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Textural Analysis of Historical Aerial Photography to Determine Change In Coastal Marsh Extent: Site of the Present-Day Grand Bay National Estuarine Research Reserve (GBNERR), Mississippi, 1955-2014

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TEXTURAL ANALYSIS OF HISTORICAL AERIAL PHOTOGRAPHY TO DETERMINE CHANGE IN COASTAL MARSH EXTENT: SITE OF THE PRESENT-DAY GRAND BAY NATIONAL ESTUARINE RESEARCH RESERVE (GBNERR), MISSISSIPPI, 1955-2014

by

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ABSTRACT

TEXTURAL ANALYSIS OF HISTORICAL AERIAL PHOTOGRAPHY TO DETERMINE CHANGE IN COASTAL MARSH EXTENT: SITE OF THE PRESENT-DAY GRAND BAY NATIONAL ESTUARINE RESEARCH RESERVE (GBNERR), MISSISSIPPI, 1955-2014

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Coastal marshlands are among the world's most highly productive ecosystems but they have diminished greatly in the past several decades owing to sea-level rise and direct anthropogenic influences. An effective means of quantifying loss or gain in marsh area is through the use of aerial image data, which offers synoptic views of the landscape at decadal-scale sampling frequencies. However, a potential problem with older panchromatic, or black-and-white, imagery is the absence of multispectral information that might be used otherwise in remote identification of vegetation types. Nevertheless, the analysis of horizontal variability in image brightness values, or image texture, can be used in deriving marsh areal coverage from even the oldest-available aerial photography. This project employed imagery acquired in 1955, 1992, and 2014 over Jackson County, Mississippi, to determine the extent of marshland loss or gain in the vicinity of the present-day Grand Bay National Estuarine Research Reserve (GBNERR). After pre-processing the images, image textural parameters were computed using the Grey-Level Co-Occurrence Matrix procedure (ENVI v X.X). A Maximum-Likelihood classification of the textural parameters to vegetation type was derived based on ground control point data. A change detection analysis then was applied among years. Preliminary results suggest that a net loss of around 5% in marsh area occurred in the GBNEER vicinity from 1955 to 2014. Results will assist resource managers in determining locations that may be most vulnerable to continued sea level rise and direct human impact.

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DEDICATION

This thesis is dedicated to my grandmother, Maurine Slater, whose love and encouragement had no bounds.

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LIST OF ABBREVIATIONS

ASM	Angular Second Moment
CV	Coefficient of Variation
DOQ	Digital Ortho Quads
ENVI	Exelis Visual Information Solution
GBNERR	Grand Bay National Estuarine Research Reserve
GCGC	Gulf Coast Geospatial Center
GCLM	Grey Level Co-Occurrence Matrix
GoM	Gulf of Mexico
NAIP	National Agricultural Imagery Program
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
ROI	Region of Interest
USGS	United States Geological Survey

CHAPTER I - Introduction

Salt marshes are currently under high stress from both relative sea-level rise and anthropogenic influences. The loss of salt marshes are a problem because they are one of the most highly productive ecosystems in the world and provide habitats for economically beneficial species. Salt marshes also act as carbon sinks for the rising greenhouse gasses from climate change. Salt marshes also help prevent flooding by absorbing both excess rain water and tides from storm surge. Because of the economic and ecological benefits that salt marshes provide, it is crucial to detect historical change of these habitats to better understand where change is greatest and better implement resources to help protect against sea-level rise and anthropogenic forces in those areas. One of the best ways to detect historical change is through the use of remote sensing, which offers a cost effective view of the entire study area as well as a consistent view throughout time. However, historical black and white images do not have the spectral information on which modern classifications are based. Methods such as texture analysis, which rely on the variation of brightness values in the image, have been devised to overcome this spectral limitation in order to classify habitats. Texture-based methods have been found to result in greater classification accuracies than spectral-based methods alone.

One salt marsh location that is currently under stress is located in the Grand Bay National Estuarine Research Reserve [GBNERR], which is in Jackson County, Mississippi. The GBNERR has been impacted by sea-level rise due to the GBNERR's proximity to the Mississippi sound, as well as natural disasters such as Hurricane Katrina.

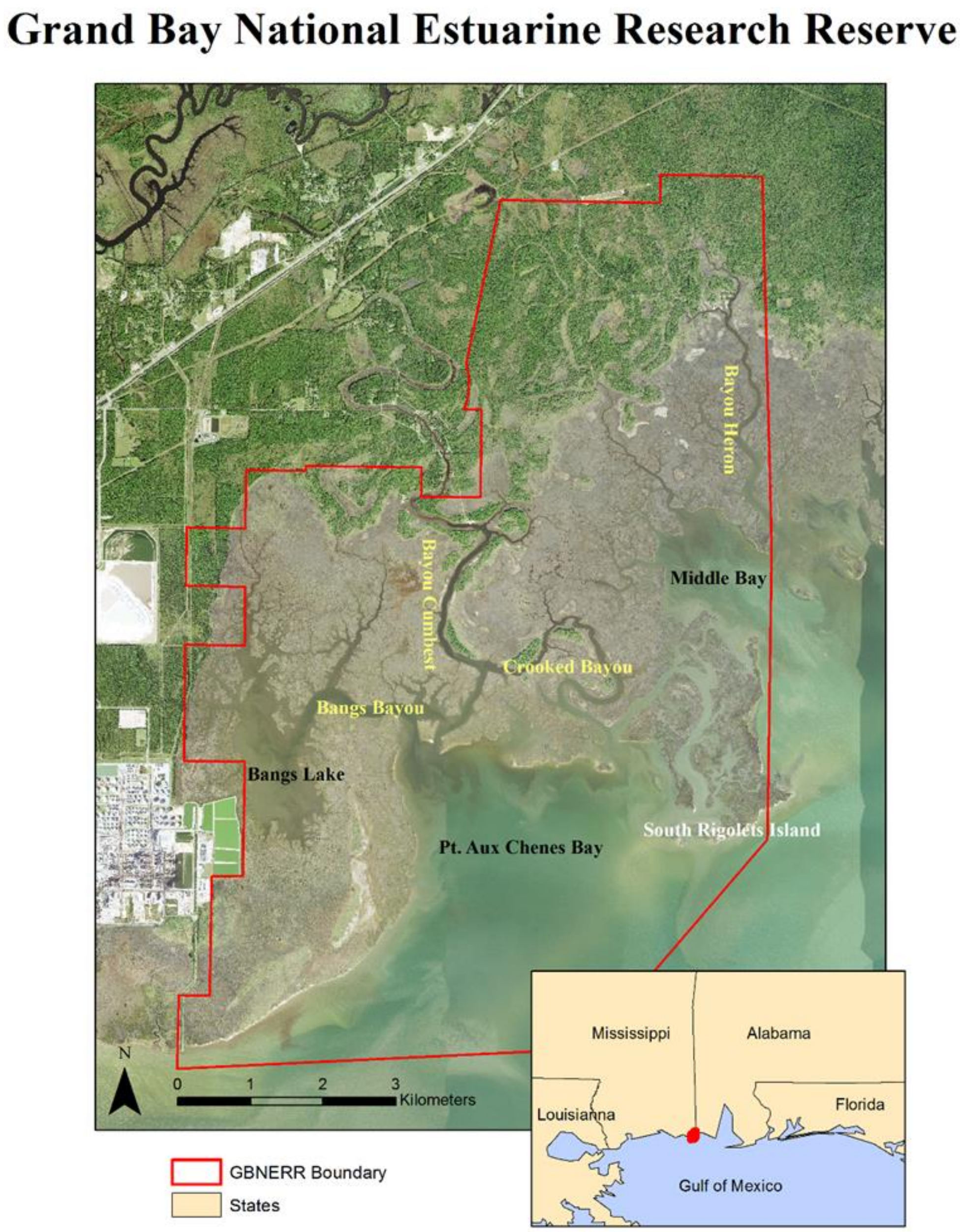

Figure 1. Map of Study Area

A map showing where the GBNERR is located and the various features found within the boundaries

A literature review showed that there was a deficiency in methods to properly identify long-term change in coastal salt marsh habitats using high spatial resolution imagery. Landsat data was used in two studies to detect habitat change at both the

GBNEER and three Mississippi Coastal Counties (English 2011; Hilbert 2006). Though both studies looked at historical changes of salt marshes (and other habitat types), the low spatial resolution can introduce classification errors in dynamic habitats that can vary greatly in small areas.

Another study on GBNERR used high resolution historical imagery to determine salt marsh habitat change using a change detection method that was more qualitative and prone to bias (Wells 2010). Though none of the previous studies used texture methods, the methods have been successfully implemented at another site along the Mississippi coast, Horn Island (Jeter and Carter 2015).

The overarching goal of this project was to detect historical change in salt marsh habitats in the Grand Bay National Estuarine Research Reserve using textural analysis of panchromatic imagery from as far back as 1955. The results from this project will help policy makers and natural habitat managers at the GBNERR better implement protection strategies against rising sea levels, climate change, and anthropogenic influences. The historical results can be used by resource managers in allowing them to see where the most change has occurred and how they can use limited resources to help implement marsh restoration techniques.

CHAPTER II – Literature Review

Wetland and Salt Marshes

Salt marshes, which are one of the most productive ecosystems in the world, are wetlands that are highly dynamic and support a variety of vegetation and wildlife (EPA n.d.). Salt marshes develop in intertidal shores in mid-to high latitudes and are highly influenced by tidal inundations and gradient of oxygen and salinity. They support a variety of vegetation including *Juncus spp.* in high marsh areas and *Spartina spp.* in low marsh areas, and also support a high variety of animals (Greller 2010; Kennish 2001). Other important ecological roles that salt marshes conduct is serving as a buffer for upland wetlands (Kennish 2001). Other reasons salt marshes are important is because they recharge groundwater supplies to nearby water bodies, help reduce damage caused by floods by storing flood water, and reduce pollution from surface water by using the nitrogen and phosphorus from fertilizer run-off (EPA 2016). However, salt marshes are heavily impacted by natural factors such as sea-level rise and anthropogenic factors such as industrialization and fishing. Sea-level rise is of particular concern to salt-marshes because they can respond to the change in sea level in ways such as submergence or receding (Orson et al. 1985). One important region to study salt marsh habitats is the Gulf of Mexico (GoM), especially in the northern GoM. The GoM has a great variety of coastal water systems that support salt marshes including estuaries and barrier islands. Wetlands in the northern Gulf of Mexico region have had a net loss of approximately 257,000 acres between 2004 and 2009 (Dahl 2011).

Due to the high susceptibility of salt marshes to sea-level rise and anthropogenic influences, there is a need to be able to detect change of these habitat types consistently and over long periods of time. One way for historical study of wetlands is through remote sensing. Remote sensing allows for time and cost saving by providing an economical way to collect data about many environmental factors through time, which includes habitat change (Jensen 2006). It offers a variety of ways to map and monitor the health and extent of wetlands through a variety of sensors, resolutions, and geospatial techniques. The resolutions can be spatial and spectral resolutions, and geospatial techniques can include bother spectral based classification methods and texture based classification methods. (Klemas 2011).

Grand Bay National Estuarine Research Reserve

The study site for this research was the Grand Bay National Estuarine Research Reserve [GBNERR] and has had both human and natural influences affecting its development overtime. The GBNERR is located in Moss Point, Mississippi, which is in southern Jackson County, Mississippi. The GBNEER was established in 1999 and is one of 28 sites throughout the United States that were created to study estuarine systems through a partnership with NOAA and state and local agencies (GBNERR 2016; OCMNERR n.d.). The GBNERR is approximately 7,284 hectares and contains a variety of habitat types. These include salt marshes, pine savannas, and salt pannes. The variety of habitats provides perfect locations for many plant and animal species. Smooth cordgrass, black needlerush, and salt meadow cordgrass are the dominant vegetation in the salt marshes. Glasswort species can be found in the salt pannes. Other plant species found in the three study areas include live oak and slash pine (Peterson et al. 2007). Animal groups include oysters, many types of frogs, turtles, alligators, and many species of birds (Peterson et al. 2007). There is also a large human impact in the GBNEER. In

Jackson County there was a large lumber, pulp, and paper industry. Recently the GBNEER has implemented restoration techniques to restore the forested area. The land in the area has had heavy agricultural uses in the past. Recreational activities in the GBNEER includes fishing and waterfowl hunting when legally permitted (Carter 2007). The GBNEER is also under threat from rising sea levels. There has already been a large loss in historical saltmarsh extent because marsh response to rising sea level includes submergence or recession (Dahl 2011; Greller 2010; Orson et al. 1985). The effect of sea-level rise has even been found at that GBNERR. One study discovered through models that sea-level rise had a larger effect on tide velocities in the GBNERR than the surrounding barrier islands, and noted that it was important because even small changes in tide dynamics can affect sediment processes and could potentially lead to erosion (Passeri 2015).

Local Research

Many research projects have shown how remote sensing can be successfully used in order to monitor habitat change in marsh and wetland habitats all across the United States. Landsat data, which is commonly used for earth observations, was used in two separate historical habitat change projects in the Lake Pontchartrain basin region and in a Maryland estuary. Researchers found through change detection that the wetland habitat types in both study areas had decreased since the earliest image date (Martinez and Penland 2009; Nosakhare et al 2012). There are also many examples of Landsat data being used to study GBNERR and surrounding local marshes.

English (2011) conducted a land-use/land cover study across the three Mississippi coastal counties using Landsat Multispectral Scanner and Landsat Thematic Mapper data.

She conducted an isodata classification to detect a variety of classes including salt marshes, vegetation, water, and urban areas. The study dates were every five years from 1975 to 2005. She found through her study that there was no clear trend in the salt marsh habitats over the years, with there being losses and gains depending on the year and the county. She found in Jackson County – where the GBNERR is located – that though there was an overall decline in salt marsh habitat from 1975 to 2005, the loss and gain between the study years varied. (English 2011).

Hilbert (2006) conducted a change detection study in the GBNERR for habitat change from 1974 to 2001 using Landsat data. The three years of the study were 1974, 1991, and 2001. A Normalized Difference Vegetation Index (NDVI) and three principle component analysis (PCA) bands were computed. The NDVI and PCA bands were combined together to create a classification using the ISODATA method. The researcher found that approximately 200 ha of wetland were lost from 1974 to 1991 and 260 ha were lost from 1991 to 2001 (Hilbert 2006).

However, the spatial resolution of Landsat data is relatively low compared with that of some other remotely-sensed data. Researchers have found that greater spatial resolutions produce higher classification accuracies in salt marsh vegetated areas than sensors that offer higher spectral resolutions (Belluco et al. 2006). There are many examples of using high spatial resolution imagery to detect salt marsh change in the Mississippi region as well.

Wells (2010) used high spatial aerial imagery from as far back as the 1940s, and National Agriculture Imagery Program [NAIP] imagery from as far back as the 1980s in order to classify *Juncus roemerianus* change in the GBNERR. Wells used a multi-date change detection algorithm on the brightness values in order to detect *J. roemerianus* change overtime. She found through visual clues vegetation patch size had gotten smaller within the salt pannes, and there was an approximately 50% percent change in brightnesss values. About 14% to 21% changed to a brighter intensity and the researcher theorized human impacts such as new construction or new sediment depositions, while 25% to 29% changed to a darker intensity and the researcher suggested either an increase in vegetation density or shoreline erosion (Wells 2010).

However, many of these studies rely on spectral-based methods. This is an issue because remote sensing studies with a long-term focus may have to use black and white panchromatic images that do not have spectral information because those may be all that is available for certain time periods (Cserhalmi et al. 2011; Kadmon and Harari-Kremer 1999). One way to overcome this is through the use of texture-based methods to classify habitats.

Textural Analysis

Texture analysis is based on spatial variation in the image brightness values that result from the reflectivities of ground objects (Bharati et al. 2004). It is defined by Haralick et al. (1973) as "...the spatial distribution of tonal variations within the bands, or the spatial (statistical) distribution of gray tones" (Haralick et al. 1973). Texture methods have been successfully used in a variety of remote sensing projects including classifying and comparing tree densities, classifying SAR sea-ice data, and detecting forest age and forest basal area (Platt and Schoennagel 2009; Clausi 2002; Kayitakire et al. 2006). Texture-based methods have been used increasingly in recent years because they can yield more accurate results than purely spectral or manual classification methods. A key advantage of texture methods is that they allow objects to be classified based on shape, size, pattern, and spatial relationships (Berberoglu et al. 2010; Cserhalmi et al. 2011; Franklin et al. 2001; Platt and Schoennagel 2009).

Many research projects have shown the successful use of texture methods in classification of wetland habitats. Texture methods were used to classify Mediterranean wetlands in order to detect change over time (Berberoglu et al 2010). Another study used texture methods in order to classify and map changes in mangrove forests in southwestern Senegal. Through a change detection analysis, it was found that the mangrove areas had changed only slightly over a 20-year period, but the classification accuracy for the most recently-dated image was 86% (Conchedda et al. 2008). In the Mississippi coastal region, Jeter and Carter (2015) applied a texture method to panchromatic imagery of Horn Island, Mississippi. They classified habitats for the years 1940 and 2010 in order to detect habitat change between the two years and found that there was an increase in marsh as a result a steadily rising water table (Jeter and Carter 2015). These are just a few of the many studies that have been done on salt marsh and wetland classification that used texture methods. There are many ways to analyze image texture, but the most common method is the grey level co-occurrence matrix (GCLM) procedure.

Many different methods have been defined to use texture to classify features that range from the use of standard deviation to the use of the gray level co-occurrence matrix method (GCLM) (Berberoglu et al. 2010; Carlucci 1971). The GCLM, which is defined by Bharati et al. (2004) as "...second order joint probability of the intensity values of two pixels a given distance apart have the same intensity" is often used in remote sensing studies (Berberoglu et al. 2010; Bharati et al. 2004; Jeter and Carter 2015). There are over 20 texture parameters that the GCLM can produce, but common texture parameters used in classifications include contrast, correlation, angular second moment (ASM), dissimilarity, and entropy (Berberoglu et al. 2010; Bharati et al 2004; Dobrowski et al. 2008; Jeter and Carter 2015). Entropy and ASM are based on the homogeneity in an image, whereas contrast measures local variations of the pixel values in an image. Correlation is the measure of gray-tone dependencies in the image, or more specifically how the BV relies on the surrounding values (Clausi 2002; Haralick et. al 1973). Texture based methods such as the GCLM offer a unique way to determine historical habitat change detection in salt marsh habitats.

All previous efforts mentioned in the review to map ecotype change in salt marshes and wetlands have used a variety of methods and data types to detect salt marsh habitat change in the coastal region, but there are some gaps in the methods including lack of combining high spatial resolution with a decadal temporal resolution. This study will build upon previous efforts by conducting historical habitat change in Mississippi's coastal marshes for multiple dates using historical and modern panchromatic imagery through the use of texture methods. After classification of each image, an analysis will be conducted that will quantify the habitat change between each date for the GBNERR.

This project seeks to answer two main questions. The first question is how has salt marsh habitat, as well as other habitat types such as forested areas, changed in the GBNEER since1955? Secondly, can texture methods be used to accurately classify habitat types and detect habitat change? Overall, the results of this study will show change in marsh habitats in the GBNEER over a period of approximately six decades.

CHAPTER III - Methods

Data

Image data sets from three different years were obtained for this study. The dates obtained were 1955, 1992, and 2014. Two of the study images were obtained from the United States Geological Survey [USGS] data repository, the USGS Earth Explorer, which is a tool that allows users to search and accesses a variety of geospatial imagery and satellite images - including historical photos (USGS LPDAAC 2014). One of the images was obtained from the United States Department of Agriculture [USDA]. The ground truth data set was obtained from the Gulf Coast Geospatial Center [GCGC].

The February 13, 1955, image data set was obtained from Earth Explorer and consists of USGS Single Frame Aerial Photos (USGS EE 2017). The USGS frames collection spans decades, and a variety of film types and sensitivities were used. The data set downloaded was black and white, and the most commonly used panchromatic film was sensitive to the visible part of the spectrum (USGS 2015a). The frames had a cell size of 1m.

The February 19, 1992 data set consisted of Digital Ortho-Quads [DOQs] and was downloaded from the USGS Earth Explorer (USGS EE 2017). DOQs are terrain-corrected ortho-images. The DOQs downloaded were in black and white, and had a resolution of 1m (USGS 2015b).

The October 16, 2014 image data set consists of National Agricultural Imagery Program [NAIP] images and was obtained from the USDA. NAIP imagery is collected by the USDA during the growing season for each state (USDA FSA n.d.). The images from 2002 to 2008 were collected on a five-year rotation, and switched to a three-year rotation in 2008. The bands contained within NAIP were originally limited to RGB but starting in 2007, a NIR band was added (USDA FSA n.d.). The spatial resolution of the NAIP imagery is 1 m.

The final data set consists of ground training data for the GBNERR that were recorded from the 2015 field observations of C.Anderson and B.Funderburk from USM's GCGC. The seven habitat types noted in the ground survey included high marsh, intermediate marsh, low marsh, pine forest, salt panne, wet coastal prairie, and wetland shrub.

Pre-Processing of Data

The first step for each of the images was to geo-rectify and mosaic the individual frames for each of the data sets. The 2014 and the 1992 images were already geo-rectified so only the 1955 image frames required geo-rectification (ArcMap 10.x).

Each individual frame was geo-rectified. In order to geo-rectify, the 2014 NAIP image was used as the base image. Common points were found between the older image and the 2014 image. Hard targets such as buildings were preferred and used if available. However, sometimes only soft targets such as ponds or trees were available, so the soft targets were used instead. All individual frames had an georectification error of 1.2m or less. The reason the higher georectification root mean square error[RMS]was allowed was because of the lack of hard ground control points in the study area. Then the geo-rectified images were mosaicked using Exelis Visual Information Solution [ENVI]. The single frames for both 1992 and 2014 were also mosaicked using ENVI.

Next, a 2014 panchromatic image was computed from the color NAIP imagery so that it could be accurately compared to the older panchromatic images. To do this, the mean of the RGB was computed, which is a standard method to create a panchromatic image (Jeter and Carter 2015; Ponti et al. 2016).

The range of the BV values is often in 8-bit and goes from 0-255. The 1955 image BV data range was slightly skewed, so the stretch tool was used to make the data range of the full mosaic go from 0-255 so that there could be a comparison between all the images.

The final step for pre-processing included creating a hand-drawn water and urban mask for the older images. A hand drawn urban mask was created for the 2014 image. The mask allowed for the water and urban areas to be ignored during the classifications.

Image Classification

The first step to classify the images after pre-processing was to compute the texture bands. This was done using the GCLM parameters pre-built into ENVI Classic. Though all of the texture bands were computed, only five bands were used in the classification. The bands used were mean, variance, entropy, angular second moment, and homogeneity. These are commonly used in habitat classification research and were found to offer the highest classification accuracy for this study (Berberoglu et al. 2010; Bharati et al. 2004; Dobrowski et al. 2008; Jeter and Carter 2015). Entropy and ASM are based on the homogeneity in an image, which was useful for detecting homogeneous habitats such as sand. Contrast, which measures the amount of local variation in the image, was useful for detecting non-homogenous habitats such as marsh or woodland habitats (Clausi 2002; Haralick et. al 1973). The co-occurrence shift and quantization level were left at the defaults, which was 1 and 64 bit, respectfully. A 25x25 pixel window size was selected for 1955, 1992, and 2014.

The first classification was computed from the 2014 imagery using the Maximum Likelihood supervised classification method. The ground truth data was imported into ENVI. Region of Interests [ROIs] were created from the ground truth geolocations. Though there were seven habitats types noted in the ground survey, the habitats were condensed into four final habitats for classification – marsh, salt panne, woodland, and water. For each habitat type, accuracy and training ROIs were created. There were three times as many pixels in the accuracy versus training ROIs. The classification was computed using the pixels in the training ROIs. After the classification, a confusion matrix was used to conduct an accuracy assessment. The accuracy ROIs were used and compared with the final classification results.

Since there were no ground training data available for the older images, a method using the Coefficient of Variation (CV) values for ground truth data was used. The CV computation, which is the standard deviation multiplied by 100 and then divided by the mean, creates dimensionless values and allows for comparisons across images (Jeter and Carter 2015). One can assume that if a habitat type is characterized by a particular CV value range in one image, then the habitat type should be represented by a similar CV range in a different image of the same study area. CV values were computed for the 2014 image, and using the habitat ROIs, the CV value range was found for each habitat type. CV values were then computed for all of the older images. From these, ground-truth ROIs were emulated for each image date. The same steps from the 2014 image were then applied to the older images to create the image classification and conduct an accuracy assessment.

Change Detection

Pixel-by-pixel change detection analysis was conducted for the time-period comparisons of 1955 to 1992, 1992 to 2014, and 1955 to 2014. In each analysis, the earlier-date image was co-registered to the later-date image. The co-registration error from 1995 to 1992 was 2.1m, from 1955 to 2014 was 2.8m, and from 1992 to 2014 was 0.9m. To make sure image were spatially inter-comparable, masks for each image were combined so that the areas masked in one image were masked in all three. Next, the middle portion of the GBNERR area was sub-setted and used for the change detection analysis. The reason for this was two-fold and is expanded upon in the results section. The same middle region was used across all image dates to accurately compare them in change detections (Figure A1).

CHAPTER IV – Results

Results include a habitat classification for each of the study years as well as a table that shows the habitat extents for each year

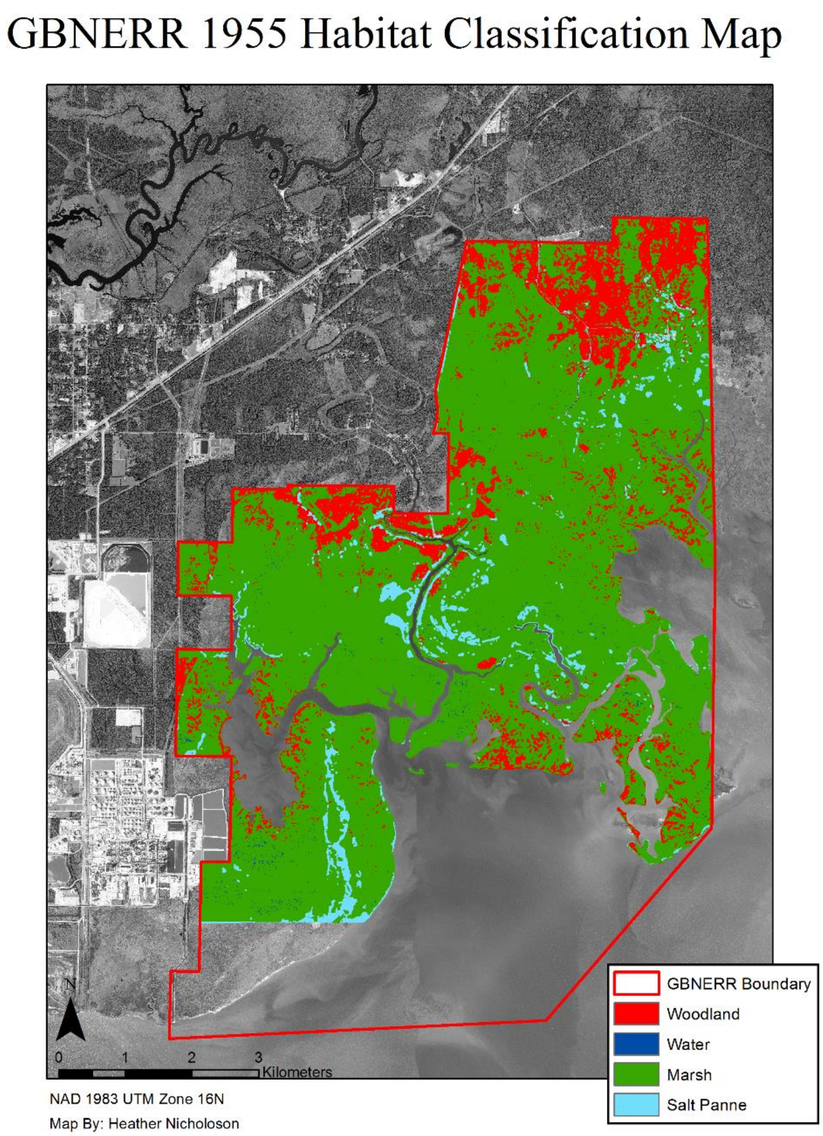

Figure 2. GBNERR 1955 Habitat Classification Map

A map showing the geographic extent for the habitat types based off of the classification from the 1955 image. Green represents salt marsh, the red is woodland, the dark blue is water, and the light blue is salt panne.

Overall classification accuracy of the 1955 image was 97% with a kappa coefficient of 0.81.

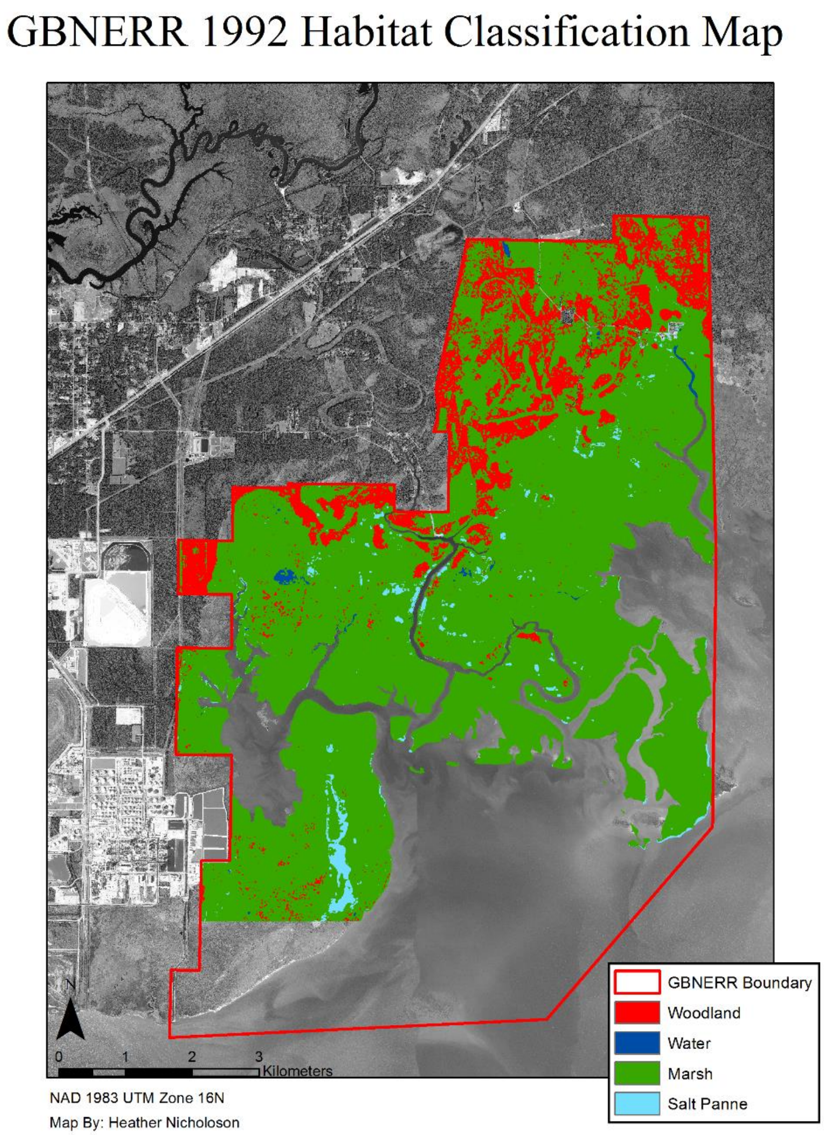

Figure 3. GBNERR 1992 Habitat Classification Map

A map showing the geographic extent for the habitat types based off of the classification from the 1992 image. Green represents salt marsh, the red is woodland, the dark blue is water, and the light blue is salt panne.

Overall accuracy of the 1992 classification was 98% with kappa coefficient of 0.90.

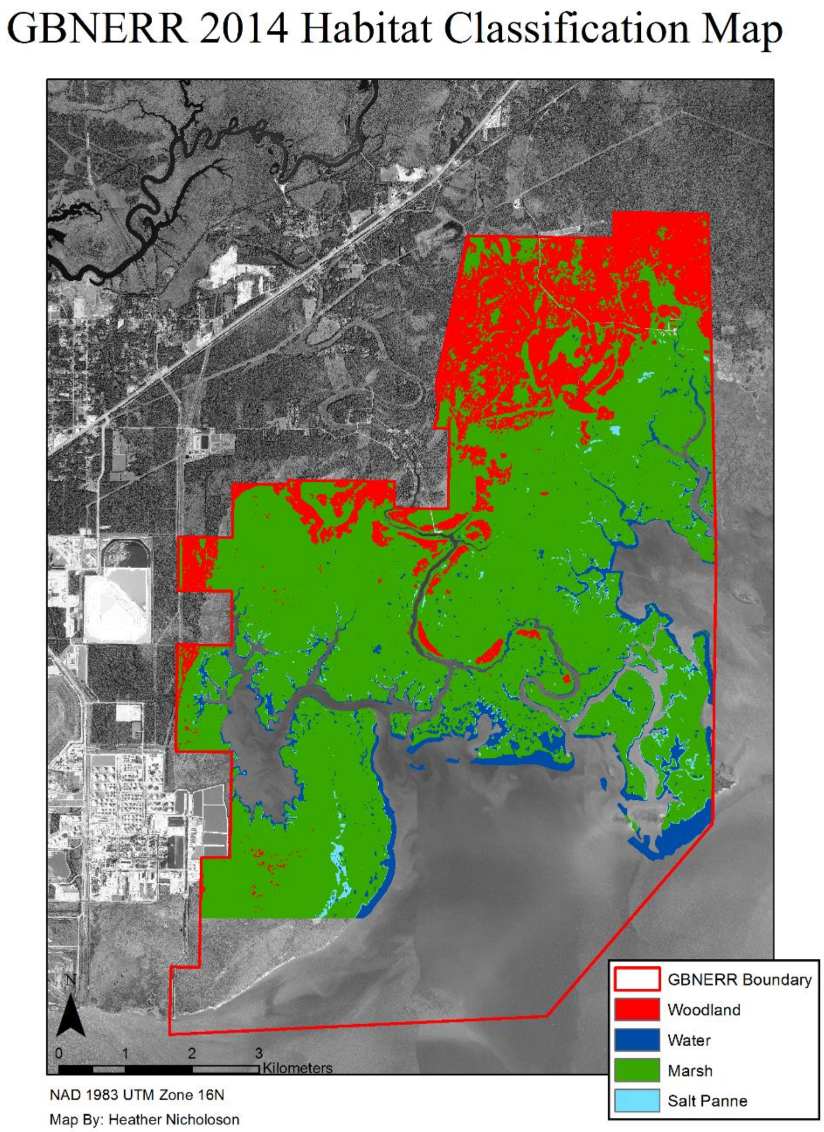

Figure 4. GBNERR 2014 Habitat Classification Map

A map showing the geographic extent for the habitat types based off of the classification from the 1955 image. Green represents salt marsh, the red is woodland, the dark blue is water, and the light blue is salt panne.

Overall classification accuracy of the 2014 image was 97% with a kappa coefficient of 95%

Table 1 *GBNERR Habitat Extent for Each Year*

	Marsh	**Salt Panne**	**Woodland**	**Water**
1955	3900.4	223.0	651.7	16
1992	3853.7	105.6	589.6	17.8
2014	3481.8	93.8	883.4	331.4

This table shows the habitat extent in hectares for each year in the entire area of the GBNERR.

The marsh habitat had a 1.2% decrease from 1955 to 1992. The marsh habitat decreased 9.6% from 1992 to 2014. The marsh habitat lost an overall extent of 10.7% from 1955 to 2014.

The salt panne habitat had a loss of 52.6% from 1955 to 1992. The habitat decreased 11.2% from 1992 to 2014. There was an overall loss of 57.9% of salt panne from 1955 to 2014.

The woodland habitat had a 9.5% decrease from 1955 to 1992. Woodland habitat increased by 49.8% from 1992 to 2014. The extent of woodland decreased by 35.5% from 1955 to 2014.

Due to a water mask that was used in the earlier study years to remove most of the water except for some small inner rivers, the water change is not comparable between each of the years.

Moss Point, Mississippi had a logging industry that ended in the 1930s. Time in conjunction with restoration practices led to a lot of the clear cut areas in the northern part of the GBNERR to grow more woodlands. The clear cut land is texturally indistinguishable from the marsh areas, and so the clear cut lands were classified as marsh. Another issue is that for the 1955 image no frame was found that covered the most southern part of the GBNERR, so there was no way to compare the southern region of the NERR from 1955 to 1992 and 2014.

To take both issues into account, the change detection among all images was only conducted in mid-region part of the GBNERR. The most southern extent of the change detection was the southern-most portion available from 1955, and the northern most part of the change detection was close to the most northern marsh ground data point from the GCGC ground truth survey. The following are the classification maps of the mid-region part of the GBNERR.

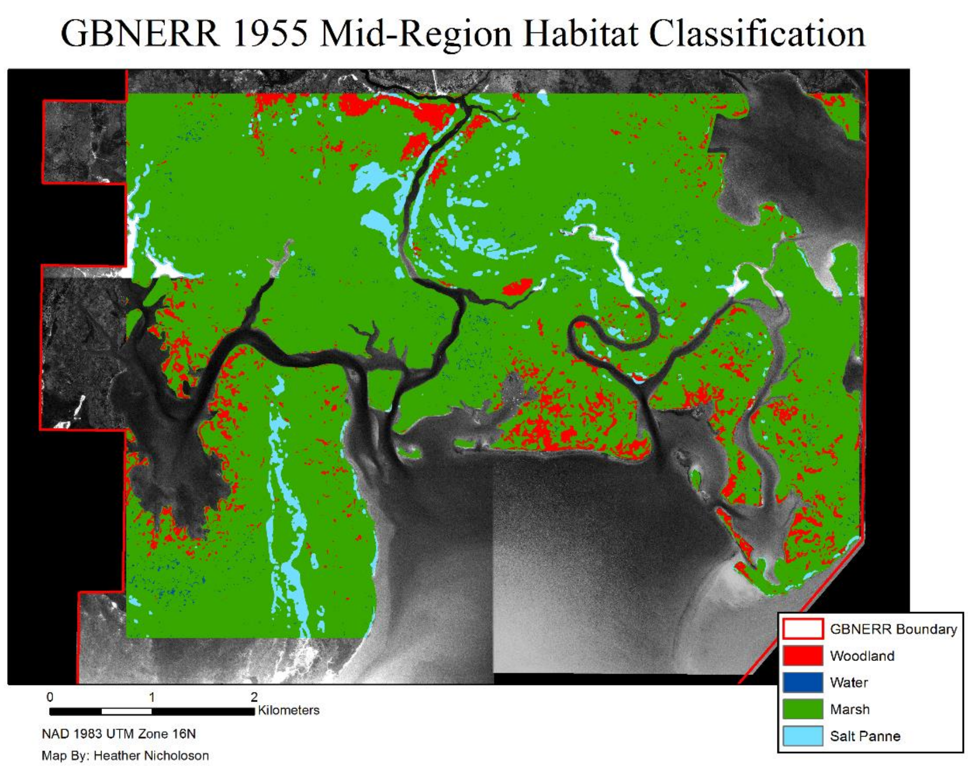

Figure 5. GBNERR 1955 Mid-Region Habitat Classification

A map showing the geographic extent for the habitat types in the mid-region of the GBNERR based off of the classification from the 1955 image. Green represents salt marsh, the red is woodland, the dark blue is water, and the light blue is salt panne.

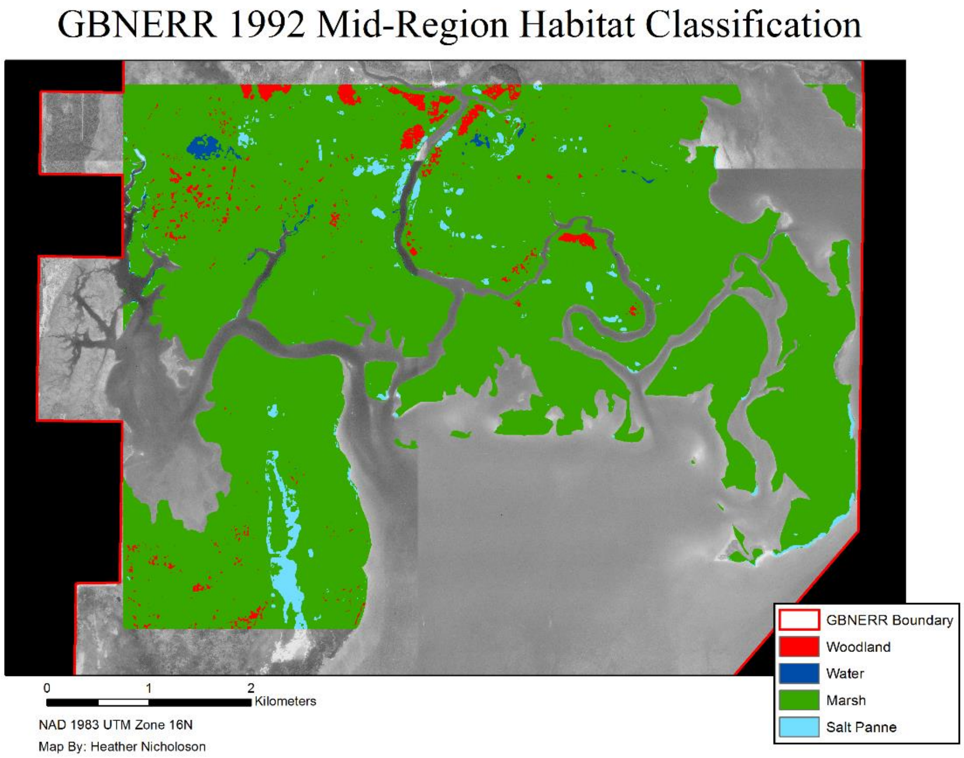

Figure 6. GBNERR 1992 Mid-Region Habitat Classification

A map showing the geographic extent for the habitat types in the mid-region of the GBNERR based off of the classification from the 1992 image. Green represents salt marsh, the red is woodland, the dark blue is water, and the light blue is salt panne.

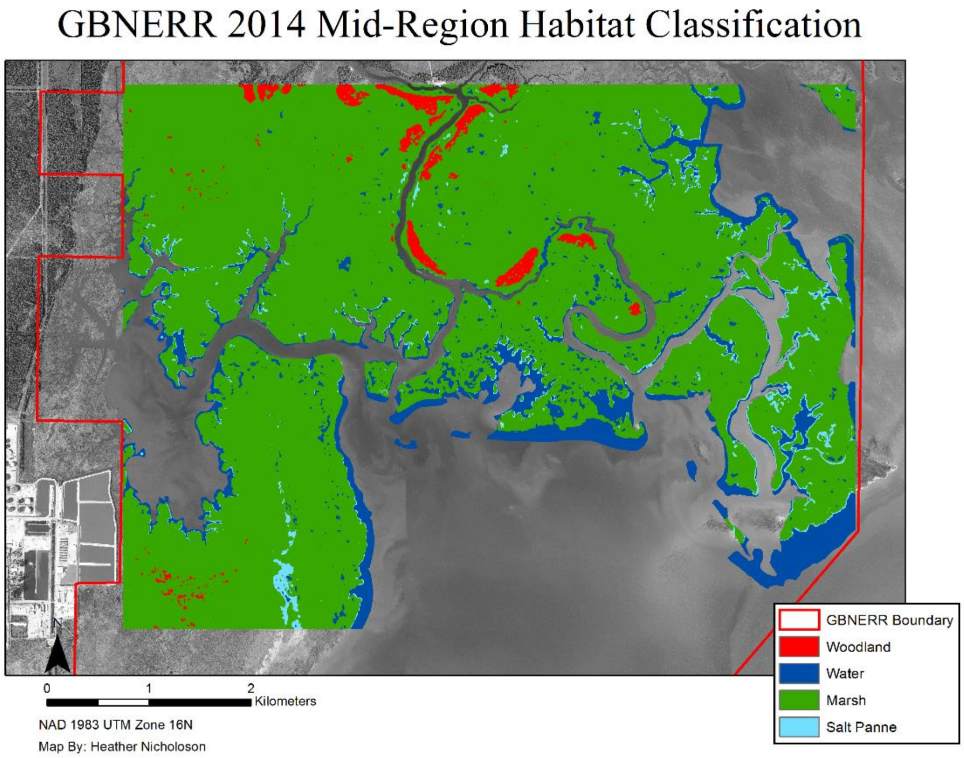

Figure 7. GBNERR 2014 Mid-Region Habitat Classification

A map showing the geographic extent for the habitat types in the mid-region of the GBNERR based off of the classification from the 2014 image. Green represents salt marsh, the red is woodland, the dark blue is water, and the light blue is salt panne.

Table 2 *GBNERR Mid Region Habitat Extent for Each Year*

	Marsh	**Salt Panne**	**Woodland**	**Water**
1955	2170.3	125.6	157	11.3
1992	2175.7	57	44.5	10.2
2014	2072.8	60.1	49.7	281.7

The table shows the habitat extent in Hectares for each year in the southern area of the GBNERR

The marsh habitat had a 0.2% increase from 1955 to 1992. The marsh habitat decreased 4.7% from 1992 to 2014. The marsh habitat lost an overall extent of 4.5% from 1955 to 2014.

The salt panne habitat had a loss of 54.6% from 1955 to 1992.The habitat increased 5.4% from 1992 to 2014. There was an overall loss of 52.1% of salt panne from 1955 to 2014.

The woodland habitat had a 71.3% decrease from 1955 to 1992. Woodland habitat increased by 11% from 1992 to 2014. The extent of woodland decreased by 68% from 1955 to 2014.

As with the habitat change for the full study area, due to a water mask that was used in the earlier study years to remove most of the water except for some small inner rivers, the water change is not comparable between each year. The following maps show the loss and gain of salt marsh in the GBNERR region.

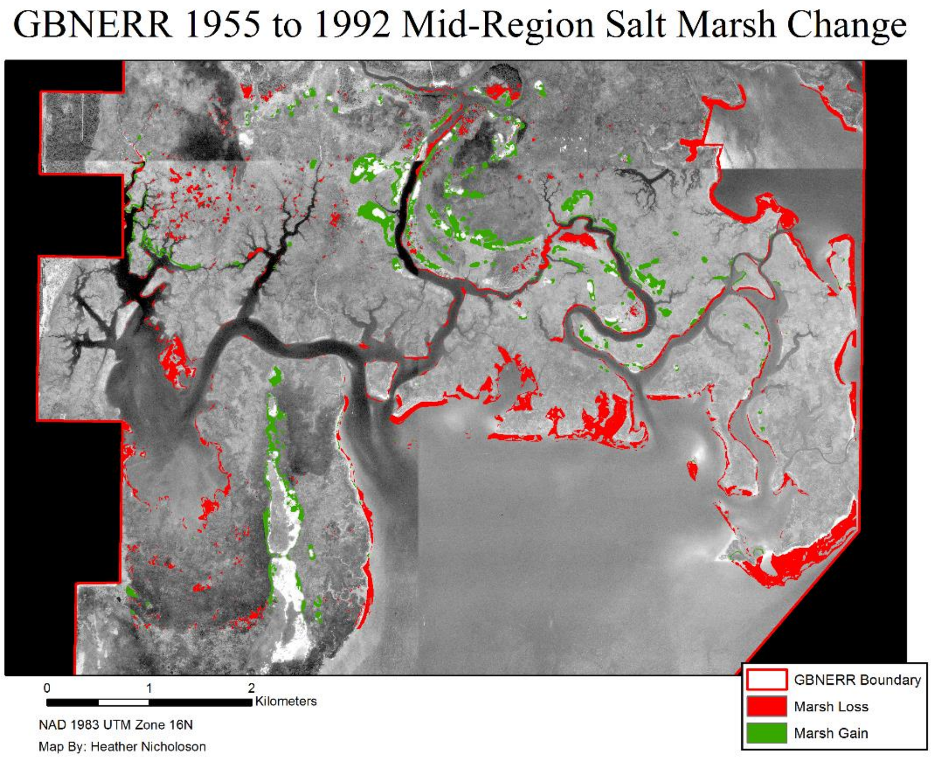

Figure 8. GBNERR 1955 to 1992 Mid-Region Salt Marsh Change

The map shows changes in marsh in the mid-region of the GBNERR from 1955 to 1992. The red areas represent marsh loss, where the green areas represent marsh gain.

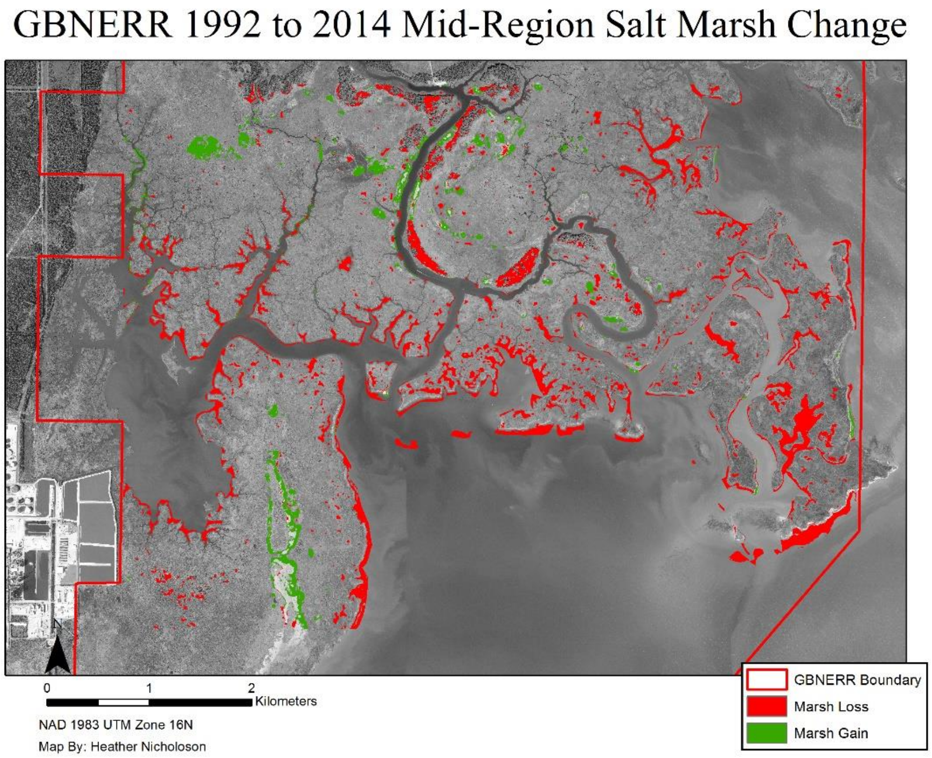

Figure 9. GBNERR 1992 to 2014 Mid-Region Salt Marsh Change

The map shows changes in marsh in the mid-region of the GBNERR from 1992 to 2014. The red areas represent marsh loss, where the green areas represent marsh gain.

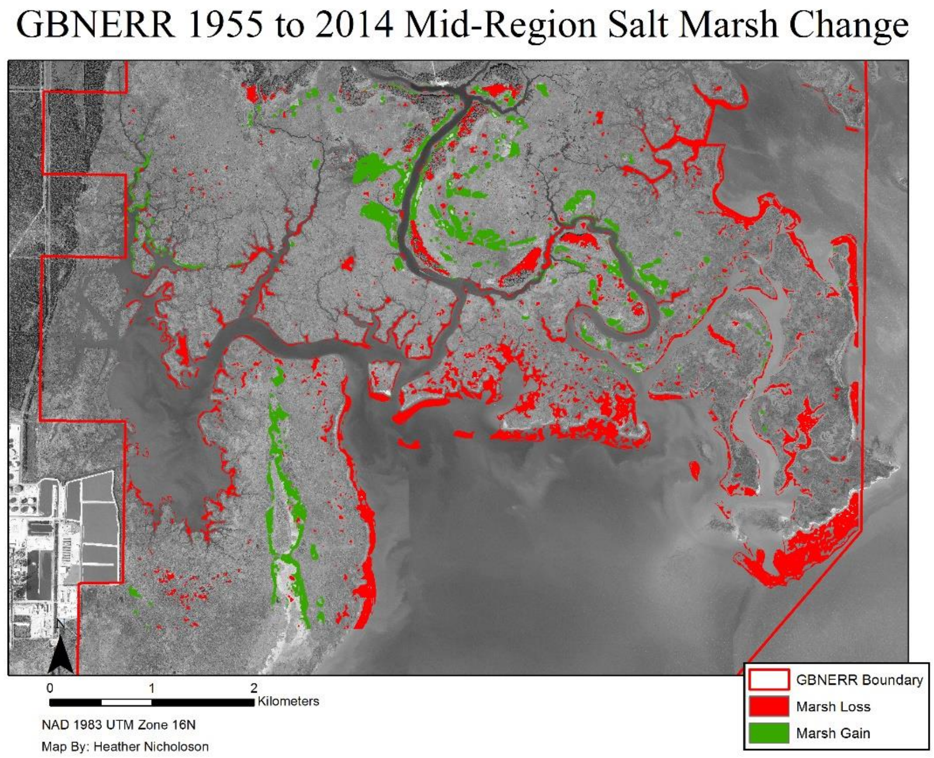

Figure 10. GBNERR 1955 to 2015 Mid-Region Salt Marsh Change

The map shows changes in marsh in the mid-region of the GBNERR from 1955 to 2014. The red areas represent marsh loss, where the green areas represent marsh gain.

CHAPTER V – Discussion

Salt Panne Habitat

The salt panne habitat had a steady decline from 1955 to 2014. The middle region of GBNERR had around a 50% decrease from 1955 to 1992, and a less drastic decrease of 5% from 1992 to 2014. Between 1955 to 2014 an overall decrease of 52%. The most reduction can be seen in the areas around Bayou Cumbest and Crooked Bayou, though there was salt panne reduction in the area between Bangs Lake and Pt .Aux Chenes Bay. One possible reason for the reduction in salt panne is due to sea-level rise and regular inundation in the historically dry salt panne habitat. One study that modeled future change of salt pannes in the GBNERR found a reduction of 92% of salt pannes by 2100 with a 1 m rise in sea-level, though there was little to no reduction in scenarios with less than a .5m rise (Linhoss and Underwood 2016). Even though the historic rates in the same area have been less than .5m, the results do suggest the salt pannes do show sensitivity to sea level rise.

Woodland Habitat

The entire GBNERR had an approximately 53% increase of woodland area from 1955 to 2014. The increase in woodland can be attributed to the fact that there used to be a logging industry that stopped. The woodland area has returned through natural growth and restoration techniques implemented by the GBNERR staff. The area of most growth occurred in the northern part of the GBNERR, however small patches of woodland area also increased near the rivers in Bayou Cumbest and Crooked Bayou. Looking at just the middle region of the GBNERR shows a loss of over 68% of woodland area, however due to issues with the 1955 classification mentioned later the rate of loss in that area may be overestimated. This can be seen when looking at the percent change in the middle region from 1992 to 2014, which was an 11% increase.

Salt Marsh Habitat

The middle region of GBNERR had an overall loss of 4.5% of marsh from 1955 to 2014, with the greatest percentage of loss of 4.7% between 1992 to 2014. The most visible portions of loss between the years can be seen on the shorelines in both Middle Bay and Pt. Aux Chenes Bay. The Bangs Lake area had some loss of marsh, though not as prevalent as the other two regions. The shoreline loss from 1955 to 2014 varied in Pt. Aux Chenes Bay depending on the location – the extent of shoreline loss on the western edge was mostly between 70m and 90m, between 90m and 130m in the northern part, and between 300m and 400m on the South Rigolet Islands (Figure 11).

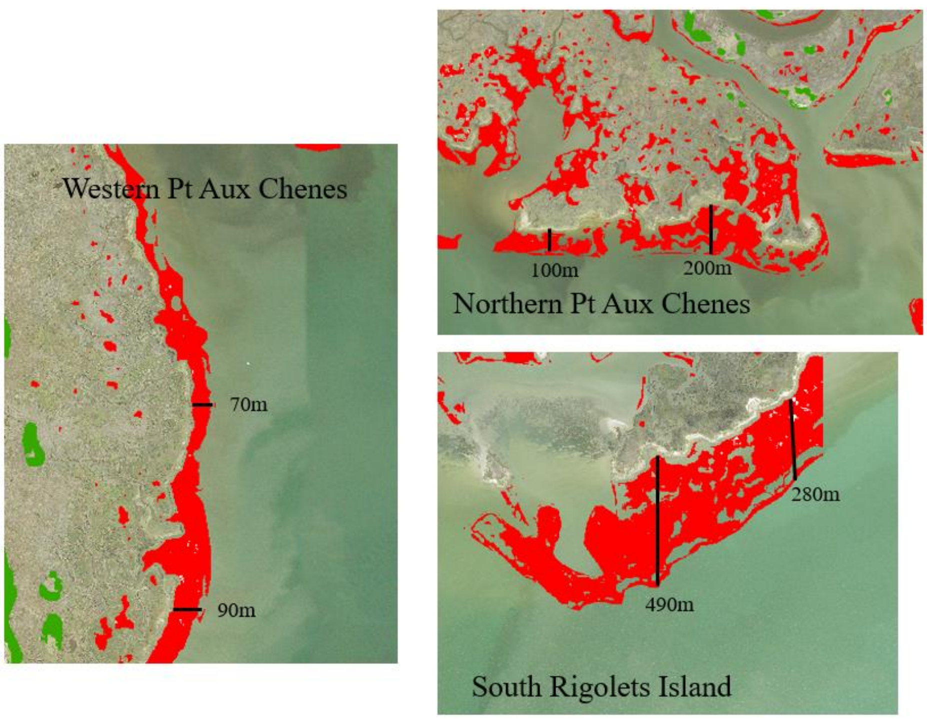

Figure 11. Shoreline loss in Pt. Aux Chenes Bay

A map showing shoreline loss in Pt. Aux Chenes Bay

For Middle Bay, the extent of shoreline loss from 1955 to 2014 was between 40m and 50m (Figure 12).

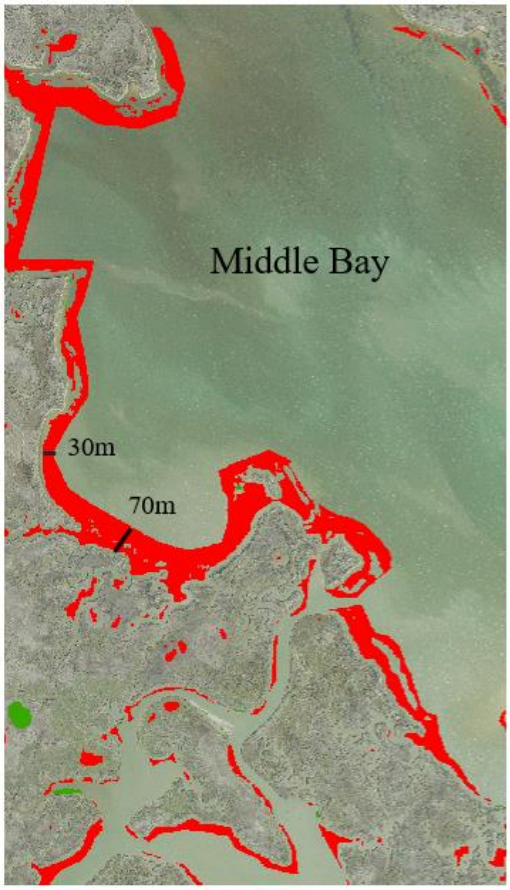

Figure 12. Shoreline loss in Middle Bay

A map showing the shoreline loss in Middle Bay

A variety of possible reasons exist as to why there is marsh loss at the GBNERR that range from historical marsh processes to current processes. According to Otvos (2007b), the Grand Bay delta began to form during the Holocene area relying on both freshwater input from the north as well as salt water input from the Mississippi sound (Otvos 2007b). Sometime around the 1850s, the Pascagoula River was suspected to have pirated the Escatawpa River which was the main supply of sediments from fresh water to the Grand Bay marsh (Otvos 2007b; Schmid 2000). This left the Grand Bay marshes reliant on obtaining sediments from the Mississippi Sound.

Many current factors that are causing change in the GBNERR. Sometime during the 1700's, a barrier island that sat towards the east of GBNERR that acted as an erosion protector was split in the middle due to a major storm. This split left an open area which allowed erosional waves to reach the GBNERR (Otvos 2007b; Schmid 2000). Another major factor that is leading to erosion in the GBNERR is a combo of global sea-level rise and local subsidence rates (relative sea-level rise). One study conducted at a barrier island near the GBNERR vicinity found relative sea-level rise rates to be between 2.7 mm y^{-1} to 7 mm y^{-1} (Lucas and Carter 2010). This suggest that the rate in the NERR over a 60 year period is approximately somewhere between .16m to .41m.

Many processes in the GBNERR help with sediment deposit. One process is the deposition of sediments as the tide is rising. The tide averages around .6m in the GBNERR, though it varies depending on time of year (Woodley 2007). However, one can assume that the rate of sediment loss is higher than sediment deposition.

One other contributing factor to the possible movement of the marsh in the NERR is due to storms and hurricanes. Most regional studies suggest that major storm events lead to a loss of sediment and marsh at the NERR (English 2011; Otvos 2007a; Wells 2010). However, a few studies done in the gulf have suggested that storms and hurricanes can actually lead to sediment deposition (Tuner 2006; Turner 2007). More research will need to be done to see the effect of hurricanes at the GBNERR, but major storms have the potential to majorly impact marsh erosion at the GBNERR.

Problems with Classification

As previously mentioned, there were problems with the data and classifications, despite the fact for the high classification accuracies. The reason the classification accuracy was so high was that one single habitat type, the marsh, dominated the study area, leading to an overestimation of accuracy because there was so much marsh.

One common problem for classification in all of the years was the texture algorithm could not distinguish between clear-cut land and marsh. This was taken into account when determining the rate of marsh area in the GBNERR, so an analysis to determine marsh loss was conducted in the middle region of the marsh.

The 1955 classification was noisy, with pixels and areas being classified as woodland in locations where there were not any. This is because the classification is having problems distinguishing between the water that was not masked out and the marsh, leading to the texture algorithm classifying the heterogeneous area of change between water distributaries and marsh the same as the heterogeneous areas of woodland. This led to the marsh extent and total area being underestimated in 1955.

The 1992 image was over-exposed in the south-west portion of the image, and since the texture algorithm had a hard time distinguishing between water and marsh; the entire area was classified as marsh. This led to overestimation of marsh in south-west portion of the GBNERR in the 1992 image.

The under-estimation of marsh from 1955 and the over-estimation of marsh in 1992 produced a net gain of 0.2% between the years. However, visual comparison of the marsh lost at the shoreline to the marsh gained from 1955 to 1992 alludes to an overall loss, but due to the classification noise in the older image the loss is not being correctly calculated.

Future Work

Improve Accuracies

More work needs to be done in order to better determine trends in salt marsh loss and gain at the GBNERR. One such endeavor includes improving the classification.

One way to improve the classification is to try a combination of different pixel sizes and texture window sizes. Resampling the pixels to larger sizes theoretically should reduce haze, shadow, and other smaller problem areas in the image such as the smaller distributaries, thereby reducing the amount of noise in the image. Though some image quality would be lost, the classification could potentially be more accurate. The same reasoning applies to the larger window sizes, which averages out the noisy areas. Another step to improving future classification accuracies is to implement the near-infrared (NIR) spectral data in classifications where that information can be obtained. The NIR band can better help distinguish between water and marsh features due to the difference in the spectral signatures of those habitats in that part of the spectrum.

Fill in Time Gaps

The original goal of the project was to have more classifications than the three that are included – 1955, 1992, and 2014. This would allow for decadal trends in salt marsh. However, images were either not readily available for certain dates, or the image quality was too poor for analysis using the current methods. As more quality images for decades not included are found, they can be classified and added to the current classification series to help create a more complete understanding of decadal-scale change in salt marsh in the GBNERR.

CHAPTER VI – Conclusion

Salt marshes are important habitat types for local communities, offering both ecological and commercial benefits. The vulnerable marsh habitats are under threat from natural factors such as relative sea-level rise and human interference. This study focused on using textural methods to classify panchromatic imagery of the GBNERR in Moss Point, Mississippi, to determine marsh dynamics over an approximately 60 year period. There was an overall decrease in marsh habitat of around 5%, and increase in water. The woodland habitat saw a steady increase. There was a general decrease in the salt panne habitat. Due to some problems with the classifications from 1955 and 1992 there was some variance and oddities in the trend results. However, it is still possible to see where the majority of loss is occurring with the marsh habitat, which is the shorelines of Pt. Aux Chenes Bay and Middle Bay. This suggests that with more modification of the methods, texture-based classifications on panchromatic images can be useful for helping to determine long term trends in marsh and estuarine habitats. Overall, the current classifications show a basic overview of trends in marsh and other habitats and offer valuable insight to resource managers as to the most vulnerable areas of the GBNERR.

APPENDIX A

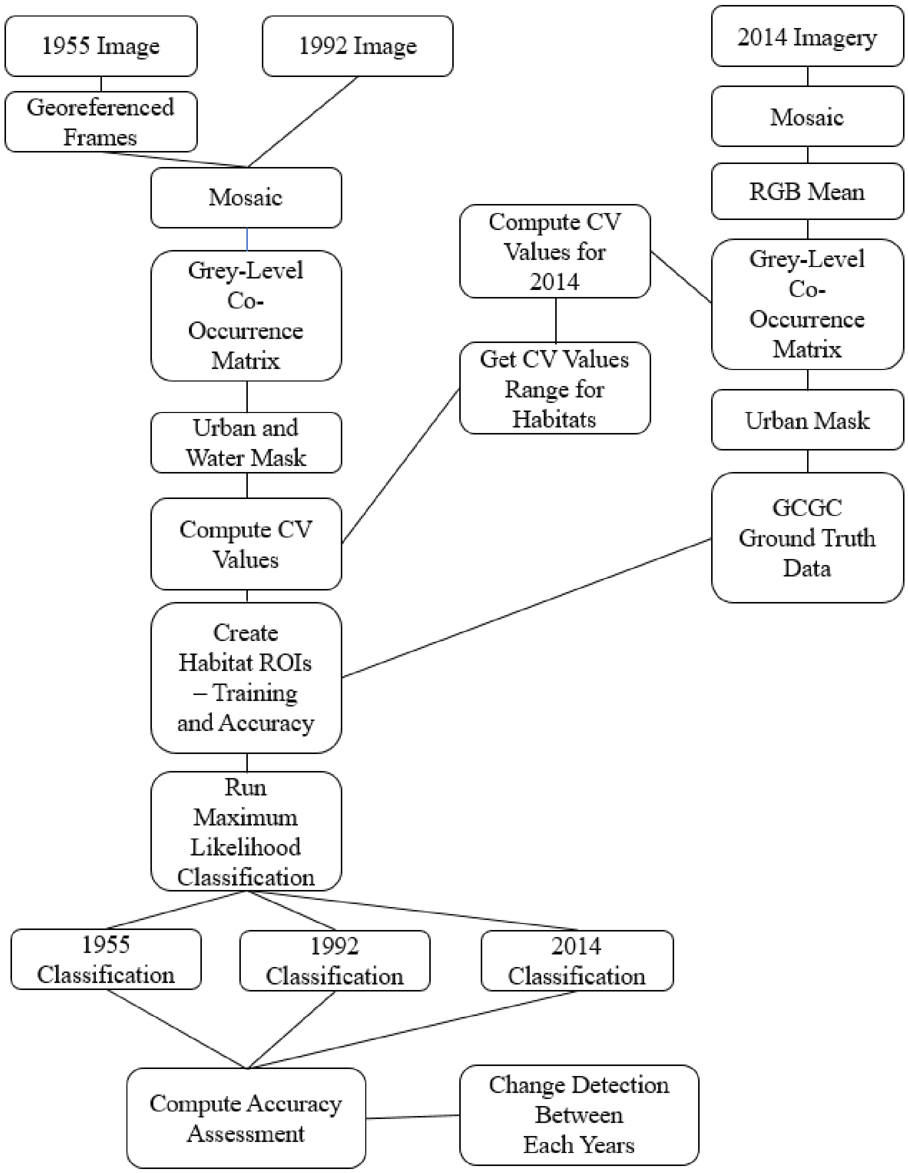

Figure A1. Flow Chart of Image Analysis Process

The above flowchart visually shows the method used to obtain the results.

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