area. The closest available data that extended throughout the time frame of the study were for Solomons Island, located directly west and across the Chesapeake Bay from BNWR. The effects of subsidence are dependent upon location within the Chesapeake Bay region (Eggleston and Pope, 2013). The linear distance between BNWR and Solomons Island of 26 km could have introduced enough error to account for the difference in my findings and those of the established literature.

Spartina alterniflora shows some amount of temperature plasticity (Crosby et al., 2017). Transplant experiments demonstrated that plants from warmer climates rapidly acclimated to cooler climates. Plants from cooler climates were less successful when transplanted to warmer climates. Crosby et al. (2017) made the conclusion that *S. alterniflora* would be vulnerable to rapid warming associated with climate change. I attempted to show a more direct link between temperature, whether air temperatures or surface water temperatures, and dieback. I found no relationship. This could be due to the same plasticity discussed by Crosby et al. (2017). Both Alber et al. (2008) and McKee et al. (2004) suggest temperature could be one of multiple stressors linked to marsh dieback. It is possible the lack of some of these stressors could be masking any direct links in my study.

Using LANDSAT to provide an inexpensive and easy way to obtain a historical record of any study area in the world is an attractive proposition. The limited resolution of LANDSAT was sufficient to show a relationship between vegetation loss and time as well as between vegetation loss and discharge rates. The lack of further relationships could be a result of using such a blunt instrument. Campbell et al. (2017) argued that the resolution of LANDSAT would be insufficient to detect the interface between water and vegetation in a salt marsh. The concerns of Campbell et al. (2017) warrant consideration as a 30 m^2 pixel represents a huge area in which the zonation of several species is present (Hickey and Bruce, 2010). The NDVI value of the 30 m^2 pixel is the reflectance of the species that covers 50% of that pixel. If no one species covers 50% of the pixel, a mean is derived. If at least 50% of the pixel is bare ground, a value of zero is displayed. The concept that different species are affected differently by different climate-related variables is lost within this poor resolution pixel. All that can be determined is that some form of vegetation is affected.

Error was introduced once the decision was made to digitally restore the data lost by scan line errors within the LANDSAT images. These scan line errors occurred on all images from 2004 to 2013, which represents a significant portion of the available data. Using the data uncorrected would have overinflated the loss of vegetation over time; a large portion of the image would include zero values for vegetation. The use of the 2003 image to recreate the missing data is not an ideal solution. However, the bias towards no vegetation change introduced by this method is preferable to the bias of vegetation loss.

Tides

Tides have the possibility of confounding the data obtained through satellite imagery. Due to the infrequency of satellite passes over a specified area, it is difficult to obtain images during the same tide cycle. This study used light from the red and the near infrared bands, bands that have relatively poor water penetration. If the brackish conditions of the marsh prevent penetration, the amount of vegetation change between low and high tides could be considerable.

Campbell et al. (2017) and Miller et al. (2017) both acknowledged the differences in tidal levels between the images used, but they left any effects caused by tides as a discussion point and only explaining what potential effects tides had on their data. Zhang et al. (1997) designed their study around the tidal cycle to limit any possible effects on imagery. I chose to directly address the tidal cycle and attempted to analyze any effects tidal cycles might have on the imagery. I performed a course, broad-scale analysis that, without proper ground-truthing, leaves the precision of the analysis somewhat questionable. However, the results suggest tides had no effect on the images. If tides were a confounding variable in this study, the greatest amount of vegetation change would be located along the coast as the retracting tides expose marsh grass. This was not the case. The bulk of the vegetation change occurred inland and not along the coastline as would be expected if tides were preventing light penetration. An independent study to definitively determine tidal effects, complete with ground-truthing, would be necessary to completely answer this question. Based on my analysis, I made the assumption that tides were not a confounding variable in my subsequent analysis.

Elevation

Miller et al. (2017) were able to negatively correlate vegetation loss with elevation. I was not able to make the same correlations. Using a measure over time of vegetation loss and a static elevation makes an assumption that elevation either remains constant or that it changes at the same rate throughout the study area. One issue is the NADV88 itself. This is an elevation database with the first set of elevation positions recorded in 1991; it used Father Point, Quebec, Canada as the reference point (NOAA, 2018). Additional positions have been added over time and corrected for the 1991 baseline. These data assume sea level changes are constant throughout North America. While this might hold true at Miller et al.'s (2017) South Carolina study area, BNWR is in an area known to be experiencing subsidence (Eggleston and Pope, 2013). It is entirely possible subsidence is affecting not only the recorded sea levels from Solomons Island but also the accuracy of the NAVD88 vertical datum. As a confounding variable, subsidence should have a reinforcing effect on sea level values in both the climate-related variable portion of the study and the elevation data in the elevation portion. Miller et al. (2017) were able to obtain a 2007 LiDAR digital elevation model of their study area for cross-reference. This allowed for a more accurate, but still static, elevation data set. LiDAR missions are now available from the USGS EarthExplorer after 2013. This limits historical elevation analysis such as my study to static data such as NAVD88. For analysis after 2013, these LiDAR missions would enable accurate data over time to be used track any elevation changes over time within a study area.

Ground-truthing is commonly used to provide an accuracy assessment for remote sensing work. Points are randomly assigned on an image and then assessed for accuracy at the study site with a GPS unit. Positive, negative, false-positive, and false-negative scores are used to generate an accuracy score with a goal of 80%. Miller et al. (2017) used 100 points to achieve a ground-truthing accuracy of 76.2%. This lends credence to the assertion that LANDSAT can be used accurately to assess salt marsh dieback. Due to the limited scope of my project, ground-truthing was not conducted. Any results or conclusions made from the images used in my analysis are suggestions until ground-truthing can be achieved. This lack of verifiable accuracy could contribute to the lack of a correlation between image-derived vegetation data and elevation that was present in Miller et al ‘s (2017) work. Likewise, this error could be contributing to the nonsignificant positive correlation between image-derived vegetation data and sea-level rise.

Conclusion

LANDSAT is a useful tool for broadly understanding of the vegetation in an area. Despite criticism (Campbell et al., 2017), Miller et al.’s (2017) results and my nonverified results suggest that LANDSAT resolution does appear sufficient to detect change at the water/vegetation interface. The tide preliminary study reinforced this point and demonstrated that despite a limited library of images, future studies are not constrained by tide cycles. The EU’s Sentinel system is now operational. With a resolution of 10 m, any future studies might consider this as a better free, publicly available option. However, this resolution is still insufficient for determining differences between species of vegetation. For multi-year studies using historical data, LANDSAT remains the option with the largest catalog.

A future study should consider how climate-related variables are gathered. Variables from May are too narrowly focused to be of much use. Calendar years have the potential to obscure statistical analysis. The mean of a growing season would be more appropriate. For example, if a 2006 May image is used, then a 2006 growing season of June 2005 to May 2006 would yield better results. Ultimately, this project provides a useful step towards using LANDSAT and other remote sensing tools in the study of salt marshes specifically and vegetation patterns generally.

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