

The University of Southern Mississippi
The Aquila Digital Community

Master's Theses

Summer 2022

Tropical Cyclone Storm Surge Detection in Slash Pine Radial Growth along the Northern Gulf of Mexico Coastline

Alyssa C. Crowell
University of Southern Mississippi

Follow this and additional works at: https://aquila.usm.edu/masters_theses



Part of the [Earth Sciences Commons](#), [Environmental Sciences Commons](#), and the [Physical and Environmental Geography Commons](#)

Recommended Citation

Crowell, Alyssa C., "Tropical Cyclone Storm Surge Detection in Slash Pine Radial Growth along the Northern Gulf of Mexico Coastline" (2022). *Master's Theses*. 928.
https://aquila.usm.edu/masters_theses/928

This Masters Thesis is brought to you for free and open access by The Aquila Digital Community. It has been accepted for inclusion in Master's Theses by an authorized administrator of The Aquila Digital Community. For more information, please contact aquilastaff@usm.edu.

TROPICAL CYCLONE STORM SURGE DETECTION IN SLASH PINE RADIAL
GROWTH ALONG THE NORTHERN GULF OF MEXICO COASTLINE.

by

Alyssa Crowell

A Thesis
Submitted to the Graduate School,
the College of Arts and Sciences
and the School of Biological, Environmental, and Earth Sciences
at The University of Southern Mississippi
in Partial Fulfillment of the Requirements
for the Degree of Master of Science

Approved by:

Dr. Thomas Patterson, Committee Chair
Dr. Franklin Heitmuller
Dr. Clay Tucker

August 2022

COPYRIGHT BY

Alyssa Crowell

2022

Published by the Graduate School



ABSTRACT

My thesis examines the ecological impact of tropical cyclone (TCs) storm surge on coastal slash pine (*Pinus elliottii* var. *elliottii* Engelm) communities along the Gulf of Mexico in the southern United States (U.S.). Previous research has shown slash pine radial growth trends can be examined to identify long and short-term growth changes associated with TC passage, providing insight into overall stand health and resiliency through time. However, this previous research encompasses just one site in Mississippi. My thesis expands the spatial footprint of TC-surge impact on slash pine radial growth with the addition of three new sites.

I examined seasonally resolved tree-ring data from two sites in Alabama and one in Florida and discovered differences in geography and seasonality to suppressions and recovery. The Weeks Bay, Fairhope, Alabama site was the most responsive to storm-surge suppressions, and this was perhaps due to lack of dune protection and proximity to a concave coastline. Latewood growth recorded the highest percentage of suppressions associated with storm surge and was generally the quickest growth metric to recover to normal growing conditions. TCs are predicted to become larger and more powerful in the 21st century, and it will be necessary to consider the negative impacts that these storms can have on coastal pine savannas while constructing plans to protect and preserve these unique environments.

ACKNOWLEDGMENTS

First and foremost, I would like to express my deepest gratitude to my thesis committee: Dr. Thomas Patterson, Dr. Franklin Heitmuller, and Dr. Clay Tucker. The advice, insight, and experience provided by my committee proved invaluable, and I could not have completed my thesis journey without their unwavering support and encouragement. I would also like to extend special thanks to Dr. David Holt who included me in countless research projects throughout my undergraduate and graduate career, inspiring me to pursue my master's degree, and instilling in me a love of research and field work that will continue after I graduate. Many thanks also go out to the exceptionally hospitable people of Gulf State Park, Topsail Hill Preserve State Park, and the Weeks Bay National Estuarine Research Reserve. I am forever grateful for their participation in this research.

DEDICATION

I would like to dedicate this thesis to my family, friends, and colleagues who supported me throughout this arduous endeavor. I do not have the words to express the sheer amount of gratitude that I have for all of the loving, supportive people that I have in my life. Their encouragement uplifted me during the difficult times and inspired me to never lose sight of my goals. I would also like to extend my gratitude to my cats who gave me my daily dose of serotonin, keeping me sane throughout my thesis journey. Many thanks to all who have believed in me. I could not have done this without you.

TABLE OF CONTENTS

ABSTRACT ii

ACKNOWLEDGMENTS iii

DEDICATION iv

LIST OF TABLES viii

LIST OF ILLUSTRATIONS ix

LIST OF ABBREVIATIONS xi

CHAPTER I – INTRODUCTION AND LITERATURE REVIEW 1

 1.1 Introduction 1

 1.2 Literature Review 2

 1.2.1 Tropical Cyclone Climatology 3

 1.2.2 Slash Pines 8

 1.2.3 State of Research 11

 1.2.4 Contribution to Research 15

CHAPTER II – METHODS 17

 2.1 Methods 17

 2.1.1 Site Selection 17

 2.1.1.1 Site descriptions 18

 2.1.1.1.1 Weeks Bay National Estuarine Research Reserve 18

 2.1.1.1.2 Topsail Hill Preserve State Park 19

2.1.1.1.3 Gulf State Park	21
2.1.2 Sampling	25
2.1.3 Preparing Samples	30
2.1.4 Tree Ring Analysis	32
2.1.5 Weather Data	42
2.1.6 Data Analysis	45
CHAPTER III – RESULTS	47
3.1 Tropical Cyclone Frequency and Storm Surge Events	47
3.1.1 Weeks Bay	48
3.1.2 Topsail Hill	48
3.1.3 Gulf State Park	49
3.2 Tree Ring Data	50
3.2.1 Weeks Bay	50
3.2.2 Topsail Hill	54
3.2.3 Gulf State Park	57
3.2.4 All Sites	60
CHAPTER IV – DISCUSSION	62
4.1 Discussion	62
CHAPTER V – CONCLUSION	70
5.1 Conclusion	70

APPENDIX A – SUPPLEMENTAL DATA	73
REFERENCES	91

LIST OF TABLES

Table 1.1 Saffir-Simpson Hurricane Rating Scale.....	4
Table 1.2 Progress of the average Atlantic season (1991-2020)	5
Table 3.1 Chronology Statistics.....	61
Table A.1 Tropical Cyclones: All Sites	73
Table A.2 Tropical Cyclones: Weeks Bay.....	75
Table A.3 Tropical Cyclones: Topsail Hill.....	78
Table A.4 Tropical Cyclones: Gulf State Park	80
Table A.5 Weeks Bay Statistics: Total Wood	82
Table A.6 Weeks Bay Statistics: Earlywood	85
Table A.7 Weeks Bay Statistics: Latewood.....	88

LIST OF ILLUSTRATIONS

Figure 1.1 Hurricane Katrina Satellite Imagery	4
Figure 1.2 Slash Pine (<i>Pinus elliottii</i> var. <i>elliottii</i>).....	9
Figure 1.3 Slash Pine Distribution Map.....	10
Figure 2.1 Weeks Bay National Estuarine Research Reserve	19
Figure 2.2 Topsail Hill Preserve State Park.....	21
Figure 2.3 Gulf State Park, Alabama	23
Figure 2.4 Site Location Map	24
Figure 2.5 Increment Borer.....	26
Figure 2.6 Using an Increment Borer	27
Figure 2.7 Prepped Cores from Weeks Bay, Alabama	29
Figure 2.8 Sanding Core Samples.....	31
Figure 2.9 Annual Growth Rings of Slash Pine.....	33
Figure 2.10 CooRecorder Screenshot	35
Figure 2.11 COFECHA final Report	38
Figure 2.12 Standard Chronologies from all Sites.....	41
Figure 2.13 SURGEDAT Web Tool.....	43
Figure 2.14 Historical Hurricane Tracks Web Tool	44
Figure 3.1 Weeks Bay Standard Chronology	52
Figure 3.2 Weeks Bay Percent Change.....	53
Figure 3.3 Topsail Hill Standard Chronology.....	55
Figure 3.4 Topsail Hill Percent Change.....	56
Figure 3.5 Gulf State Park Standard Chronology	58

Figure 3.6 Gulf State Park Percent Change	59
Figure 4.1 Percent Change of all Chronologies	65
Figure 4.2 Weeks Bay Shoreline	67
Figure 4.3 Topsail Hill Shoreline.....	68

LIST OF ABBREVIATIONS

<i>GSP</i>	Gulf State Park
NOAA	National Oceanic and Atmospheric Administration
<i>TC</i>	Tropical Cyclone
NWS	National Weather Service
<i>TSH</i>	Topsail Hill State Preserve
<i>U.S.</i>	United States of America
USDA	United States Department of Agriculture
<i>WB</i>	Weeks Bay National Estuarine Research Reserve

CHAPTER I – INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

TCs are highly destructive climatological events that impact much of the lower to mid-latitude coastal regions around the world. Some of the most recent climate models forecast TCs may become less frequent into the 21st century under the influence of climate change; however, the models also show that TCs may become larger in size, produce higher wind speeds, and harbor more precipitation (Bacmeister et al. 2018; Barcikowska et al. 2017; Mori et al. 2019; Sajjad et al. 2020; Trenberth et al. 2018; Trepanier and Tucker 2018; Zhao et al. 2018; Zhou and Matyas 2018). It is well understood that TCs have negative impacts on human life and infrastructure (Blake et al. 2011), and these systems also influence the health of maritime forest (Fernandes et al. 2018; Gresham et al. 1991; Harley et al. 2015; Knapp et al. 2016; Platt et al. 2000; Ross et al. 2019; Saha et al. 2011; Tucker et al. 2018), and in the case of the coastal pine savannas, these influences are still poorly understood due to lack research in old growth, and secondary growth stands (Platt et al. 2000). With little research on how coastal pine savanna communities have been impacted in the past and present, it may not be possible to infer what may happen to these communities under a changing climate.

In my thesis, I will examine the ecological impact that TCs have on coastal slash pine (*Pinus elliottii* var. *elliottii* Engelm) communities along the Gulf of Mexico in the southern U.S. These impacts will be examined in the context of radial growth changes that can be quantified through dendrochronological techniques. Several studies have examined the impacts of TCs on the south Florida variety of the slash pine (*Pinus elliottii*

var. densa) (Harley et al. 2015; Platt et al. 2000; Ross et al. 2019; Saha et al. 2011), but fewer have examined TC impacts on the typical variety of slash pine with a wider geographic context (Tucker et al. 2018). Dendrochronology/TC focused studies for both varieties of slash pine are even fewer (Harley et al. 2015; Tucker et al. 2018).

Previous research by Tucker et al. (2018) has shown that an examination of radial growth trends in slash pine (*Pinus elliottii* var. *elliottii*) can be used to identify long and short-term growth patterns associated with TC passage, providing some insight into overall stand health and resiliency through time. However, with just one existing study site from this previous research, it is difficult to establish the geographic implications of these findings. My thesis aims to spatially expand upon previous findings to gain an enhanced understanding of geographic implications. The influences of site geography and TC climatology will also be addressed as it is suspected that these factors will influence slash pine responsiveness to storm surge. As TCs become larger and more powerful through time, it will be necessary to consider the negative impacts that these storms can have on coastal pine savannas while constructing plans to protect and preserve these unique environments (Stanturf et al. 2007).

1.2 Literature Review

I have compiled some of the most relevant research examining the impacts that TCs have on slash pine and other trees in the *Pinus* genus. Other *Pinus* species are included due to the lack of research focused solely on the impacts that TCs have on the typical slash pine (*Pinus elliottii* var. *elliottii*). In general, little research has focused on the impact that TCs have on pine communities due to the rarity of old-growth pine stands.

Although the coastal pine communities along the northern Gulf of Mexico in the southern U.S. are frequently impacted by TCs, studies examining the impacts of TCs on these communities are rare at least partly because logging, alteration to fire regimes, fire suppression, and land conversion has left almost no old growth and few unaltered second growth pine stands to study (Platt et al. 2000). This has led to a need for more research examining the impacts that TC's have on slash pines and other species in coastal pine communities. Before delving into the research on *Pinus* and TCs, it will be necessary to explore basic TC climatology and *Pinus elliottii* ecology.

1.2.1 Tropical Cyclone Climatology

TCs are classified as cyclones: Weather phenomena that can be identified by surface winds that swirl into an enclosed low-pressure center, creating a rising motion, and then diverging in the upper atmosphere leading to cloud formation and precipitation (see figure 1.1) (Rohli and Vega 2018). In the U.S., TCs in the Atlantic basin are referred to as hurricanes once they strengthen to 74 mph; however, TCs may be referred to as typhoons or cyclones in other regions around the world. TCs form exclusively between 23.5° N to 23.5° S latitude where tropical air masses are essentially homogenous lacking fronts or air masses with conflicting temperatures and where sea surface temperatures can climb higher than 26°C (Christopherson 2012). The National Oceanic and Atmospheric Administration (NOAA) (2021) describes the scale on which hurricanes are rated, the Saffir-Simpson wind scale. Hurricanes are given a rating of category 1 – 5 based on wind speed and their potential for wind related damage. Factors such as storm surge, rainfall, and tornadoes are not considered in the ratings (see Table 1.1 for rating descriptions).

Figure 1.1
Hurricane Katrina Satellite Imagery



This satellite image shows the swirling clouds and distinct eye of Hurricane Katrina as it approaches the shore (NOAA 2005).

Table 1.1

Saffir-Simpson Hurricane Rating Scale

Saffir-Simpson Hurricane Rating Scale		
Cat. 1	Sustained winds 74-95 mph	Very dangerous winds will produce some damage.
Cat. 2	Sustained winds 96-110 mph	Extremely dangerous winds will cause extensive damage.
Cat. 3	Sustained winds 111-129 mph	Devastating damage will occur.
Cat. 4	Sustained winds 130-156 mph	Catastrophic damage will occur.
Cat. 5	Sustained winds 156 mph or higher	Catastrophic damage will occur.

Ratings based on wind speed and damage (NOAA 2021).

According to NOAA’s “Tropical Cyclone Climatology”, the Atlantic TC season is from June first to November 30th each year in the U.S., and TCs can strike anywhere along the lower to mid latitudes of the U.S. Atlantic coast and along the Gulf of Mexico. In total,

the Atlantic basin can include TCs that impact the Atlantic Ocean, the Caribbean Sea, and the Gulf of Mexico. The average frequency of TCs in the Atlantic basin is 14 named storms with seven becoming Saffir-Simpson rated hurricanes, and three of those becoming major hurricanes (Category 3 – 5) based on a 30-year climate period encompassing the years 1991 – 2020 (see table 1.2). On average, the first storm of the year is usually formed in mid to late June while the first hurricane forms in early-mid August, and the first major hurricane a bit later in late August to early September.

Table 1.2

Progress of the average Atlantic season (1991-2020)

Number	Named Systems	Hurricanes	Major Hurricanes
1	Jun 20	Aug 11	Sep 1
2	Jul 17	Aug 26	Sep 19
3	Aug 3	Sep 7	Oct 28
4	Aug 15	Sep 16	
5	Aug 22	Sep 28	
6	Aug 29	Oct 15	
7	Sep 3	Nov 15	
8	Sep 9		
9	Sep 16		
10	Sep 22		
11	Oct 2		
12	Oct 11		
13	Oct 25		
14	Nov 19		

Dates upon which the following number of TCs would normally have occurred (NOAA Tropical Cyclone Climatology).

Although TCs have different regional names, their formation is the same regardless of where they are formed. The process always begins in the tropics where slow-moving waves of low-pressure lead to convergence in the atmosphere and precipitation. These low-pressure areas are then subjected to an inflow of surface air that climbs high into the atmosphere flowing away from the high-pressure air aloft. This divergence aloft pulls warm moisture-laden air inward at the surface and upward into the system creating

entrained, vertical convective circulation. High wind shear can interfere with this vertical wind flow, so low wind shear is necessary for TCs to form and strengthen. TCs have a unique structure when fully developed, and they extend to the top of the troposphere. Swirling rain bands surround an eye containing an area of calm weather while the eyewall surrounding the eye has the most intense precipitation. Fully developed TCs can range in size from 100 – 1,000 miles in diameter, and they can travel at a forward speed of 10 – 25 mph (Christopherson 2012).

When TCs reach land, they can produce torrential rain, gale-force winds, tornadoes, and storm surge. The most intense precipitation is contained within the eyewall, but the strongest winds and highest likelihood for tornadoes can be found within the front-right quadrant of the TC in relation to direction of travel (Christopherson 2012). The front-right quadrant is also typically the location for the most intense storm surge as the strong winds push water inland (Gigi and Wert 1986). NOAA's "Storm Surge Overview" defines storm surge as, "an abnormal rise of water generated by a storm, over and above the predicted astronomical tides." Sometimes the term "storm tide" may be used. This is defined as, "the water level rise due to the combination of storm surge and the astronomical tide." It is important to note that these terms refer to the same phenomenon but are not interchangeable.

The intensity of storm surge is determined by several factors. According to the National Weather Service's (NWS) "Introduction to Storm Surge", wind is above all the most dominant factor when it comes to determining the intensity of storm surge while central pressure makes a minor contribution in comparison. Where TC winds are blowing, storm surge is a possibility. Winds circulate cyclonically around the eye of the TC, and the

cyclonic motion of winds over the surface of the ocean leads to vertical circulation in the water. Storm surge is harder to detect in deep waters because the circulation of the water is undisturbed, but this changes once the TC approaches the shallower shores. The ocean floor interferes with the circulation of the water preventing it from propagating downward. This means that the water must travel up and inland instead, and storm surge is the result. Along with winds and central pressure, the other determining factors for storm surge are forward speed, radius of maximum winds (storm size), approach angle, and the geography and bathymetry of the coast.

The NWS “Introduction to Storm Surge” addresses these factors with greater detail. First and foremost, higher windspeeds produce a more intense storm surge. Slower forward moving storms are known to produce higher storm surge in enclosed bodies of water like bays and sounds. On the other hand, faster storms create larger surge in open waters. Larger TCs with broader wind fields will have greater storm surge because they are impacting a larger area of the ocean. The winds of these larger storms will also remain in the same area for a longer period of time giving them more time to produce surge. A TC that approaches the coast perpendicularly will have more surge and surge lessens when a storm approaches more parallel. If the coastline is more concave, storm surge will be higher when compared to an area with a more convex coastline. Storm surge is also higher when the continental shelf is wide, and the slope is gentle. Narrow and steep continental shelves lead to lower storm surge. Finally, the local geography can add complexity to incoming storm surge. Features such as barrier islands can block storm surge and features such as inlets, sounds, bays, and rivers can affect the way that water flows over an area.

1.2.2 Slash Pines

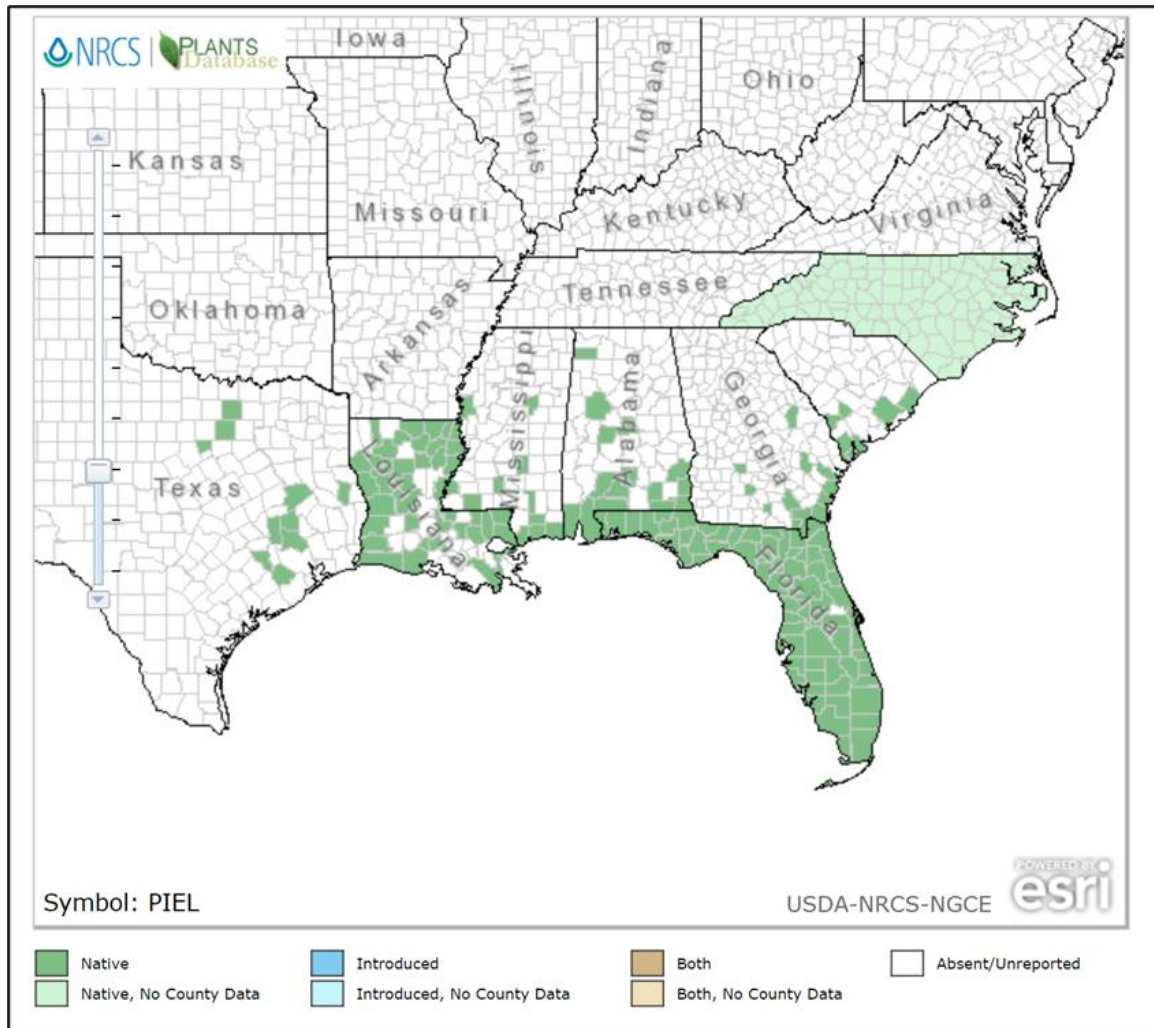
The slash pine (*Pinus elliottii*) (see figure 1.1) is an evergreen conifer native to the U.S. There are two geographic varieties of *Pinus elliottii* with distinct morphological traits: The more widespread variety with the scientific name *Pinus elliottii* var. *elliottii* and the south Florida variety, *Pinus elliottii* var. *densa*. The slash pine has a native range that covers much of the southeastern U.S. coasts from Texas to South Carolina (see figure 1.2) at elevations from sea level up to 500 ft. Slash pine grow rapidly, live around 200 years, and can reach heights of 60 to 100 ft with a diameter breast height of around two feet. Slash pine has a moderate taproot that can penetrate as deep as nine to 15 ft, and the lateral root system is extensive (Carey 1992; Hardin et al. 2001).

Figure 1.2
Slash Pine (*Pinus elliottii* var. *elliottii*)



Slash pine at Topsail Hill Preserve State Park, Santa Rosa Beach, Florida (Patterson 2021).

Figure 1.3
Slash Pine Distribution Map



This map displays the distribution of both varieties of *Pinus elliottii*: *Pinus elliottii* var. *elliottii* and *Pinus elliottii* var. *densa* (USDA *Pinus elliottii* Engelm).

Slash pine is found in warm, humid climates with a preference for saturated, poorly drained sites and the margins of ponds and streams. It can also be found in swamp, upland, and old field environments (Carey, 1992). Much of the slash pine native range is located within the coastal forests along the Gulf of Mexico. These coastal forests are defined by Barrow et al. (2005) as, “wooded communities that develop within 100 km of

the coast”. Barrow et al. (2005) divide the coastal forests along the Gulf of Mexico into 19 community types based on the plant species that are found within them. Of the 19 communities, slash pine is common within three: Beach ridge and dune (on barrier islands along the northeast Gulf of Mexico), interdunal pine (along the east and northeast Gulf of Mexico), and pine savanna (along the east, northeast, and northwest Gulf of Mexico).

Barrow et al. (2005) designate the interdunal pine and pine savanna communities as threatened by several factors including human development, pine plantations, pulpwood production, logging, agriculture, cattle grazing, exotic species invasion, and climate change. Within the threat of climate change, Barrow et al. (2005) note the threat of increasing TC severity. This increase in severity can lead to the extensive damage and loss of coastal forests, altering the landscape and shifting the structure and composition of plant communities. For the *Pinus* genus, there are other publications that document and explore the impacts that TC factors have on coastal trees as well as the environmental factors that may exacerbate or contribute to tree survival. These factors include wind speed, storm surge, precipitation, drought, and elevation (Fernandes et al. 2018; Gresham et al. 1991; Harley et al. 2015; Knapp et al. 2016; Platt et al. 2000; Ross et al. 2019; Saha et al. 2011; Tucker et al. 2018).

1.2.3 State of Research

Past studies show that wind speed may not play an integral role in *Pinus* damage. It is well documented that coastal *Pinus* trees are resilient when it comes to the stress of TC strength winds (Gresham et al. 1991; Harley et al. 2015; Platt et al. 2000; Tucker et

al., 2018). Gresham et al. (1991) note that this is at least partly due to morphological traits that allow some trees to be less susceptible to TC force winds. They suggest that longleaf pine (*Pinus palustris*) may be more resilient to wind damage due to a large taproot and a widespread lateral root system that allows the trees to stay more firmly anchored in high wind conditions. Slash pine shares the same root traits, so this may contribute to resilience in powerful TC winds. Platt et al. (2000) obtained similar results when they studied the effects that Hurricane Andrew had on south Florida slash pine (*Pinus elliottii* var. *densa*) in the Florida everglades. They noted that the south Florida slash pine were resistant to the hurricane's strong winds, and they suspected that it was because the trees were rooted firmly in limestone. Only five to 14% of the south Florida pine sampled were tipped up or snapped off by the winds.

Storm surge on the other hand, plays a more significant role in damaging *Pinus* species (Fernandes et al. 2018; Ross et al. 2019; Tucker et al. 2018). Tucker et al. (2018) found that slash pine (*Pinus elliottii* var. *elliottii*) showed a suppression in secondary growth the year after nearby TC landfall in at least 85% of the series, and these suppression events lasted anywhere from 1 – 6 years after TC landfall. Tucker et al. (2018) suggest that this suppression occurred because of saltwater inundation from storm surge. In the case of 2005 Hurricane Katrina, only 25% of the slash pine in the study area returned to their previous average growth rate within an eight-year period. Tucker et al. (2018) speculate that growth could be permanently stunted in some cases, and this could eventually lead to total mortality in the affected area. Fernandes et al. (2018) came to a similar conclusion as Tucker et al. 2018 when they found loblolly pines (*Pinus taeda* L.) at their eastern Virginia site experienced suppression in radial growth for up to four years

after the passage of an extreme TC or Nor'easter. They also found suppression events may not show up until up to three years later.

Ross et al. (2019) note that storm surge played a key role in damage to Florida slash pines (*Pinus elliottii* var. *densa*) on Big Pine Key after the 2017 Hurricane Irma. Nine months after Irma's passage, 32% of the trees in their plots were found to be dead because of the passing TC. Of that 32%, 40% were left standing dead with no notable structural damage, and Ross et al. (2019) suggest that trees in this category died as a result of the eight-foot surge that infiltrated Big Pine Key. This was further supported by that fact that mortality increased as elevation decreased closer to sea level within the standing dead category. In their study, storm surge swept over the island from the east and penetrated the island's aquifer to the extent that its effects could still be detected in 2018 (Ross et al. 2019). The Florida slash pine is a fresh water dependent species with a moderate tolerance for salt (Gilman et al. 2019), and Ross et al. (2019) believe that salt water infiltrated into the freshwater lens, and storm surge exacerbated by sea level rise, contributed to the number of standing dead trees on the island.

TC Precipitation may also play a role in radial growth after TC landfall (Knapp et al. 2016), but further research will be needed to gain a more complete understanding of this relationship. Knapp et al. (2016) examined the relationship between TC precipitation and the latewood radial growth rates of long leaf pines (*Pinus palustris*) in coastal North Carolina. Within their study area, low radial growth was found to be a significant indicator of below average TC precipitation years (91% occurrence) while high radial growth years were found to reflect above average TC precipitation years (73% occurrence). These findings offer a slightly different perspective on the impact that TCs

may have on the radial growth of pine trees as they show suppression and release to both be possible after TC passage. As Tucker et al. (2018) note, the differences between their study and Knapp et al.'s reflect a need for further research into the role that TCP may play in the radial growth/TC relationship.

Maxwell et al. (2013) describe TC precipitation as a possible “drought busting” event. This means that landfalling TCs within an area experiencing hurricane-season drought may then experience a cessation due to the high amount of precipitation. However, it is unclear how this relationship impacts the slash pine which is noted as being more drought tolerant than other pines (Gilman and Watson 1994). Knapp et al. (2016) mention drought busting TC precipitation within their study. They suggest that TC precipitation can penetrate the soil at a greater depth than most non-TC precipitation events, causing a rise in the regional water table, and bringing more water to the extensive lateral root system of the longleaf pine (*Pinus palustris*). Thus, explaining an increase in latewood production after a TC. It is also worth noting that TC precipitation may act in a protective role against storm surge as it has been noted to flush salt water from the soil leading to less salt stress (Fernandes et al. 2018).

Elevation is also thought to play a role in slash pine health and survival after a TC. Harley et al. (2015) found a relationship between south Florida slash pine (*Pinus elliottii* var. *densa*) basal area, age, and elevation on two pine rockland savanna islands. The trees located at a slightly higher elevation were found to have a larger basal area and an older age than the younger, smaller trees located several feet lower. Harley et al. (2015) attribute this to the protective nature that higher elevations have during TC storm surge events. Even an increase of six to ten feet meant the difference between total

inundation and safety from the surge. TC precipitation and drought along with elevation may all lead to increases in radial growth, so all three of these could be considered when increases in radial growth are seen.

1.2.4 Contribution to Research

Storm surge, strong winds, TC precipitation, drought, and elevation may all play a significant role when it comes to anomalies in slash pine radial growth. Although the strong winds of TCs can be damaging, they are thought to have a lesser influence in creating stress due to the wind resistant nature of *Pinus* trees. Many researchers have examined the effects of TCs on various *Pinus* trees; however, much of the research cited here was not dendrochronologically focused, reflecting a need for more research in this area. Additionally, few of these studies examined the impact of TCs on the more geographically widespread variety of slash pine (*Pinus elliottii* var. *elliottii*).

This thesis focuses on the impact that TCs have on the radial growth of the typical variety of slash pine (*Pinus elliottii* var. *elliottii*) in just one region of the Gulf of Mexico, but these methods and results have broader implications that contribute to a larger assessment of coastal resilience under climate change. The methods of this project can be duplicated with other *Pinus* species, and in other study sites along the Gulf of Mexico or the Atlantic coast to identify species and regions that are susceptible to TC storm surge. If TCs are predicted to become larger and stronger, susceptible species and regions will continue to become more at risk as climate change progresses into the 21st century, so it will be important to know where to focus further research and conservation efforts.

This project may also contribute to the field of paleotempestology: A field that aims to reconstruct TCs beyond the historical record using proxies such as tree-rings (Mora et al. 2006). Coastal *Pinus* species may not be the most useful for TC reconstruction due to the lack of available old growth stands and their short-lived nature, however, as noted by Tucker et al. (2018), remnants from dead trees could be sampled and tested using similar methods, temporally expanding tree-ring records. It is also plausible that these results could apply to longer-lived coastal tree species outside of the *Pinus* genus. Further research will be needed to establish viability in other species, and my thesis contributes to a proof of concept showing that research in this area can be worthwhile.

CHAPTER II – METHODS

2.1 Methods

Trees are able to record environmental stressors with annual precision within their radial growth rings, and these data can be used to make assessments on climate and weather factors impacting tree growth including TCs (Speer 2010). The methods used for this project are based heavily on those outlined by Phipps (1985) in *Collecting, Preparing, Crossdating, and Measuring Tree Increment Cores*, and Speer (2010) in *Fundamentals of Tree-Ring Research*. Tucker et al.'s (2018) research project was also consulted to establish successful methods that were used with *Pinus elliottii* var. *elliottii* in the past.

2.1.1 Site Selection

Sites were selected following the principle of site selection as outlined by Speer (2010). According to this principle, sites should be in areas that are likely to amplify the signal of the stressor of interest which in this case would be TC storm surge. The south-central Gulf of Mexico experiences TCs, so study sites were selected in this area of the U.S. The coastlines of Alabama and Florida were selected based on their proximity to the Gulf of Mexico and the occurrence of *Pinus elliottii* var. *elliottii*. In Alabama, Gulf State Park (hereafter GSP) and Weeks Bay National Estuarine Research Reserve (hereafter WB) were selected for sampling along with Topsail Hill State Park in Florida (hereafter TSH). This broad range between sites allowed access to both local and broad applications that could be applied to the Gulf Coast as a whole.

2.1.1.1 Site descriptions

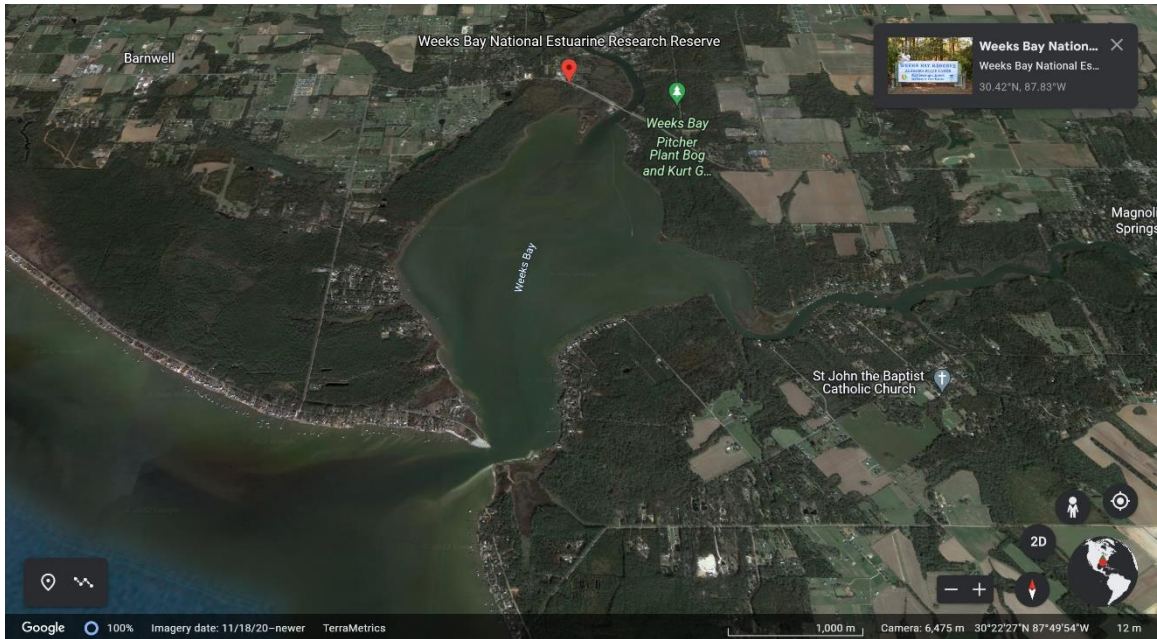
2.1.1.1.1 Weeks Bay National Estuarine Research Reserve

Weeks Bay National Estuarine Research Reserve (WB) in the city of Fairhope, Baldwin County Alabama encompasses 6,525 acres of land and water along the Alabama coast with Weeks Bay, a small tidal inlet, connecting to Mobile Bay to the west (see figure 2.1 and 2.4). Upland and bottomland hardwood forests, freshwater and saltwater marshes, tupelo and cypress swamps, and bog habitats can all be found within WB (Ress 2016). The forest wetland and swamp habitats within WB are known to contain slash pine (*Pinus elliottii* var. *elliottii*) along with sweetbay (*Magnolia virginiana*) and longleaf pine (*Pinus palustris*) with a dense shrubby understory. These wetlands are also noted to inundated during storm events by either heavy precipitation or wind-driven storm surge (WBNERR 2017).

The U.S. Department of Agriculture (USDA) Web Soil Survey returned an abundance of soil types around WB. Approximately 41% of the returned results account for water. The most dominant soil type is wet loamy alluvial land at around 13%, the rest of the soils are primarily sandy loams or loamy sands at less than 10% each. The slope at WB ranged 0 – 12%. The wet loamy alluvial land category of soils at WB is split into Johnston and similar soils at 45% and Pamlico and similar soils at 40% with minor components making up the remainder. The profile of a typical Johnston soil at WB is composed of loamy sands, and they are found in floodplains. They are very poorly drained with about zero inches depth to the water table. The Pamlico soils are similar;

however, they have an Oa layer which is made up of muck. The minor components are hydric soils found in backswamps and depressions.

Figure 2.1
Weeks Bay National Estuarine Research Reserve



Aerial view of Weeks Bay, Fairhope, Alabama (Google Earth, 2022 Weeks Bay).

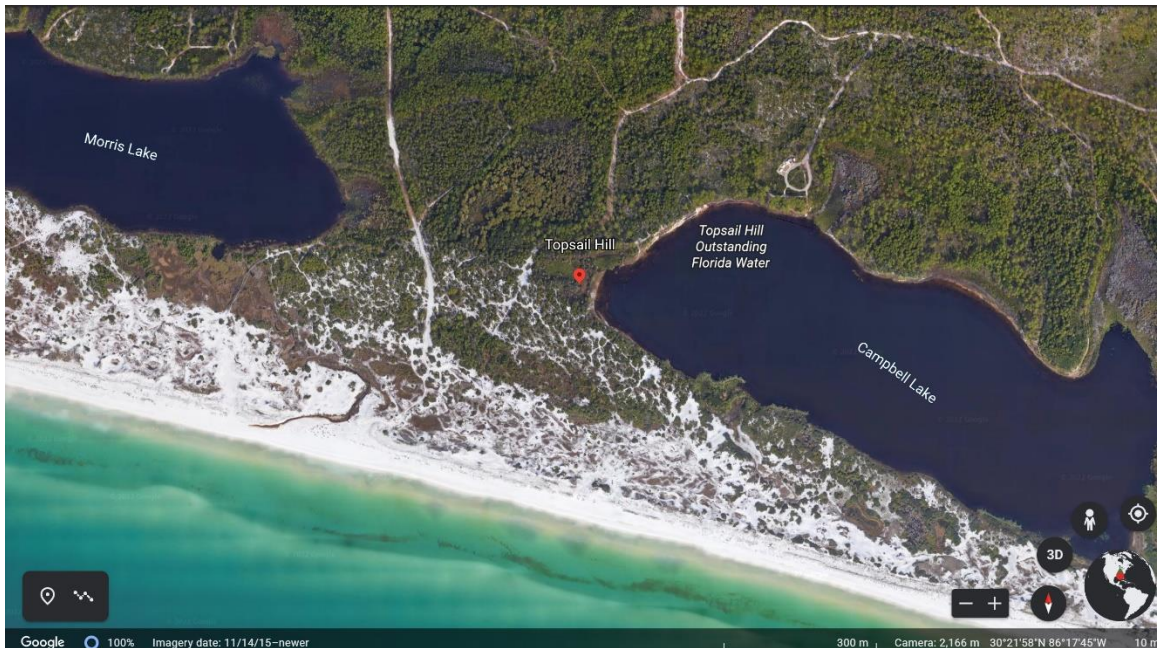
2.1.1.1.2 Topsail Hill Preserve State Park

Located in Santa Rosa Beach, Walton County Florida, TSH encompasses 1,637 acres along the Florida panhandle Gulf Coast (see figure 2.2 and 2.4). Sixteen natural communities are identified within TSH based on the Florida Natural Areas Inventory: Beach dune, maritime hammock, mesic flatwoods, mesic hammock, scrub, scrubby flatwoods, basin marsh, basin swamp, coastal interdunal swale, depression marsh, dome, seepage slope, wet flatwoods, wet prairie, coastal dune lake, estuarine tidal marsh. Of

these 16 natural communities, the beach dune and mesic flatwood communities are noted to contain slash pine (*Pinus elliottii* var. *elliottii*). In the beach dune community, slash pine can be found along the landward sides of the frontal and secondary dunes along with other scrub vegetation. The mesic flatwood community is primarily composed of a mixed upper canopy of slash pine and longleaf pine (*Pinus palustris*) with a shrub layer and an herbaceous layer beneath (State of Florida 2007).

The soils at TSH are mostly made up of Leon sands at about 20% followed by Newham-Corolla Sands, rolling at 18% according to the USDA Web Soil Survey. Sixteen percent of the returned results account for water while the remaining 54% is composed of various mucks and sands at less than 10% each. The slope at TSH is 0 – 8%. The Leon sands at TSH are composed of sand throughout the entire profile, and they can be found in flatwoods and marine terraces. They are poorly drained, around two to 18 inches to the water table, and non-saline to very slightly saline. The Newham-Corolla sands, rolling are also composed of sand throughout the entire profile. Similarly, these sands can be found in dunes, rises on dunes, and marine terraces. They are excessively to somewhat poorly drained, around 18 to greater than 80 inches to the water table, and slightly to strongly saline.

Figure 2.2
Topsail Hill Preserve State Park



Aerial view of the coastline at Topsail Hill State Preserve, Santa Rosa Beach, Florida (Google Earth, 2022 Topsail Hill).

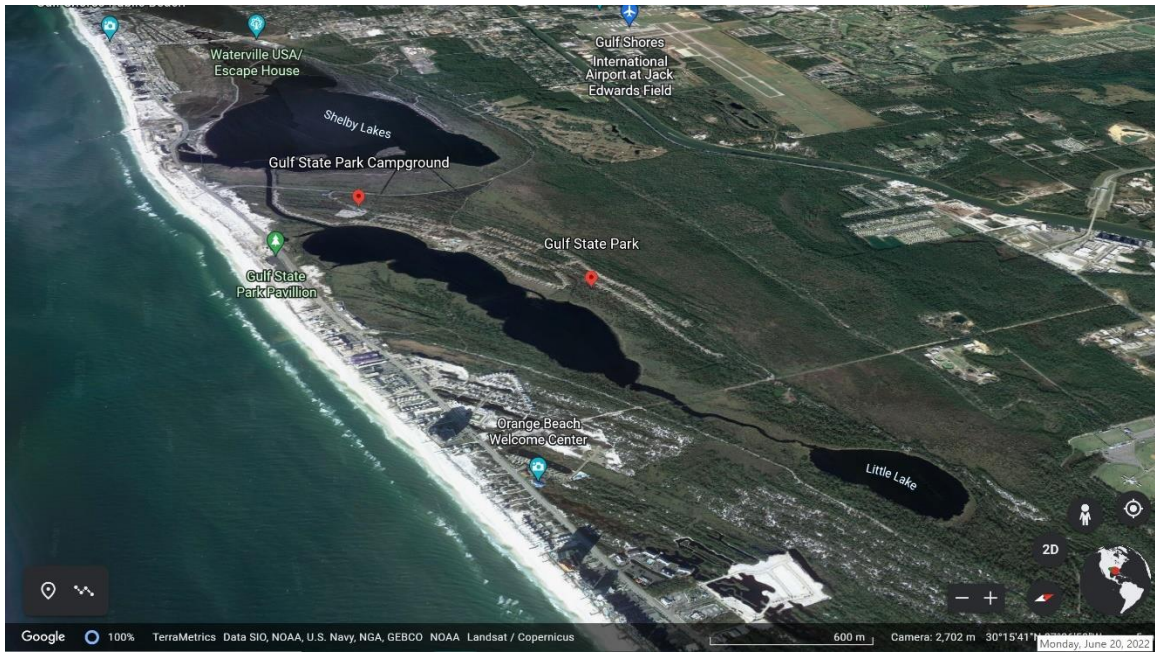
2.1.1.1.3 Gulf State Park

GSP is located along the Alabama coast within the city of Gulf Shores in southern Baldwin County (see figure 2.3 and 2.4). Covering 6,150 acres of land, GSP encompasses nine unique ecosystems: Evergreen forests, pine savannas, maritime forests, dune ridges/sand scrubs, fresh and salt marshes, freshwater and brackish lakes, coastal swales, dunes, and the beach and gulf. Of these ecosystems, three are known to support slash pine (*Pinus elliottii* var. *elliottii*). The evergreen forests of GSP are pine flatwoods with an upper canopy of longleaf (*Pinus palustris*) and slash pine and an understory composed primarily of saw palmetto (*Serenoa repens*). The pine savannas are similar to the evergreen forests, but they differ from them due to their more open nature. The fresh and

saltwater marshes are also known to contain slash pine along with the common buttonbush (*Cephalanthus occidentalis*), sawgrass (*Cladium*), marsh fern (*Thelypteris palustris*), scarlet hibiscus (*Hibiscus coccineus*), and black needlerush (*Juncus roemerianus*) (Sasaki Associates 2016).

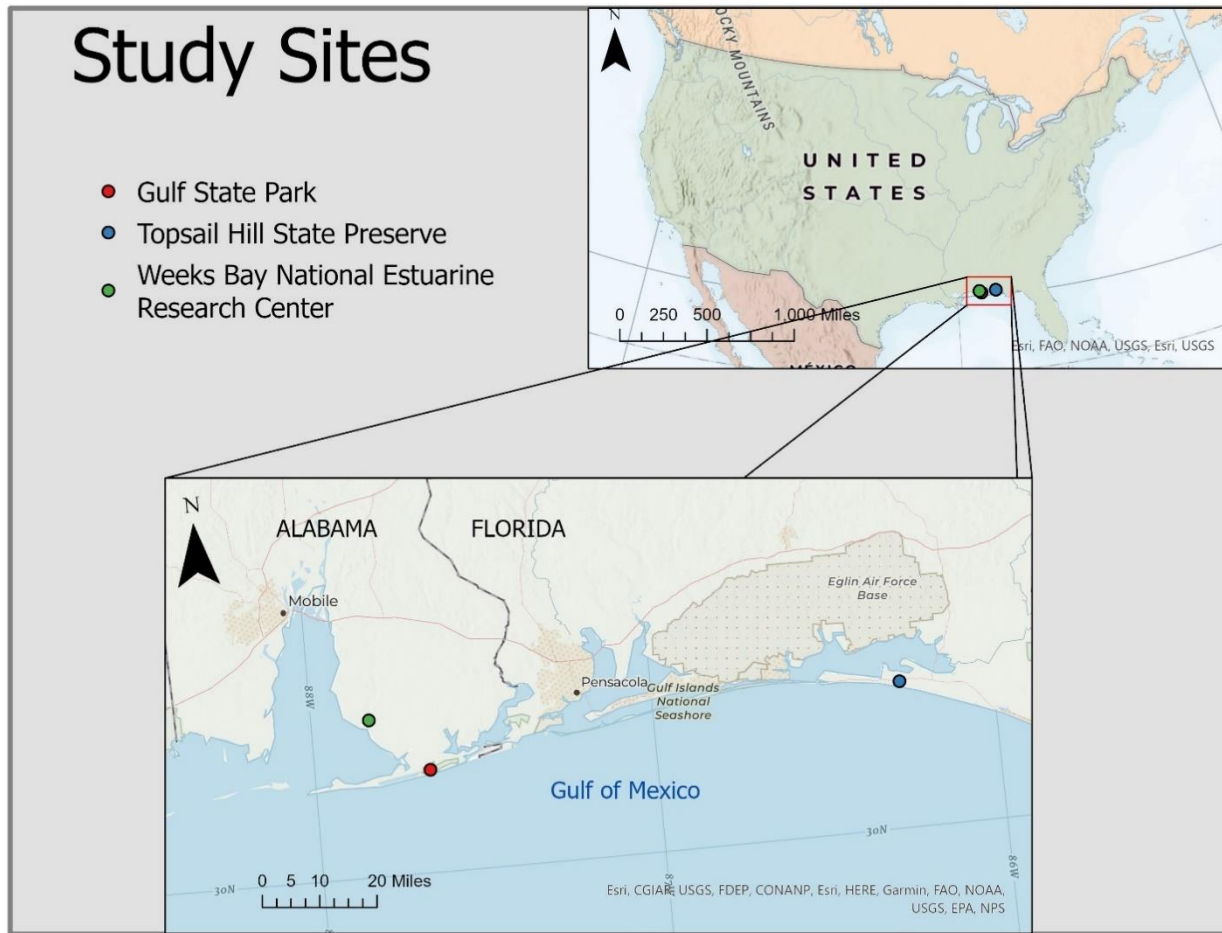
GSP soils are primarily classified as tidal marsh and Leon sand at around 25% each according to the USDA Web Soil Survey. The returned results show around 18% water within the area of interest, and the remaining soils are classified as sands, loamy sands, and sandy loams at less than 15% each along with a small component of muck soils. The slope at GSP range 0 – 8%. The tidal marsh soils at GSP occur in tidal flats, tidal marshes, and backswamps. Muck, clay, sandy loam, and mucky sandy loam make up the profiles of the tidal marsh soils. They are slightly to moderately saline, and very poorly drained with only about zero in depth to the water table. The Leon sands at GSP are both hydric and non-hydric and occur in depressions. The profiles are mostly sand with muck in the Oa horizon of the hydric soils. Leon sands soils are non to very slightly saline and poorly to very poorly drained. The hydric Leon sands have a depth of just around zero inches to the water table while the non-hydric soils range from 30 inches.

Figure 2.3
Gulf State Park, Alabama



Aerial view of the coastline at Gulf State Park, Gulf Shores, Alabama (Google Earth, 2022 Gulf State Park).

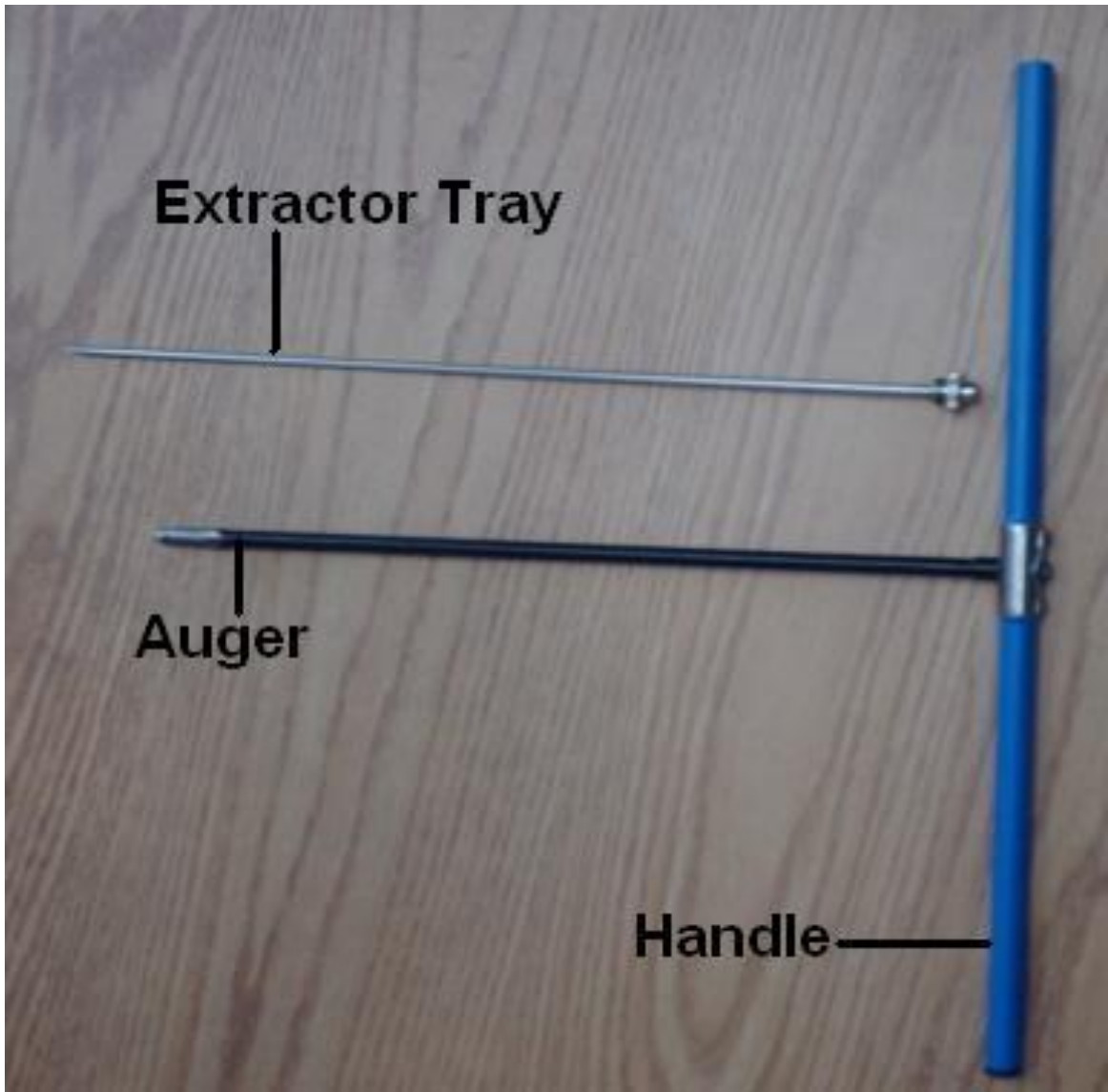
Figure 2.4
Site Location Map



2.1.2 Sampling

Two cores were obtained from each tree using an increment borer at approximately breast height (See figures 2.5 and 2.6). Two cores allow for each tree to be crossdated at the individual tree level. Following the principle of site selection, trees were selected using targeted sampling based on the probability that their growth would be sensitive, recording the signal of interest which in this case is stress induced by storm surge. According to the principle of site selection, trees are likely to be complacent or lacking variation in ring width if they are located at the center of their ecological amplitude and in climates conducive to healthy growth of the species (Speer 2010). Trees located several miles from the coast or located on steeper slopes were determined to not be as reliably responsive to storm surge events and were therefor not taken in consideration.

Figure 2.5
Increment Borer



Basic example of Increment borer and its parts (Pradtke 2008).

Figure 2.6
Using an Increment Borer



I am seen here using an increment borer to core a tree at the Weeks Bay, Alabama site (Patterson 2019).

Appearance of age and general health of the trees was also considered. Age was estimated visually. Factors such as height, width, and appearance of the crown helped determine whether a tree could be of greater age. Exact age could not be determined by visual inspection, but it was possible to determine which trees might be some of the oldest at the site using these general qualitative assessments (Pederson 2010). General health was also assessed using a visual inspection. Trees with significant scarring, rot, and those that appeared to be significantly damaged, or dead were excluded from sampling. Scarring, rot, and damage could have interfered with sampling because it could

impact the appearance of rings or make it difficult to extract the sample. Dead trees are sometimes useful in dendrochronology, but the wood is often too degraded to be sampled, and it is unknown if they will cover the most recent years needed in analysis (Speer 2010). For this reason, dead trees were not considered for my research although they could prove useful in future research.

An increment borer was used to withdraw samples approximately the width of a pencil from living trees (see figure 2.7). The increment borer was composed of three parts: The auger, the handle, and the extractor. The tip of the increment borer's auger was threaded, so it could bore through the bark and into the tree towards the pith or center parallel to the wood rays, as the handle was turned clockwise. The probable location of the pith was determined by visual inspection. Usually aiming towards the center of the tree is sufficient. The increment borer was then turned repeatedly until it was estimated to have reached the pith. Then, the extractor was used to remove the sample from the inside of the tube-like bit (Phipps 1985; Speer 2010).

Figure 2.7
Prepped Cores from Weeks Bay, Alabama



Prepped cores from slash pine and cypress trees obtained from the Weeks Bay, Alabama site (Crowell 2020).

The extractor was pushed into the bit and slid beneath the sample, and then one full counterclockwise turn was executed ensuring that the core broke off into the spoon. The core was then withdrawn from the auger. Finally, the increment borer was turned counterclockwise until it could be removed from the tree (Phipps 1985; Speer 2010). A small hole was left behind after coring the trees, but the damage to the trees was minor. In the case of conifers, pitch may fill the core hole, sometimes within hours of coring, sealing up the hole and reducing the likelihood that it would lead to further damage (Speer 2010). Samples were transferred from the spoon into plastic or paper straws for

safe keeping during transportation and while they dried. Paper straws were the ideal choice because their porous nature allows the cores to dry without molding. Each straw was labeled with the site code, tree number, and an A or B to denote the side it was taken from (Phipps 1985; Speer 2010).

2.1.3 Preparing Samples

Samples were brought back to the lab and given time to air dry before mounting. Dry cores were preferred because fresh ones may have warped or cracked when mounted. The cores were removed from the straws and mounted onto wooden core mounts using water-based glue to hold them. When mounting cores, it was important to make sure the core was mounted with one of its cross-sectional views facing upwards and its vessels and fibers at right angles to the surface. Tape was then wrapped along the length of the core mounts to prevent the cores from moving or warping from the moisture of the glue as they dried (Phipps 1985; Speer 2010). Once the glue was adequately dried, the final step of sample preparation could be performed before analysis.

The final step of sample preparation involved using a series of increasingly finer grit sandpapers on an inverted belt sander to remove approximately one half of the wood from each sample and leave behind a polished surface (see figure 2.8). The literature recommends sandpapers starting at a course grit as low as 50 particles per inch all the way up to a super-fine grit of 500 – 600 particles per inch. The course grit paper was used to take off bulk while the finer grits polished down the surface for a smooth finish. It was important to get a finish that was as smooth as possible because a smooth surface makes

ring boundaries more readily visible when viewing under a microscope (Phipps 1985; Speer 2010).

Figure 2.8
Sanding Core Samples



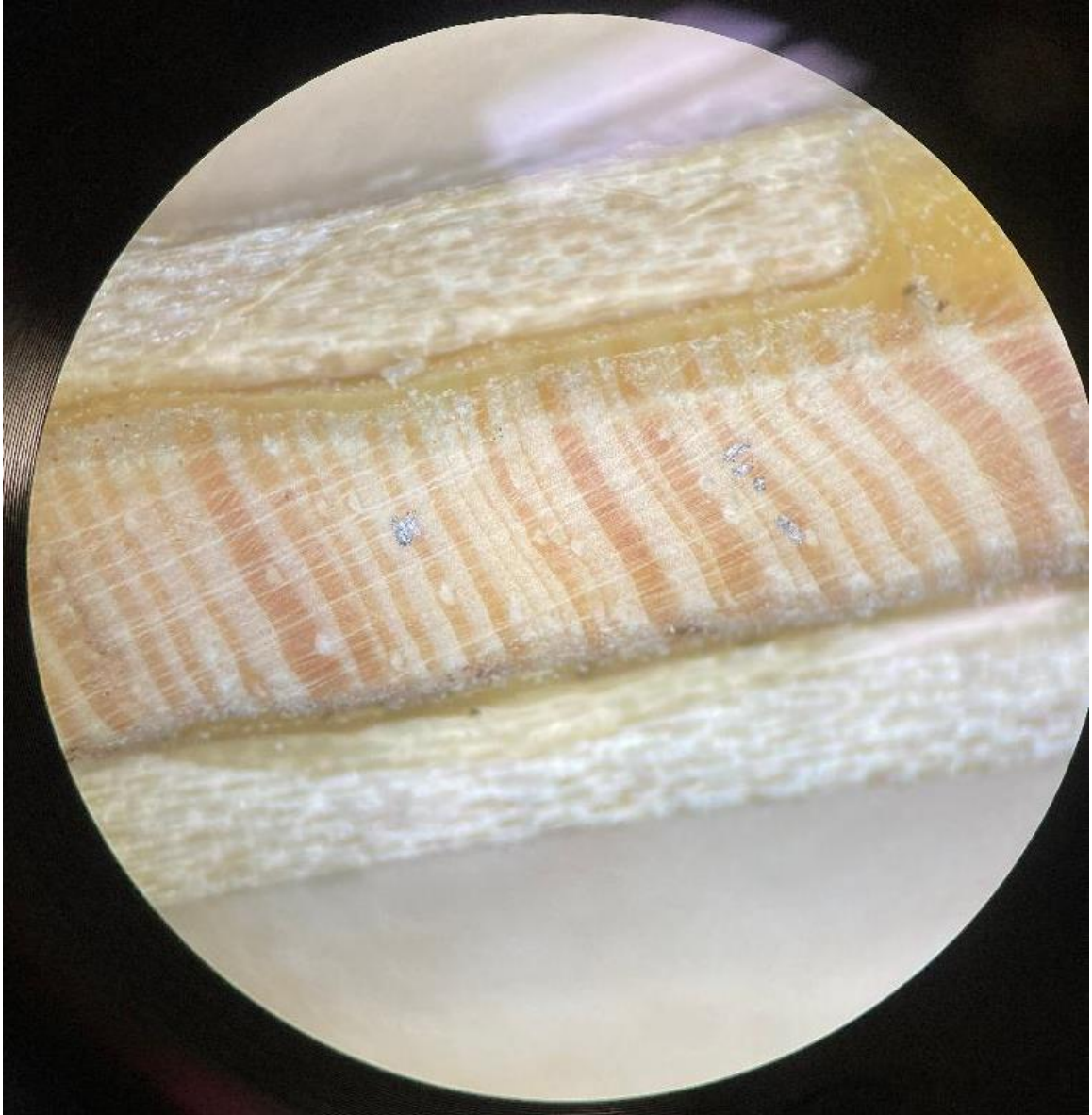
An inverted belt sander was used to prepare the samples for visual inspection (Crowell 2021).

2.1.4 Tree Ring Analysis

After sample preparation, crossdating assigns a calendar year to each growth ring found in a sample (hereafter a series). This was done not only by simply counting each ring in a series, but also by matching up ring patterns between series to determine the presence of missing and false rings. Conifers in temperate climates such as *Pinus elliottii* have an earlywood growing season in the spring, and a latewood season during the summer and fall. This means that there is a light colored and dark colored component making up each year of growth allowing them to be counted with the annual precision that is the basis of dendrochronology (See figure 2.9) (Phipps 1985; Speer 2010).

Crossdating was performed at least twice to ensure a higher level of accuracy. There are many ways to perform the first round of crossdating, however, they all share one key similarity: They are performed manually and visually without the aid of computer programs. It is acceptable for the second count to be performed with the aid of a computer program although it can also be performed without one and traditionally was in the past (Speer 2010).

Figure 2.9
Annual Growth Rings of Slash Pine



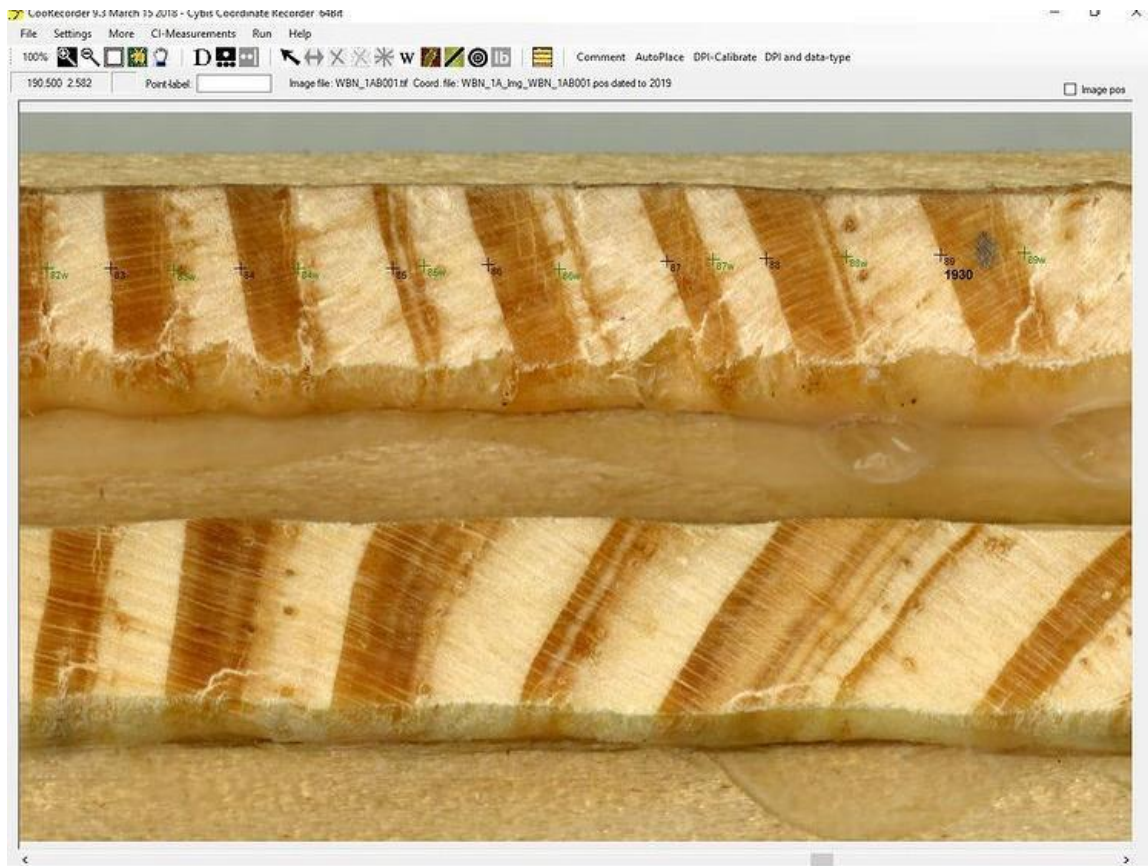
The darker Latewood and lighter Earlywood are seen under the microscope (Crowell 2021).

The first count was performed by analysis under a microscope in which each growth ring was counted, leaving a pencil mark(s) on each decade (see figure 2.9) (Phipps 1985; Speer 2010). The date of the last complete outermost ring was known

because it corresponded with the date of when each collection of samples was taken. The remainder of the years were then counted backwards from the bark and in towards the pith. During this first count, it was noted which years seemed to have some of the narrowest rings. These are called marker years, and the identification of these marker years help when comparing a sample of one side of the tree to a sample from the other side, and later when troubleshooting during the second round of crossdating (Speer 2010).

After visually crossdating, all samples were measured using the program CooRecorder (Larsson 2014). Before CooRecorder could be used, an image of each core was needed to load into the program. Each core was scanned into the computer using an Epson scanner set at 1,200 DPI (Maxwell and Larsson 2021). CooRecorder was then opened, set to “Measure Latewood and Earlywood”, and the high-resolution images were loaded in providing a much larger scale to assess the tree-rings under. CooRecorder allows the user to place points at the boundaries between growth rings, perpendicularly across each ring, starting at the bark end of the core sample (see figure 2.10). Measurement points were also placed at the boundaries between the earlywood and latewood within each ring. The outermost, complete year was assigned a date, and this allowed each year that came before to be assigned a date as well (Maxwell 2019; Maxwell 2020). Crossdating accuracy was assessed as each core was dated, and dates were sometimes revised from the visual count. This was often the case when a closer examination revealed ring anomalies that were previously unable to be detected or overlooked.

Figure 2.10
CooRecorder Screenshot



The black marks denote latewood boundaries and the green earlywood (Larson 2014).

Ring anomalies such as absent, discontinuous, pinched, micro, and false rings interfere with crossdating, and can be difficult to identify. Absent and discontinuous rings occur when a tree's growth hormone reproduction is inhibited by a stressor causing uneven growth rates within the stem. A proper ring may appear in some parts of the stem but may be missing in another. This same lack of circuit uniformity is also seen in pinched rings (Phipps 1985; Speer 2010) Micro rings, just two cells wide, are so small that they may be initially missed (Speer 2010). False rings usually appear as a gradual

transition into latewood that thins back out to earlywood again. This is because the tree had shut down growth for part of the year due to a limited resource but began to grow again when conditions were more favorable (Phipps 1985; Speer 2010). These anomalies can be identified with careful examination and by comparison to other trees in the data set that may not have the anomaly present for that year.

Points delineating boundaries were moved, added, or deleted to correct mistakes and improve accuracy. Points were placed demarcating gaps and cracks in the samples and points that hold the place of missing rings. Once all points are placed, CooRecorder then calculated the distance between each point providing widths for the total ring, earlywood growth, and latewood growth for each sample in the collection. This process was repeated for each core collected from all three sites. These results were exported as coordinate files compatible with other dendrochronology computer programs such as COFECHA (Maxwell 2019; Maxwell 2020).

A final verification of crossdating accuracy was performed utilizing the quality control program COFECHA (Holmes 1983). COFECHA uses statistical analyses to compare each series against a master chronology, an average of all series, in order to detect possible crossdating errors. COFECHA's defaults have been determined to be acceptable for most basic dendrochronology endeavors, so they were left unchanged. First, each series is standardized by applying a 32-year cubic smoothing spline. The 32-year cubic smoothing spline detrended the data by applying a flexible mathematical curve (Cook and Peters 1981; Holmes 1983; Speer 2010). Standardization was necessary because trees produce larger growth rings when they are younger, but as they age, and they grow less each year. Variations in ring width based on age related growth decline

were considered noise in the data since they could mask other variances such as those based on weather and climate. The noise had to be removed so other growth trends, such as those based on TC passage, could stand out (Speer 2010).

The second setting in COFECHA specified a 50-year segment length with 25-year overlapping periods in which a correlation coefficient will be calculated. 50 years lagged by 25 years has been determined to be suitable for chronologies in which the series average at least 100 years in length as was the case for my chronologies (Holmes 1983; Speer 2010). The third setting applies autoregressive modeling which was used to remove growth trends that carry over from one year to the next due to autocorrelation. Autocorrelation is when a variable, in this case the climate of previous years, correlates with itself: Meaning the climate of one year impacts growth in the next years. This trend can be considered noise in the data because it may mask the year-to-year, the high frequency variation that is necessary for crossdating (Cook 1985; Speer 2010).

The next COFECHA setting asks the user if they would like to turn on log transformations which are used to weight proportional differences in ring measurements more equally (Holmes 1983). This setting is turned on by default, but it was turned off for this project as it was determined that log transformations would not be necessary. The final COFECHA setting allows the user to choose the correlation coefficient and apply a critical level. The Pearson product moment correlation coefficient was selected as it is commonly used in tree-ring analysis. The Pearson product moment correlation coefficient measures the linear correlation between two data sets by taking the ratio between the covariance of two sets and the product of their standard deviations. To

preserve precision, a 99% one-tailed confidence level is automatically applied by COFECHA (Speer 2010).

A final report provided a wealth of information about the chronology (see figure 2.11), but one of the key pieces of information it provided was the flagging of segments or individual years within each series that did not meet to 99% confidence level threshold for crossdating. COFECHA either could not find a better match for a particular ring and flagged it accordingly, or it suggested a number of years to add or remove within a 20-year window with 10 years on either side of the problem year. COFECHA suggested adding or removing a certain number of rings within these windows on problem cores, but I had to figure out exactly how to execute these changes (Holmes 1983; Speer 2010). Flagged segments were examined once again in CooRecorder, looking for marking errors along with absent, micro, and false rings. The process was repeated until the number of flags were minimized and a high level of confidence in the accuracy is achieved (Holmes 1983).

Figure 2.11
COFECHA final Report

```
*****  
*C* Number of dated series      29 *C*  
*O* Master series 1923 2019    97 yrs *O*  
*F* Total rings in all series  2385 *F*  
*E* Total dated rings checked  2384 *E*  
*C* Series intercorrelation    0.716 *C*  
*H* Average mean sensitivity   0.466 *H*  
*A* Segments, possible problems  0 *A*  
*** Mean length of series      82.0 ***  
*****
```

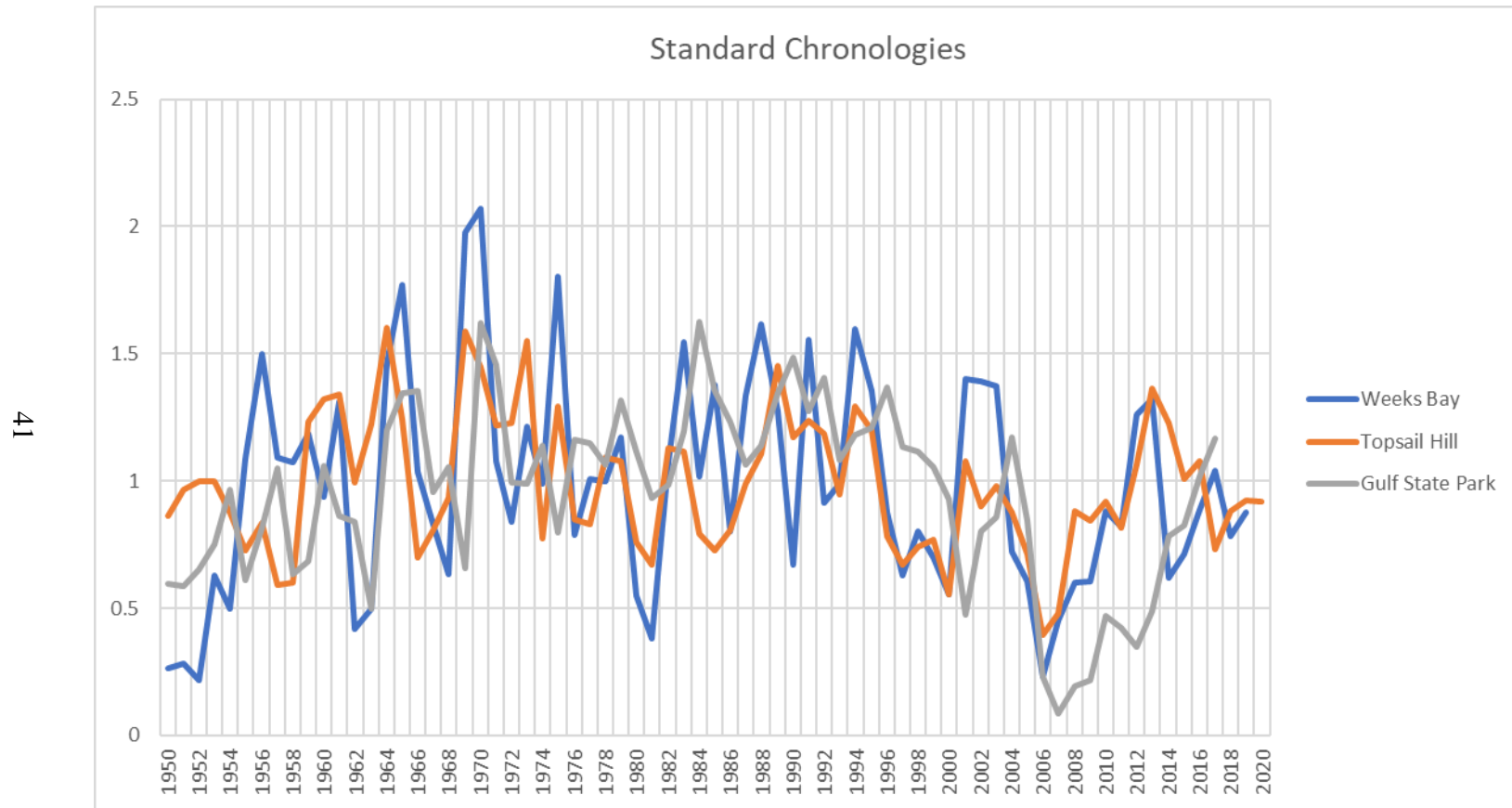
Some of the highlights of a COFECHA report (Holmes 1983).

COFECHA's output reports also provided important descriptive information about the master chronology including the number of dated series, length of the master series, total rings in all series, total dated rings checked, series intercorrelation, average mean sensitivity, possible problems segments, and mean length of the series. Series intercorrelation and mean sensitivity were the two main descriptive factors that are provided in research as they are used to describe site-level signal and sensitivity between sites. Series intercorrelation measures the relationship between series or the stand-level signal of the chronology. It is correlation of all series averaged together from a value of zero (no common signal) to one (perfect common signal). Mean sensitivity reflects the year-to-year variability within the chronology. A mean sensitivity value closer to zero reflects complacent growth that does not respond well to its environment whereas a value closer to one indicates sensitive growth that is highly impacted by environmental influences. It may also fall somewhere in between which is ideal for climate reconstruction (Speer 2010).

The three site-level chronologies built in COFECHA were not ready for analysis until they were processed with the computer program ARSTAN (Cook et al. 2017). This program is the final standardization and detrending package used to remove all stand-level autocorrelation in data. ARSTAN—short for autoregression standardization—detrended the raw ring width data and removed autoregression via autoregressive modeling such that data can be used for statistical analysis. I removed age related growth decline using a negative exponential curve and maintained the program defaults for removing autocorrelation. As a result, ARSTAN produced four different types of stand-

level chronologies: Raw, standard, residual, and ARSTAN chronologies. The raw chronology is the average of the ring widths for each year without any standardization. ARSTAN's standard chronology, however, provided the average growth of each year based on the index values from the standardization process that I specified in the ARSTAN settings (Speer 2010). The residual chronology was the average residuals from the standardization modeling and the ARSTAN chronology was the standardized chronology with some autoregression reintroduced. For this project, I used the standard chronology for all analyses (see figure 2.12).

Figure 2.12
Standard Chronologies from all Sites



The three standard chronologies from ARSTAN showing average growth at each site.

2.1.5 Weather Data

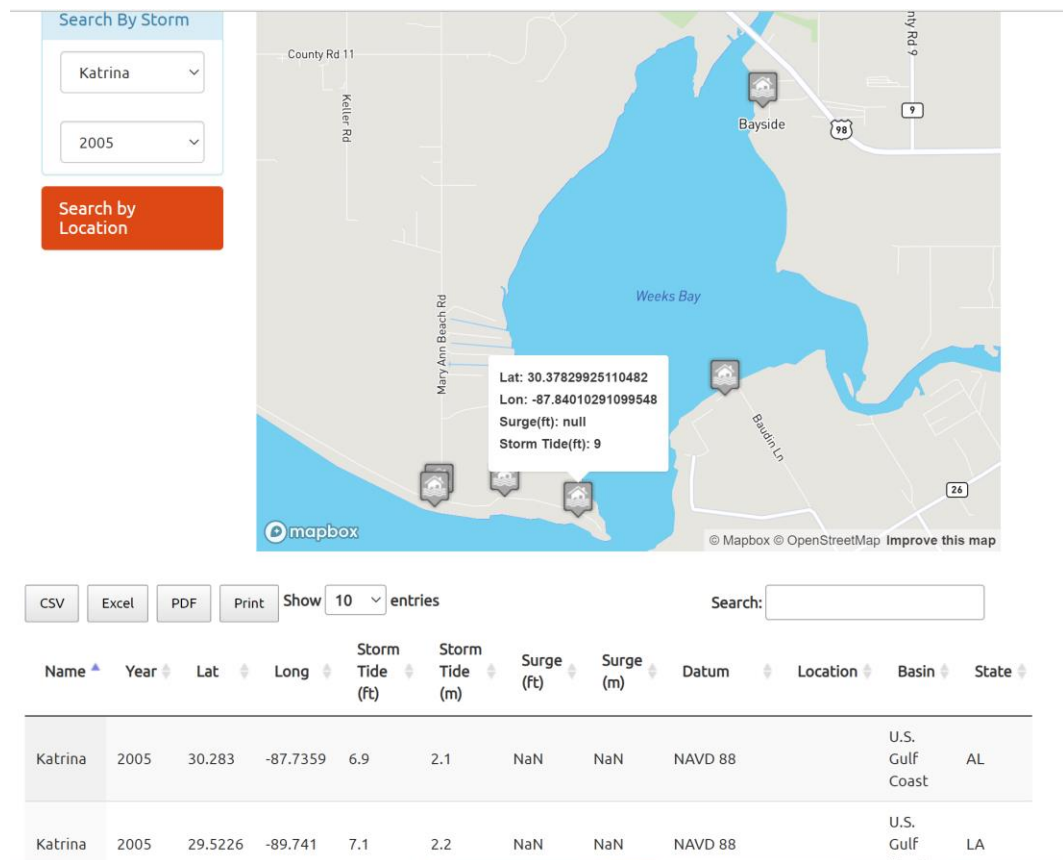
Meteorological data were collected from sources maintained by NOAA. TC storm surge and storm tide data was obtained through the SURGEDAT webtool maintained by the Regional Integrated Sciences and Assessments and Southern Climate Impacts Planning Program (SCIPPS) (see figure 2.13). NOAA's Historical Hurricane Tracks web tool provided access to data from the National Center for Environmental Information's IBTrACs and the National Hurricane Center's HURDAT2 conveniently together in one place (see figure 2.14). Basic TC data such as storm track, maximum category within the area of interest, minimum pressure, and maximum wind speed were obtained. All data were organized in Microsoft Excel by study site (see tables A1, A2, A3, and A4).

At times, storm surge values were not reported for sites even when the probability of storm surge occurring from a particular TC seemed high based on other storm factors such as wind speed. In these cases, various sources such as Wikipedia and other NOAA or NWS webpages were used to supplement the missing data when possible. If a reliable source could be found noting surge in an area close to the study site, then surge could be noted as occurring. If no source could be found, then no surge was recorded regardless of how high the probability seemed.

The Historical Hurricane Tracks web tool allows the user to set a search radius, and within that radius, it can identify all the recorded TCs with an eye that passed through the area. With trial and error, I set the search radius to 150 miles based on the following reason: According to the NWS' "Hurricane Facts", hurricanes have a broad range when it comes to size, but the average is around 300 miles wide. Based on this information, the 150-mile search radius was wide enough to capture the average TC since

it results in a search area with a 300-mile diameter. When using SURGEDAT to identify storm surge events for each site, the closest recording weather station was used in order to gain the most accurate measurement for each site. Stations were selected within 50 miles or less of each site.

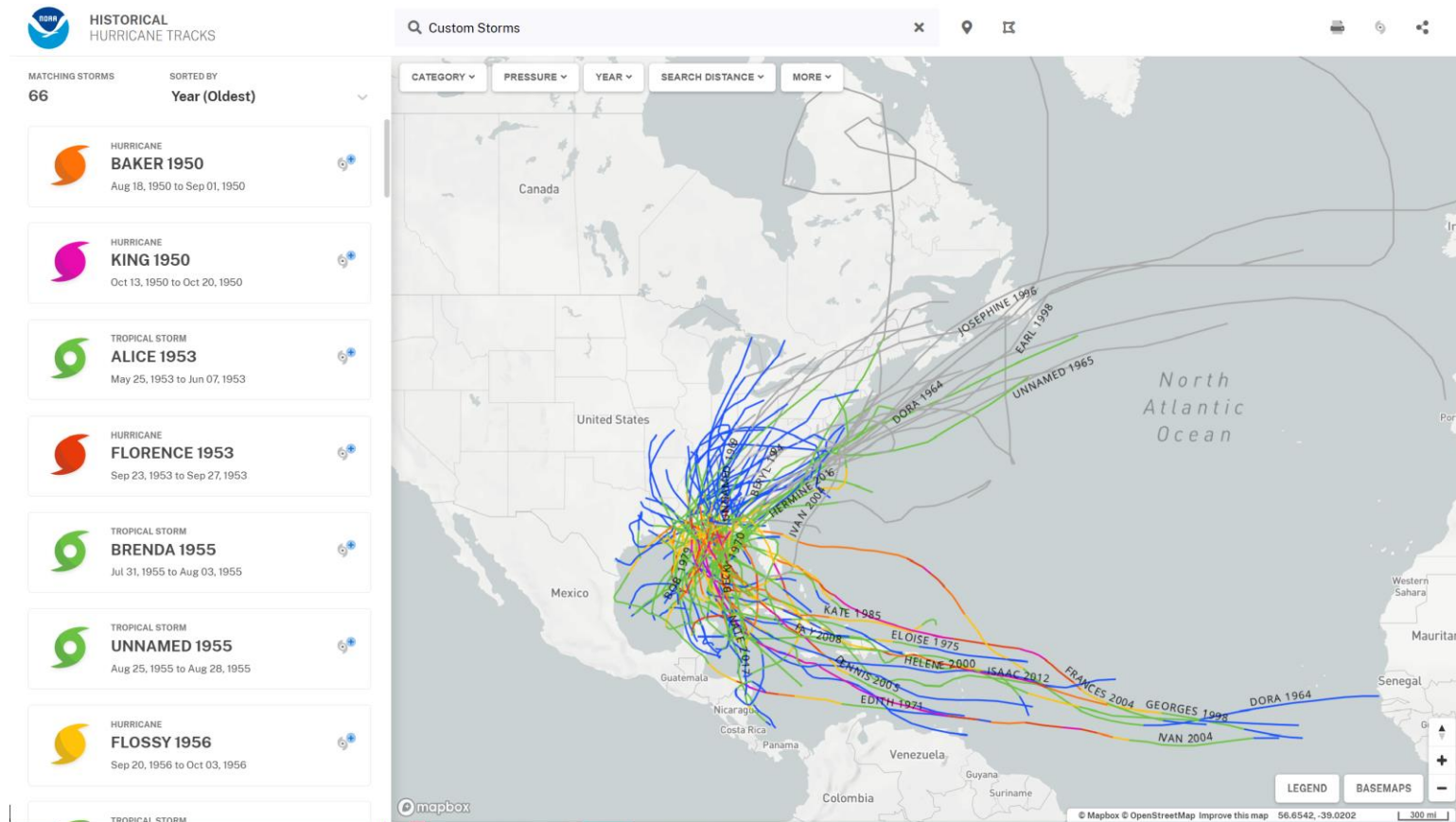
Figure 2.13
SURGEDAT Web Tool



A screenshot from the SURGEDAT web tool showing an example of data for Hurricane Katrina in Weeks Bay, Alabama. (SCIPP 2022).

Figure 2.14
Historical Hurricane Tracks Web Tool

44



A screenshot from NOAA's Historical Hurricane Tracks web tool showing all of the storms that impacted my study sites (NOAA 2022).

2.1.6 Data Analysis

Microsoft Excel was used for all data management aspects of this project along with data analysis. Spreadsheets were built for each study site containing columns for the years, the standard chronology values obtained from ARSTAN, five year moving averages of the average growth chronology for each year, the percent change from year-to-year for the chronology, and a binary account of storm surge for each year (see figures A5, A6, and A7). With these basic values, it was possible to calculate the percent of storm surge events that produced a suppression of 10% or greater within 1 – 3 years following the storm surge event (hereafter “suppression”), and the amount of suppressions that corresponded with a storm surge event.

The values from the standard chronology could not be used alone to determine if a suppression had occurred. To determine this, a few calculations had to be made first. Average growth was calculated for each year and the four years that preceded by using a five-year moving window. The five-year moving window averages allows normalizing large changes in growth within the context of potential decadal-scale growth trends. Next, percent change was calculated by subtracting the growth of the previous year from the current year in 5-year moving window average column, dividing it by the growth of the previous year, and multiplying by 100. This calculation gave a number that represented the percentage of suppression or release from one year to the next.

A hit or miss ratio was used to calculate the percent of storm surge events that produced a suppression within 1 – 3 years following a storm surge event. A binary account of storm surge by year indicated whether storm surge occurred (one) or did not occur (zero). If a suppression was noted 1 – 3 years after a one was marked on the

spreadsheet, then this was considered a storm surge event that led to a suppression (a hit). If a one was marked on the spreadsheet and three years passed without a suppression, this was considered a miss. The total number of storm surge events was then divided by the total number of hits to obtain the percent of storm surge events that produced a suppression within 1 – 3 years following. This process was completed for all TC storm surge events, and it was also completed for category 1 – 5 TCs as I suspected a difference would be observed when excluding small-scale storms.

The amount of suppressions that corresponded with storm surge events was also calculated using a hit or miss ratio. In this case, I noted where suppression events occurred in the spreadsheet. If the suppression event corresponded with storm surge marked within the previous 3 years, this was considered a hit. If a suppression event occurred, but no storm surge event was noted within the three previous years, then this was a miss. The total number of suppression events was then divided by the total number of hits to obtain the amount of suppressions that corresponded with storm surge events. This process was completed for all TC storm surge events, and it was also completed for just category 1 – 5 TCs. Finally, recovery periods were calculated for each study site. When a suppression occurred in the chronology after TC passage, the years following were counted until average growth returned to average growth. The recovery periods for each event were averaged together to get the overall average recovery time at each site.

CHAPTER III – RESULTS

3.1 Tropical Cyclone Frequency and Storm Surge Events

A total of 66 TCs tracked within 150 miles of the three study sites from the years 1950 to 2020 (see figure A1). Of those 66 TCs, 45% never surpassed tropical storm strength while the remaining 55% strengthened to reach categorized hurricane status. 30% of the 66 TCs went on to become major hurricanes ranked at category three or higher. The year 2005 had the highest amount of TCs with three hurricanes and one tropical storm impacting the study sites. This is not surprising as 2005 was noted to be the most active hurricane season on record until the record was broken in 2020 (NOAA 2020). The 2020 season is only represented by one study site for this project due to data collection limitations, therefore only one TC is reflected in the data for that year. The most active month across all sites was August with 27% of the 66 TCs occurring during this month. This was closely followed by September at 26% of all recorded TCs. The least active month was a tie between May, the earliest month for TCs in this record, and November, the latest month, at 3% each.

Sixty five percent of the 66 TCs led to storm surge or tide at one or more of the study sites. Between all sites, storm surge events averaged 3.74 feet and storm tide (surge plus tidal increase) averaged 4.55 feet. The highest storm surge/tide values were associated with Hurricanes Katrina (2005), Ivan (2004), Opal (1995), Frederic (1979), and Eloise (1975) with storm surge/tide values exceeding 10 ft. The absolute highest storm surge/tide value between all sites was a recorded 15.6 feet storm tide west of

Miramar Beach (about five and a half miles from TSH). This storm tide was caused by the category four Hurricane Opal in 1995.

3.1.1 Weeks Bay

WB had a total of 52 TCs that tracked within 150 miles from 1950 to 2019. Fifty eight percent of the TCs at WB ranked as tropical storms while the remaining 42% were categorized hurricanes, and seventeen percent of the 52 TCs reached major hurricane status. 2005 was the most active year at WB with three hurricanes and one tropical storm tracking near the site. The most active month at WB was September with 31% of TCs occurring during this month. The least active month was a tie between May, the earliest month for TCs at WB, and November, the latest month, at 4% each. Sixty two percent of the TCs that tracked near WB led to recorded storm surge or tide. Storm surge at WB averaged 4.04 feet while storm tide averaged 4.46 ft. The highest storm surge at WB was produced by category three hurricane Ivan (2004) which led to 15 ft of storm surge recorded for Baldwin County. The highest storm tide was produced by category five Hurricane Katrina (2005) which led to 10 feet of storm tide in Baldwin County.

3.1.2 Topsail Hill

TSH had a total of 51 TCs that tracked within 150 miles from 1950 to 2020. This accounted for 77% of the total TCs. Tropical storms accounted for 63% of these TCs while 37% reached hurricane strength. Sixteen percent of the total 51 TCs reached major hurricane status. There was no one most active year, instead, it was a tie between the years 1985, 1995, 2004, 2005, and 2018 which each had 3 TCs. Of these years, 1995 was

the only one with all three TCs reaching hurricane strength. The most active month at TSH was August with 25% of the TCs. The least active month was November at 2%. Fifty five percent of the TCs that tracked near TSH led to recorded storm surge or tide. Storm surge at TSH averaged 3.52 feet while storm tide averaged 5.05 feet. The highest storm surge at TSH was 10 feet recorded in Walton County produced by category three Hurricane Ivan (2004). The highest storm tide was 15.6 feet recorded west of Miramar Beach produced by the category four Hurricane Opal (1995).

3.1.3 Gulf State Park

GSP had a total of 47 TCs that tracked within 150 miles from 1950 to 2017. This accounts for 71% of the total TCs. Of the 47 TCs, 57% never surpassed tropical storm status while the remaining 43% reached hurricane status. Only 17% went on to become major hurricanes. 2005 was the most active year at GSP with four total TCs: two major hurricanes and two tropical storms. The most active month at GSP was August with 32% of TCs occurring during this month. The least active month was May at only 2%. Fifty three percent of TCs tracking near GSP produced storm surge or tide. Storm surge at GSP averaged 3.93 feet while storm tide averaged 4.13 feet. The highest surge event recorded at GSP was produced by category three Hurricane Ivan (2004) which led to 15 feet of storm surge recorded for Baldwin County. The largest storm tide event was associated with category five Hurricane Katrina (2005) which produced 10 feet of storm tide recorded in Baldwin County.

3.2 Tree Ring Data

3.2.1 Weeks Bay

Weeks Bay had a total of 29 dated series from 1923 to 2019. The series intercorrelation for this site was 0.716, and the average mean sensitivity was 0.466. For total wood, 67% of all storm surge events (TS to category 5) produced a suppression in 1 – 3 years following the event. This number is raised to 77% if only category 1 – 5 storms are considered. 80% of all suppressions corresponded with a storm surge event. For earlywood, the number of storm surge events that produced a suppression in 1 -3 following the event was 61%. When only considering category 1 – 5 TCs, it increased to 69%. Eighty eight percent of all suppressions corresponded with a storm surge event for early wood. For latewood, 67% of all storm surge events produced a suppression in 1 – 3 years following the event. This number increased to 77% if only category 1 – 5 storms are considered. Seventy three percent of all suppressions corresponded with a storm surge event.

Total wood and latewood performed similarly when assessing the number of storm surge events that produced a suppression of in 1 – 3 years following the event at WB. Earlywood, however, detected less. When it came to the amount of suppressions that corresponded with a storm surge event, earlywood detected the highest percentage followed by total and then latewood. The average recovery period at WB was 2 – 2.6 years with the shortest period being detected in latewood and the longest for earlywood. The longest period of suppression in the latewood occurred after the year 2005. Growth remained below average for four years following this active year. In earlywood, the

longest recovery period is a four-year period after 1996. The longest recovery period for total wood was a five-year period after 1995.

Figure 3.1
Weeks Bay Standard Chronology

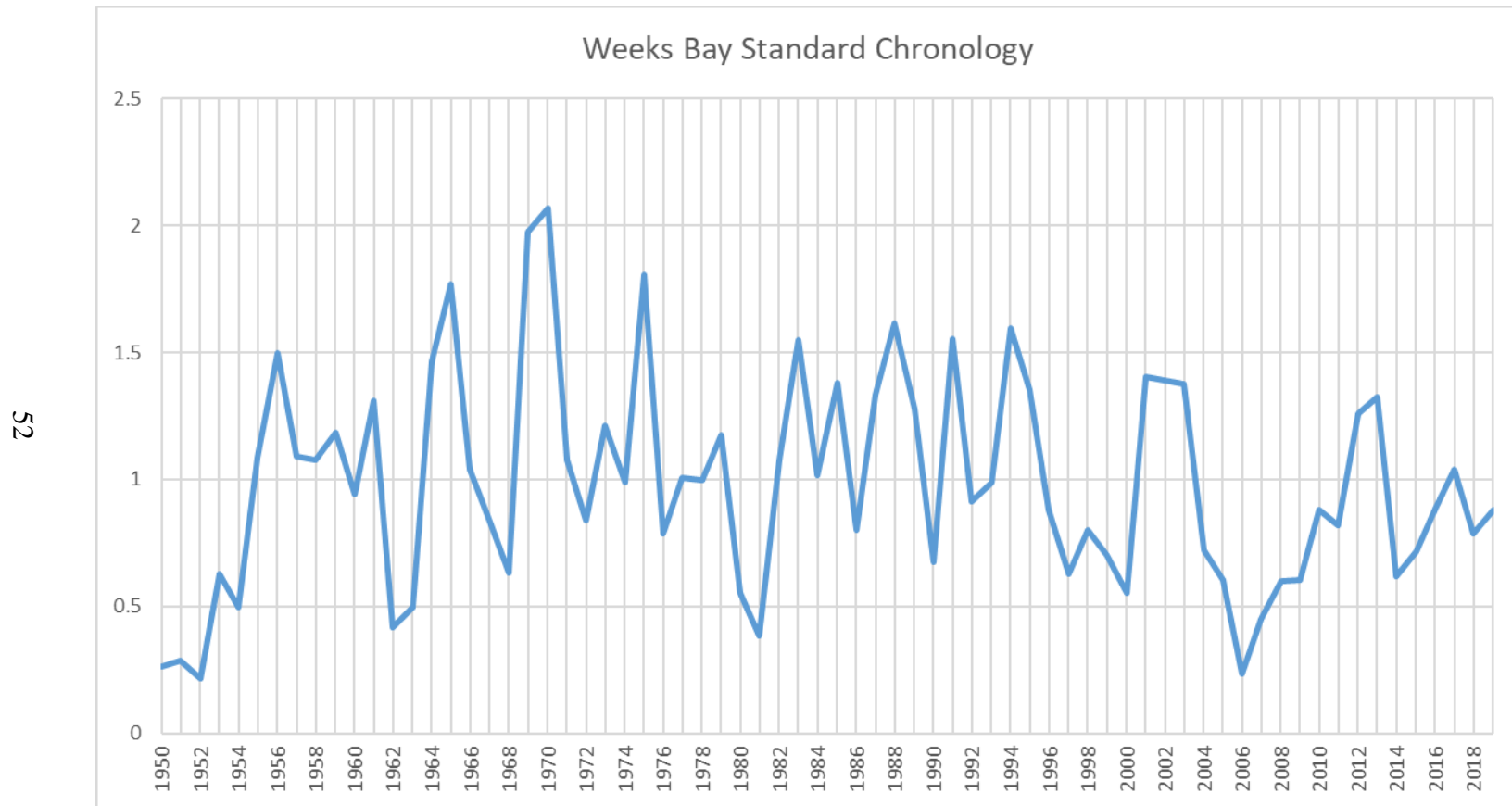
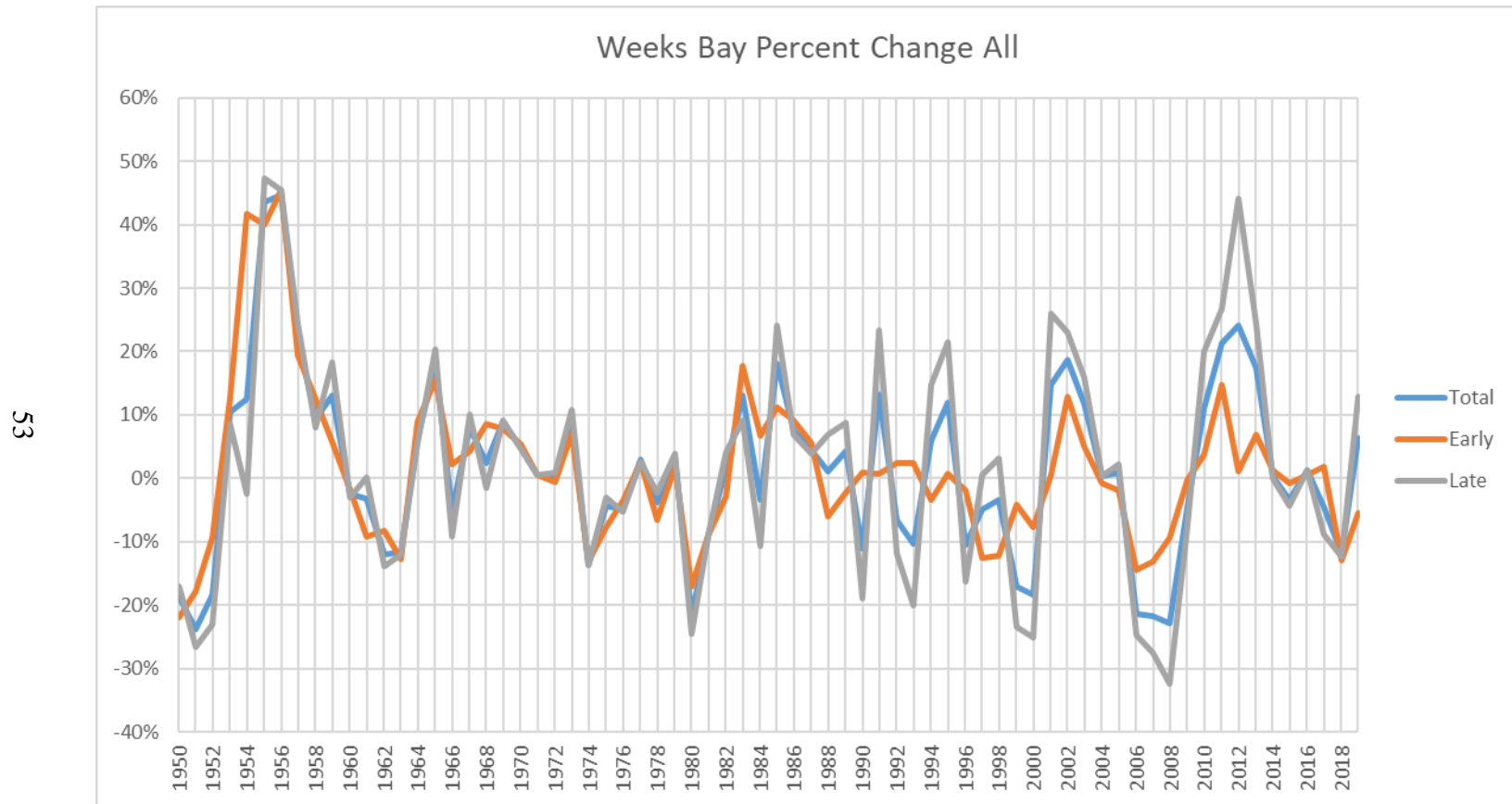


Figure 3.2
Weeks Bay Percent Change



3.2.2 Topsail Hill

Topsail Hill had a total of 24 dated series from 1872 to 2020. The series intercorrelation for this site was 0.553, and the average mean sensitivity was 0.348. For total wood, 40% of all storm surge events produced a suppression of in 1 – 3 years following the event. This number raised to 58% if only category 1 – 5 storms were considered. Eighty six percent of all suppressions corresponded with a storm surge event. For earlywood, the number of storm surge events that produced a suppression of 10% or greater in 1 -3 following the event was 35%. When only considering category 1 – 5 TCs, it became 42%. All of the suppressions corresponded with a storm surge event for earlywood. For latewood, 45% of all storm surge events produced a suppression in 1 – 3 years following the event. This number raised to around 67% when only category 1 – 5 storms were considered. Eighty percent of suppressions corresponded with a storm surge event.

Latewood detected the most events when assessing the number of storm surge events that produced a suppression in 1 – 3 years following the event at TSH. This was followed by total wood and earlywood. When it came to the amount of suppressions that corresponded with a storm surge event, earlywood detected the highest percentage followed by total and latewood. The average recovery period at TSH was 1.6 – 3.3 years with the shortest recovery period seen in latewood and the longest in earlywood. The longest period of suppression in the latewood occurred after the year 2005. Growth remained below average for three years following this active year. In earlywood, the longest recovery period was a five-year period after 1973. The longest recovery period for total wood was also a five a five-year period after 1973.

Figure 3.3
Topsail Hill Standard Chronology

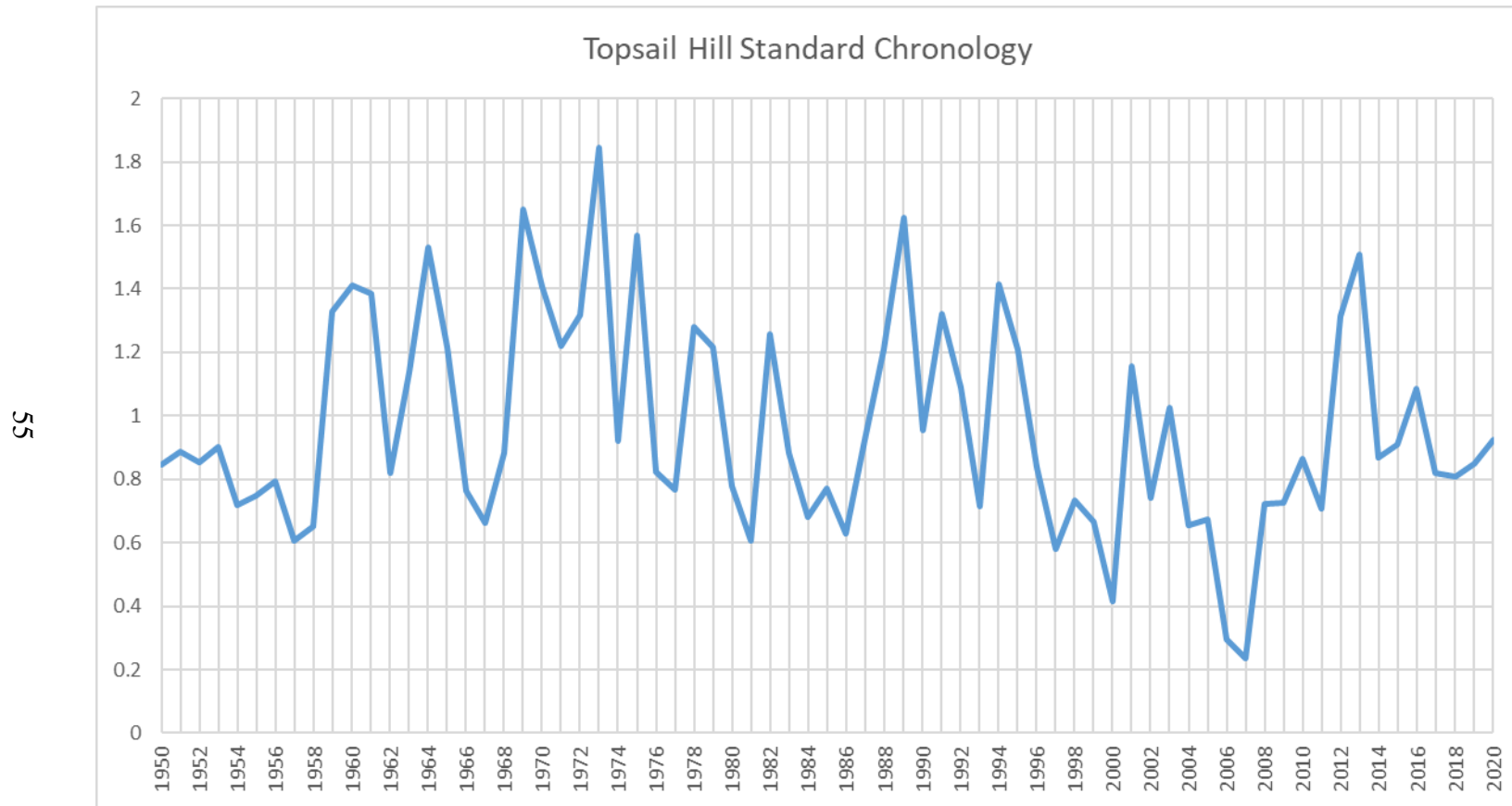
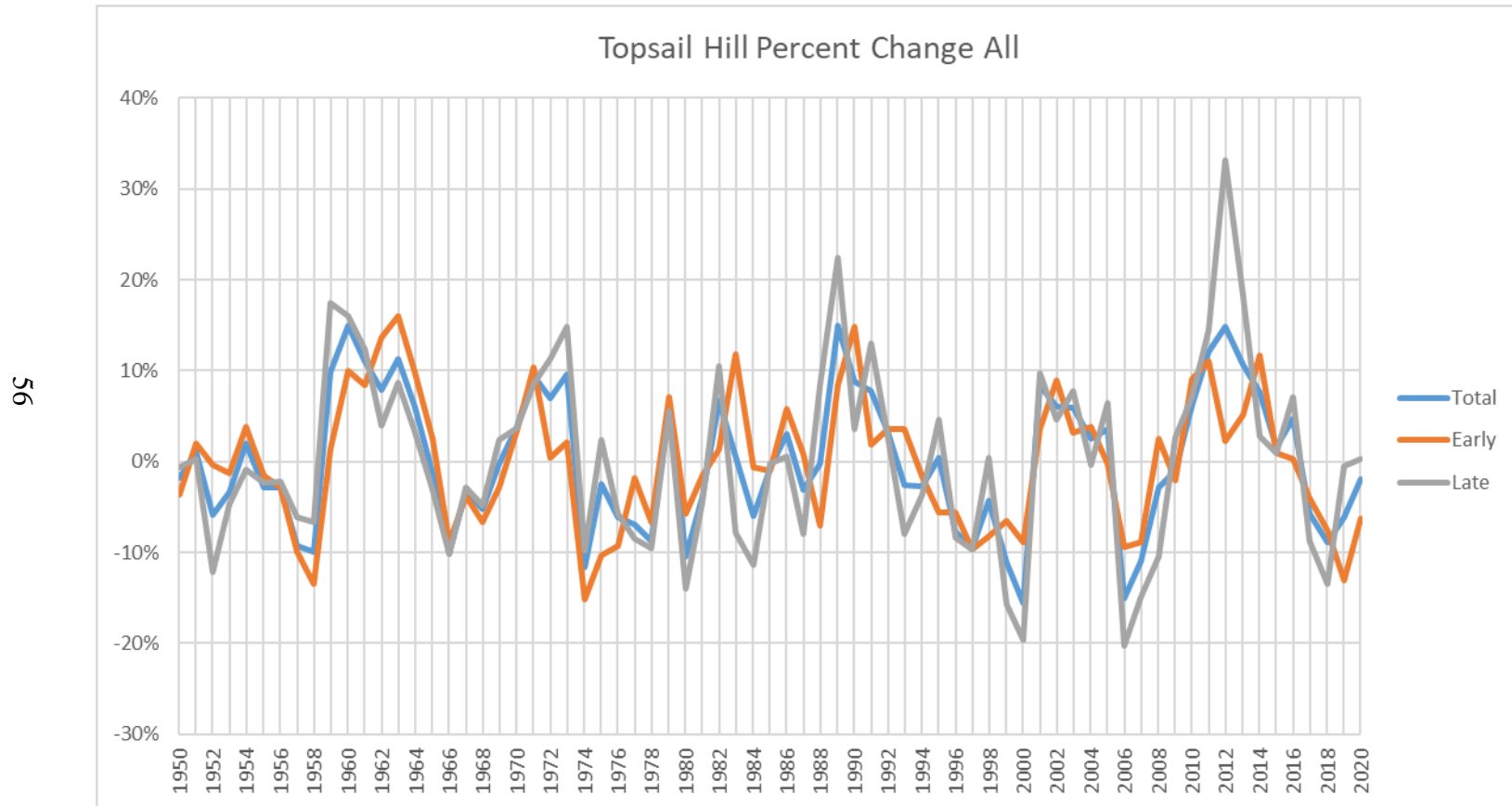


Figure 3.4 Topsail Hill Percent Change



3.2.3 Gulf State Park

Gulf State Park had a total of 20 dated series from 1921 to 2017. The series intercorrelation for this site was 0.554, and the average mean sensitivity was 0.383. For total wood, 38% of all storm surge events (TS to category 5) produced a suppression in 1 – 3 years following the event. This number raised to 33% if only category 1 – 5 storms were considered. All suppressions corresponded with a storm surge event. For earlywood, the number of storm surge events that produced a suppression in 1 -3 following the event was 25%. when only considering category 1 – 5 TCs, it remained 25%. All suppressions corresponded with a storm surge event for earlywood. For latewood, around 56% of all storm surge events produced a suppression of 10% or greater in 1 – 3 years following the event. This number fell to 42% if only category 1 – 5 storms are considered. Eighty eight percent of all suppressions corresponded with a storm surge event.

Latewood detected the most events when assessing the number of storm surge events that produced a suppression in 1 – 3 years following the event at GSP. This was followed by total wood and then earlywood. When it came to the amount of that corresponded with a storm surge event, earlywood and total wood detected the highest percentage followed by latewood. The recovery period at GSP was 2.3 – 2.5 years with the shortest recovery period seen in earlywood and latewood and the longest in total wood. The longest period of suppression in the latewood occurred after the year 2006. Growth remained below average for four years following this year. In earlywood and total wood, the longest recovery period was also the four-year period after 2006.

Figure 3.5
Gulf State Park Standard Chronology

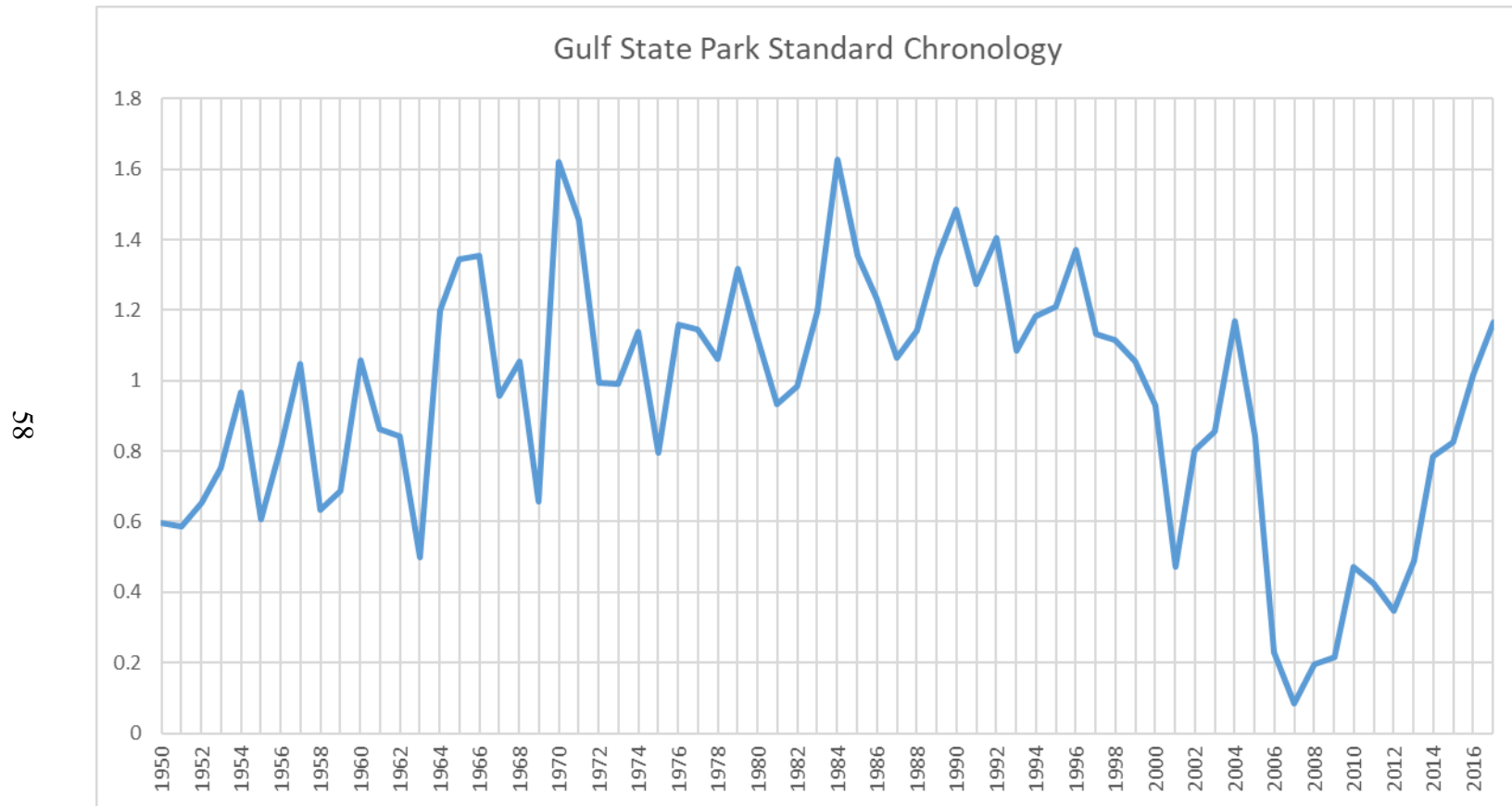
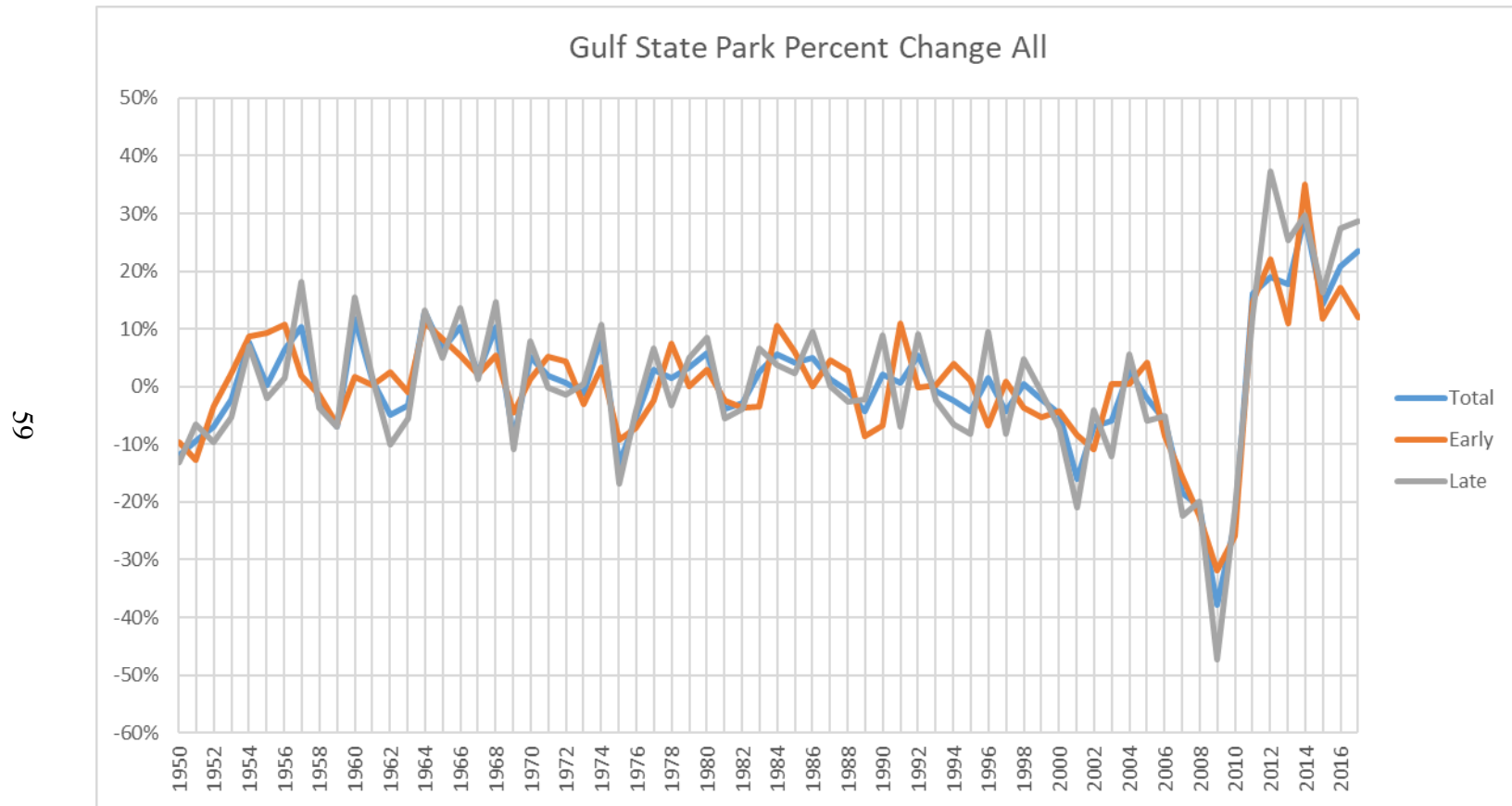


Figure 3.6
Gulf State Park Percent Change



3.2.4 All Sites

When it came to storm surge events producing a suppression, WB was the most responsive. The least responsive site for suppression producing storm surge was GSP. However, GSP had the highest values for suppressions associated with storm surge events while WB had the lowest values. This means growth at WB most reliably responded to storm surge events, but it also had a higher number of suppressions that could not be associated with a passing TC. At GSP, suppressions were more likely to be associated with storm surge events, but many events went undetected. TSH fell in the middle under both comparisons. The longest recovery periods were seen at TSH in total wood (three years) and earlywood (3.3 years) while the shortest recovery time was also seen at TSH in latewood (1.6 years). When averaging all site values together, total wood and earlywood took the longest to recover from suppression (2.7 years), while latewood took two years in comparison (see table 3.1 for chronology statistics).

Table 3.1

Chronology Statistics

Storm Surge Events producing a Suppression			
	Total Wood	Earlywood	Latewood
Gulf State Park			
All	37.5%	25.0%	56.3%
Cat 1-5	33.3%	25.0%	41.7%
Topsail Hill			
All	40.0%	35.0%	45.0%
Cat 1-5	58.3%	41.7%	66.7%
Weeks Bay			
All	66.7%	61.1%	66.7%
Cat 1-5	76.9%	69.2%	76.9%
Suppression Associated with a Storm Surge Event			
	Total Wood	Earlywood	Latewood
Gulf State Park	100.0%	100.0%	87.5%
Topsail Hill	85.7%	100.0%	80.0%
Weeks Bay	80.0%	87.5%	72.7%
Years to Recovery			
	Total Wood	Earlywood	Latewood
Gulf State Park	2.5	2.3	2.3
Topsail Hill	3	3.3	1.6
Weeks Bay	2.5	2.6	2
All Average	2.7	2.7	2.0

CHAPTER IV – DISCUSSION

4.1 Discussion

Each site had TC storm surge events that did not produce suppressions in growth. The most notable undetected surge events were those associated with category five Hurricane Camille (1969) which tracked within 100 miles of GSP and WB. Both sites recorded storm tide of 6 feet and 7 feet respectively; however, neither site showed a suppression in earlywood, latewood, or total wood. It is possible that Camille's forward speed was high enough to reduce the length of time that storm surge impacted the study sites, however, Camille's average forward speed was within the average range (12 mph) the day before landfall according to NOAA (1969). Further research would be needed to explore inquiries such as this and determine why this event did not result in any significant suppression.

There are several possible reasons why some TC storm surge events did not lead to suppressions in growth and why suppressions could not be associated with TC storm surge. The availability of surge data was perhaps the most significant limiting factor for this project. Surge values for each site were inferred from measurements that could be as much as 50 miles away from each site. This locational discrepancy has caused some spatial limitations in surge data. It is possible that no surge occurred at all in the study site if three feet occurred 50 miles away, but there is no way to know for sure without reliable within-site records. This may have resulted in many "false negatives" when analyzing the data where TC surge was noted to have occurred, but no suppression followed. Surge records were also temporally limited, becoming less frequent and more spatially sporadic when looking further back in time (i.e., prior to 1950). For future research, it would be

beneficial to select sampling sites with more comprehensive surge records such as those seen for Pensacola, for example.

It is possible that some larger TCs were not captured in the 150-mile radius search area yet were capable of producing surge that was undetected in the methods of this study. Along with missing surge values, this may explain why some suppressions do not appear to be associated with any TC storm surge events. In my thesis, storms outside of the 150-mile radius were assumed to have not created any surge at all due to the distance of the eye from the site, but it is possible for TCs to reach up to 1,000 miles leading to a much larger field of impact. Future researchers may find it beneficial to examine TCs on a case-by-case basis paying close attention to anomalous growth in the tree-ring record where unexpected suppression occur.

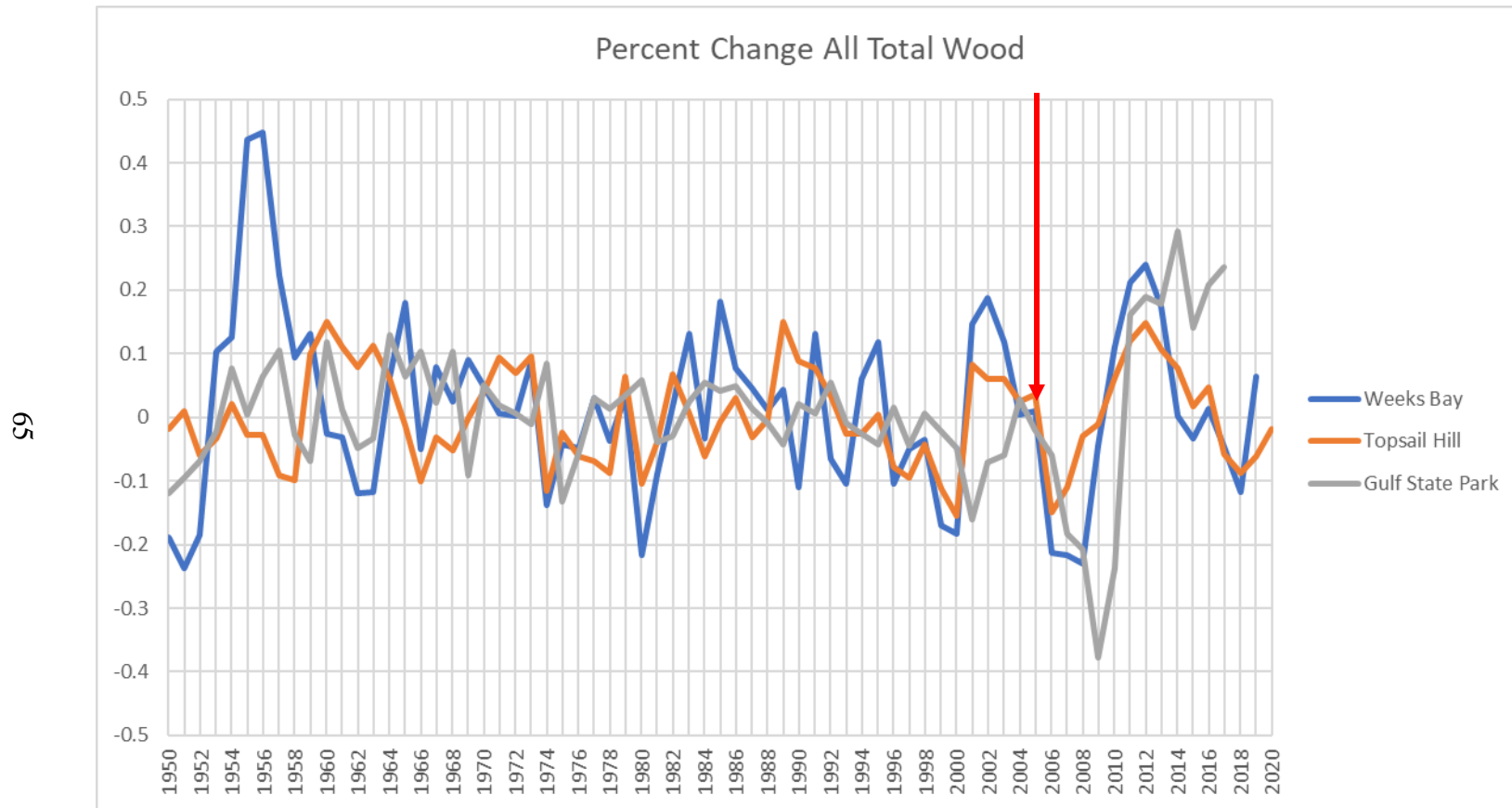
There are several additional theories that could explain why some of the TCs impacting my sites did not reflect suppressions. The trees in this study are not only responding to the storm surge from passing TCs: Their growth is also impacted by other climate factors such as precipitation (TC and non-TC related). I suspect that larger, longer lasting suppressions may be tied to a TC stacking effect from repeated TC storm surge impacts within the same year or year-after-year. Finally, site geography (convexity, concavity, local terrain, soils, etc.) can impact how a site responds to incoming surge in terms of inundation and duration.

As discussed in Knapp et al. (2016) and Maxwell et al. (2013), TC precipitation has been noted to be a drought busting event in some cases, and it has also been noted to possibly flush out the effects of storm surge inundation (Fernandes et al. 2018). If a site was suffering from drought prior to TC passage, then it is possible that a release would

occur rather than a suppression, masking the impacts from storm surge. This may also be the case if surge was “washed away” by heavy TC precipitation. Additionally, rain preceding storm surge could fill the water table with fresh water and not permit saltwater to infiltrate the soil column. It is also worth noting that faster moving storms may not permit storm surge to infiltrate the site for long enough duration influence growth.

I suspect that larger, longer lasting suppressions may be tied to a TC stacking effect (see figure 4.1). If one TC storm surge event occurs in isolation, then suppression may be minimal, but multiple surge events within the same year, or year after year can lead to greater suppressions. This effect was evident after 2004 and 2005, which were both active years in the record with large surge events occurring. All three sites displayed a steep suppression in total and latewood beginning in 2006 or in some cases by 2007. Growth did not return to average for three to four years following the start of the suppression. Significant surge events occurred at other periods in the growth records without the same results, and this was perhaps because they were more isolated events.

Figure 4.1
Percent Change of all Chronologies



2005 is marked with a red arrow. All chronologies show a steep decline after the active years of 2004 and 2005.

All three sites responded differently to storm surge events, and I attribute this to differences in geography. Growth at WB was the most responsive to storm surge events, while growth at TSH was the less impacted. The landscape at WB is quite different from that of TSH (see figure 4.2 and 4.3). WB is an estuary system located within the larger Mobile Bay while TSH is an open coastline protected by sand dunes. Storm surge will be greater when a TC impacts a concave shoreline such as that of Mobile Bay versus a more convex one. Sand dunes are also known for having a protective nature against storm surge (Brunn 1998). The least reactive site, GSP, is also an open coastline; however, the sampling location at GSP was located much further inland than the sites for WB and TSH. This distance inland may have been enough to protect from many of the smaller surge events which could explain why the “hit ratio” was lowest for GSP.

The trees at GSP were located the furthest from the coastline when compared to the other two sites, however, it should be noted that the vast majority of the trees sampled for WB and TSH were not located along the immediate coastline. While this does not entirely rule out the possibility that long-term sea-level rise could have had an impact on growth at the study sites, the chances were at least more minimal when compared to trees growing on the immediate shoreline. Sea level rise has been a documented culprit in the decline of wetland forests along the U.S. coasts (Fagherazzi et al. 2019; Pezeshki et al. 1990). For this reason, it may be beneficial to consider the impacts of sea-level rise more closely at future study sites as some locations have been more susceptible than others.

Figure 4.2
Weeks Bay Shoreline



A view of the shoreline at Weeks Bay, Alabama (Crowell 2019).

Figure 4.3
Topsail Hill Shoreline



The ocean was just beyond the dunes seen in the photograph (Crowell 2021).

It is also suspected that soil factors would play a role in how storm surge behaved at my study sites and how it impacted tree growth, but the soil data for my specific sites were limited to the more general assessments of soil factors that I was able to obtain from the USDA Web Soil Survey. More research would be needed to determine how the soils at each of my sites “hold onto” surge and how long impacts of surge remain traceable in the soil. Pezeshki et al. (1990) have noted that for bottomland hardwood and swamp-forest tree species on the Gulf Coast, flooding and saltwater intrusion such as that from storm surge could alter the normal chemical, physical, and biological functions of soils

leading to reductions in net photosynthesis. Further soil assessments expand beyond the scope of this thesis but could be beneficial for future research endeavors.

Total wood, earlywood, and latewood measurements produced different results for each site. Total wood and latewood performed the best when it came to detecting the number of storm surge events that produced a suppression in 1 – 3 years following the event. There was no difference between the number of detected events at WB when using total wood or latewood, however, latewood detected more events at TSH and GSP. Latewood has proven to be a reliable choice when reconstructing climate factors from *Pinus* in the southeast (Knapp et al. 2016; Mitchell et al. 2019). Earlywood performed poorly when it came to detecting the number of storm surge events that produced a suppression; however, it should be noted that earlywood reflected a high number of suppressions corresponding to storm surge event. At GSP and TSH, this number was 100% meaning all the suppressions seen in earlywood could be associated with TC storm surge events at these sites.

CHAPTER V – CONCLUSION

5.1 Conclusion

Much of the recent TC modeling projections for the 21st century show an overall decrease in the total number of TCs, but an increase in the occurrence of larger TCs with higher wind speeds, heavier precipitation, and more storm surge under future climate warming scenarios. Currently, there is a lack of information on how this forecasted trend may impact maritime forests such as the coastal pine savannas. Present research has examined the impacts that TCs have on different members of the *Pinus* genus, but little of this research has been conducted from a dendrochronology perspective and even fewer research projects have focused on the more geographically widespread variety, *Pinus elliottii* var. *elliottii*, or on the impacts of TC storm surge.

Previous research by Tucker et al. (2018) has shown that slash pine (*Pinus elliottii* var. *elliottii*) radial growth trends could be used to identify long and short-term growth patterns associated with TC passage at their site on the Mississippi Gulf Coast. My thesis has produced similar findings at three additional sites, two in Alabama and one in Florida, with varying degrees of success while establishing greater geographic implications for these findings. WB had the most promising response to TC storm surge events with latewood recording 77% of all category 1 – 5 events. GSP, in comparison, reflected 42%, and TSH fell in between at 67%. I believe that response rates could be even higher if research limitations such as those imposed by temporally and spatially limited surge data could be overcome in the future.

When it comes to the impacts that storm surge may have on slash pine radial growth, my results show that geography and TC climatology matter. Each site produced different results based on site geography, and it seemed that not all TC surge events were equal in impact with some leaving their imprint on average growth trends while others, like Hurricane Camille (1969) for example, left no notable imprint at all at any of the sites. Future research will need to take into consideration different site characteristics and differences in TCs to gain a more complete picture of the impacts that TC storm surge can have. Future site selection should be made with geography in mind.

This research has broader implications for other fields of research including climatology, forestry, and ecology. Coastal *Pinus* species may not be the most useful for TC reconstruction due to the lack of available old growth stands and their short-lived nature; however, dead trees and other species may be more useful. If this is the case, then the historical record for TCs could be extended further back in time allowing climatologists to learn more about past TC factors such as frequency and perhaps intensity. The findings from research in this area could also be used in forestry and ecology for planning and preservation purposes. Slash pine has a native range covering only 8 states (Carey 1992; Hardin et al. 2001), and the south Florida variety (*Pinus elliottii* var. *dense*) is only found in the state of Florida. These pine savannas are unique, and there are ecological benefits to maintaining these habitats using dendrochronological methods.

The native range of the slash pine coincides with the greater range of the North American coastal plain. Noss et al. (2014) identify the North American coastal plain as a biodiversity hotspot that harbors the richest number of endemic plant species in eastern

North America. If TCs increase in strength as projected, they will become a more significant threat to the preservation of the ecologically important pine savanna environment along the Gulf Coast. Those working to maintain slash pine stands should consider the impacts of stronger TCs in preservation and conservation efforts as they have been found to affect the health and longevity of slash pine stands along the Gulf Coast.

APPENDIX A – SUPPLEMENTAL DATA

Table A.1

Tropical Cyclones: All Sites

Year	Name	Date	Max Cat	Surge (Y/N)
2020	Sally	9/11/2020	H2	Y
2019	Nestor	10/17/2019	TS	Y
2018	Alberto	5/25/2018	TS	Y
2018	Gordon	9/2/2018	TS	Y
2018	Michael	10/6/2018	H5	Y
2017	Nate	10/3/2017	H1	Y
2016	Colin	6/5/2016	TS	Y
2016	Hermine	8/28/2016	H1	Y
2012	Debby	6/23/2012	TS	Y
2012	Isaac	8/20/2012	H1	Y
2009	Claudette	8/16/2009	TS	Y
2009	Ida	11/4/2009	H2	Y
2008	Fay	8/15/2008	TS	N
2006	Alberto	6/10/2006	TS	N
2005	Arlene	6/8/2005	TS	Y
2005	Cindy	7/3/2005	H1	Y
2005	Dennis	7/4/2005	H4	Y
2005	Katrina	8/23/2005	H5	Y
2004	Bonnie	8/3/2004	TS	N
2004	Frances	8/25/2004	H4	N
2004	Ivan	9/2/2004	H5	Y
2003	Bill	6/28/2003	TS	Y
2002	Bertha	8/4/2002	TS	N
2002	Hanna	9/12/2002	TS	Y
2002	Isidore	9/14/2002	H3	Y
2001	Allison	6/5/2001	TS	Y
2001	Barry	8/2/2001	TS	Y
2000	Helene	9/15/2000	TS	Y
1998	Earl	8/31/1998	H2	Y
1998	Georges	9/15/1998	H4	Y
1997	Danny	7/16/1997	H1	Y
1996	Josephine	10/4/1996	TS	N
1995	Allison	6/3/1995	H1	N
1995	Erin	7/31/1995	H2	Y
1995	Opal	9/27/1995	H4	Y

Table A1 (continued).

1994	Beryl	8/14/1994	TS	N
1994	Alberto	6/30/1994	TS	Y
1988	Beryl	8/8/1988	TS	Y
1988	Florence	9/7/1988	H1	Y
1985	Kate	11/15/1985	H3	N
1985	Elena	8/28/1985	H3	Y
1985	Juan	10/26/1985	H1	Y
1979	Bob	7/9/1979	H1	Y
1979	Frederic	8/29/1979	H4	Y
1975	Eloise	9/13/1975	H3	Y
1972	Agnes	6/14/1972	H1	Y
1971	Edith	9/5/1971	H5	Y
1970	Becky	7/19/1970	TS	N
1969	Unnamed	9/29/1969	TS	N
1969	Camille	8/14/1969	H5	Y
1966	Alma	6/4/1966	H3	N
1965	Unnamed	7/13/1965	TS	N
1964	Dora	8/28/1964	H4	N
1964	Hilda	9/28/1964	H4	N
1960	Brenda	7/27/1960	TS	N
1960	Ethel	9/12/1960	H3	N
1959	Irene	10/6/1959	TS	Y
1957	Unnamed	6/8/1957	TS	N
1957	Debbie	9/7/1957	TS	N
1956	Flossy	9/20/1956	H1	Y
1955	Brenda	7/31/1955	TS	N
1955	Unnamed	8/25/1955	TS	N
1953	Alice	5/25/1953	TS	N
1953	Florence	9/23/1953	H3	Y
1950	King	10/13/1950	H4	N
1950	Baker	8/18/1950	H2	Y

Table A.2

Tropical Cyclones: Weeks Bay

Name	Year	Max Category in Search Area	Station	Storm Surge (ft)	Storm Tide (ft)	Surge Y/N
Nestor	2019	TS	Weeks Bay, Mobile Bay (WBYA1) NOS	1.89	NA	Y
Alberto	2018	TS	Weeks Bay, Mobile Bay	1.37	2.14	Y
Michael	2018	H5	Weeks Bay, Mobile Bay (WBYA1) NOS	2.50	3.15	Y
Gordon	2018	TS	Weeks Bay, Mobile Bay	2.52	3.26	Y
Nate	2017	H1	Weeks Bay, Mobile Bay	4.61	1.55	Y
Isaac	2012	H1	Weeks Bay NOS Site	2.96	NA	Y
Ida	2009	TS	Bayou La Batre (Wiki)	4.38	NA	Y
Claudette	2009	TS	NA	NA	NA	N
Fay	2008	TS	NA	NA	NA	N
Dennis	2005	H3	Dauphin Island	2.76	3.51	Y
Katrina	2005	H4	Baldwin County	NA	10.00	Y
Cindy	2005	TS	Mobile State Docks	NA	5.30	Y
Arlene	2005	TS	Mobile State Docks	NA	3.03	Y
Ivan	2004	H3	Baldwin County	15.00	NA	Y
Bonnie	2004	TS	NA	NA	NA	N
Bill	2003	TS	Alabama Coastline	?	?	Y
Isidore	2002	TS	Middle Bay - Mobile Bay	NA	5.74	Y
Hanna	2002	TS	Dauphin Island - DPIA1	NA	3.70	Y
Bertha	2002	TS	NA	NA	NA	N
Allison	2001	TS	Alabama Coastline (Wiki)	?	?	Y
Barry	2001	TS	Mobile (NWS)	1.50	NA	Y
Helene	2000	TS	NA	NA	NA	N
Georges	1998	TS	Weeks Bay	6.50	NA	Y
Earl	1998	H2	Little Dauphin Island Bay	NA	2.60	Y

Table A2 (continued).

Danny	1997	H1	Hwy 182 between Gulf Shores and Ft. Morgan	NA	6.54	Y
Erin	1995	H2	Pensacola (NWS)	3.50	NA	Y
Opal	1995	H3	Perdido Pass Orange Beach	NA	5.40	Y
Beryl	1994	TS	NA	NA	NA	N
Alberto	1994	TS	NA	NA	NA	N
Beryl	1988	TS	Mobile	1.90	NA	Y
Florence	1988	H1	Mobile - MOB	1.97	NA	Y
Juan	1985	TS	Mobile - WSO	2.95	NA	Y
Elena	1985	H3	Dauphin Island (wiki)	8.40	NA	Y
Kate	1985	H2	NA	NA	NA	N
Frederic	1979	H4	Mobile River at Mobile	NA	8.05	Y
Bob	1979	H1	Mouth of Mobile River	NA	4.20	Y
Eloise	1975	H3	NA	NA	NA	N
Agnes	1972	H1	Mobile Bay	NA	1.30	Y
Edith	1971	TS	Mobile - WSO	NA	2.70	Y
Unnamed	1969	TS	NA	NA	NA	N
Camille	1969	H5	Mobile	NA	7.00	Y
Unnamed	1965	TS	NA	NA	NA	N
Hilda	1964	TS	NA	NA	NA	N
Ethel	1960	H1	NA	NA	NA	N
Irene	1959	TS	NA	NA	NA	N
Debbie	1957	TS	NA	NA	NA	N
Flossy	1956	H1	NA	NA	NA	N
Unnamed	1955	TS	NA	NA	NA	N
Brenda	1955	TS	NA	NA	NA	N
Florence	1953	H2	NA	NA	NA	N
Alice	1953	TS	NA	NA	NA	N

Table A2 (continued).

Baker	1950	H1	Pensacola	NA	5.50	Y
-------	------	----	-----------	----	------	---

Table A.3

Tropical Cyclones: Topsail Hill

Name	year	Max Category in Search Area	Station	Storm Surge (ft)	Storm Tide (ft)	Storm Surge Y/N
Sally	2020	H2	Pensacola (PCLF1) NOS	5.54	6.53	Y
Michael	2018	H5	Shalimar	NA	3.31	Y
Gordon	2018	TS	Pensacola (PCLF1) NOS	1.57	2.19	Y
Alberto	2018	TS	Pensacola (PCLF1) NOS	1.31	2.11	Y
Nate	2017	TS	Pensacola (PCLF1) NOS	3.22	4.01	Y
Hermine	2016	H1	Pensacola (PCLF1) NOS	1.71	2.62	Y
Colin	2016	TS	Panama City Beach	1.75	2.7	Y
Debbie	2012	TS	Panama City (NOS) PACF1	1.73	2.18	Y
Claudette	2009	TS	Panama City	1.1	2.8	Y
Fay	2008	TS	NA	NA	NA	N
Alberto	2006	TS	NA	NA	NA	N
Dennis	2005	H4	Panama City Beach	5.72	6.79	Y
Cindy	2005	TS	NA	NA	NA	N
Arlene	2005	TS	Walton County	5	NA	Y
Ivan	2004	H3	Walton County	10	NA	Y
Frances	2004	TS	NA	NA	NA	N
Bonnie	2004	TS	NA	NA	NA	N
Hanna	2002	TS	Walton County	NA	4	Y
Barry	2001	TS	Walton County	NA	3	Y
Allison	2001	TS	NA	NA	NA	N
Helene	2000	TS	Destin Airport (DTS)	1	NA	Y
Earl	1998	H2	Santa Rosa County	3	NA	Y
Georges	1998	TS	Destin Harbor	5.2	NA	Y
Danny	1997	H1	NA	NA	NA	N

Table A3 (continued).

Josephine	1996	TS	NA	NA	NA	N
Opal	1995	H4	West of Miramar Beach	NA	15.6	Y
Erin	1995	H2	Navarre Beach	6.5	6.56	Y
Allison	1995	H1	NA	NA	NA	N
Beryl	1994	TS	NA	NA	NA	N
Alberto	1994	TS	Destin	NA	5	Y
Kate	1985	H3	NA	NA	NA	N
Juan	1985	TS	Pensacola NAS	3.94	NA	Y
Elena	1985	H3	FL Panhandle (30.38, -86.44)	NA	9	Y
Frederic	1979	H4	Destin at Choctawhatchee Bay (USGS)	NA	1	Y
Eloise	1975	H3	Dune Allen Beach	NA	13.8	Y
Agnes	1972	H1	Pensacola	NA	2	Y
Becky	1970	TS	NA	NA	NA	N
Alma	1966	H2		NA	NA	N
Unnamed	1965	TS				N
Hilda	1964	TS	NA	NA	NA	N
Dora	1964	TS	NA	NA	NA	N
Brenda	1960	TS				N
Irene	1959	TS	Pensacola	1.6	NA	Y
Debbie	1957	TS	NA	NA	NA	N
Unnamed	1957	TS				N
Flossy	1956	H1	Fort Walton Beach	NA	6.1	Y
Unnamed	1955	TS				N
Florence	1953	H2	Panama City	NA	4.7	Y
Alice	1953	TS				N
King	1950	TS	NA	NA	NA	N
Baker	1950	H2				N

Table A.4

Tropical Cyclones: Gulf State Park

Name	Year	Max Category in Search Area	Station	Storm Surge (ft)	Storm Tide (ft)	Surge Y/N
Nate	2017	TS	Big Lagoon State Park	NA	3.6	Y
Isaac	2012	H1	Pensacola NOS Site (PCLF1)	3.47	3.7	Y
Ida	2009	TS	Bayou la Batre (Wiki)	NA	NA	Y
Claudette	2009	TS	Fort Walton	1.7	2.29	Y
Fay	2008	TS	NA	NA	NA	N
Katrina	2005	H4	Perdido Pass	NA	5.81	Y
Dennis	2005	H3	Pensacola	4.16	5.52	Y
Cindy	2005	TS	Perdido Pass	NA	2.6	Y
Arlene	2005	TS	Perdido Pass	NA	3.69	Y
Ivan	2004	H3	Perdido Pass Orange Beach	NA	2.69	Y
Bonnie	2004	TS	NA	NA	NA	N
Bill	2003	TS	NA	NA	NA	N
Isidore	2002	TS	Perdido Pass Orange Beach	NA	4.68	Y
Hanna	2002	TS	Pensacola - PNS	NA	3.4	Y
Bertha	2002	TS	NA	NA	NA	N
Barry	2001	TS	NA	NA	NA	N
Allison	2001	TS	NA	NA	NA	N
Helene	2000	TS	Pensacola Beach	1	NA	Y
Georges	1998	H2	Gulf Shores	9	NA	Y
Earl	1998	H2	Escambia County	2.5	NA	Y
Danny	1997	H1	Gulf Beach - AL-FL State Line	NA	2.59	Y
Opal	1995	H3	Perdido Pass Orange Beach	NA	5.4	Y

Table A4 (continued).

Erin	1995	H2	Pensacola Beach	3.5	3.61	Y
Beryl	1994	TS	NA	NA	NA	N
Alberto	1994	TS	NA	NA	NA	N
Florence	1988	H1	NA	NA	NA	N
Beryl	1988	TS	Pensacola	NA	NA	N
Kate	1985	H2	NA	NA	NA	N
Juan	1985	TS	Pensacola NAS	3.94	NA	Y
Elena	1985	H3	Dauphin Island (WIKI)	8.4	NA	Y
Frederic	1979	H4	Gulf State Park	NA	9.5	Y
Eloise	1975	H3	Pensacola FFA	NA	1.8	Y
Agnes	1972	H1	Pensacola	NA	2	Y
Becky	1970	TS	NA	NA	NA	N
Unnamed	1969	TS				N
Camille	1969	H5	Dauphin Island	NA	6	Y
Unnamed	1965	TS				N
Hilda	1964	TS	NA	NA	NA	N
Ethel	1960	H1	NA	NA	NA	N
Irene	1959	TS	Pensacola	1.6	NA	Y
Debbie	1957	TS	NA	NA	NA	N
Flossy	1956	H1	NA	NA	NA	N
Unnamed	1955	TS				N
Brenda	1955	TS	NA	NA	NA	N
Florence	1953	H2	NA	NA	NA	N
Alice	1953	TS				N
Baker	1950	H1	Pensacola	NA	5.5	Y

Table A.5

Weeks Bay Statistics: Total Wood

Standard	year	Avg	Std	Chang	Std	Surge	Binary	to Sup	Surge	1-5	surge	Sup to	Recovery
0.264	1950		0.489		-0.18825		1		Y	Y		Y	2
0.284	1951		0.3726		-0.23804		0						
0.216	1952		0.304		-0.18411		0						
0.628	1953		0.3356		0.103947		0						
0.497	1954		0.3778		0.125745		0						
1.088	1955		0.5426		0.43621		0						
1.498	1956		0.7854		0.447475		0						
1.092	1957		0.9606		0.223071		0						
1.075	1958		1.05		0.093067		0						
1.185	1959		1.1876		0.131048		0						
0.939	1960		1.1578		-0.02509		0						
1.311	1961		1.1204		-0.0323		0					N	
0.418	1962		0.9856		-0.12031		0						
0.498	1963		0.8702		-0.11709		0						
1.463	1964		0.9258		0.063893		0						
1.769	1965		1.0918		0.179304		0						
1.038	1966		1.0372		-0.05001		0						
0.831	1967		1.1198		0.079637		0						
0.632	1968		1.1466		0.023933		0						
1.976	1969		1.2492		0.089482		1		N	N			
2.07	1970		1.3094		0.048191		0						
1.077	1971		1.3172		0.005957		1		Y				
0.84	1972		1.319		0.001367		1		Y	Y			

Table A5 (continued).

1.214	1973	1.4354	0.088249	0			Y	3
0.989	1974	1.238	-0.13752	0				
1.805	1975	1.185	-0.04281	0				
0.787	1976	1.127	-0.04895	0				
1.006	1977	1.1602	0.029459	0				
0.998	1978	1.117	-0.03723	0				
1.173	1979	1.1538	0.032945	1	Y	Y	y	2
0.551	1980	0.903	-0.21737	0				
0.383	1981	0.8222	-0.08948	0				
1.075	1982	0.836	0.016784	0				
1.548	1983	0.946	0.131579	0				
1.015	1984	0.9144	-0.0334	0				
1.379	1985	1.08	0.181102	1	N	N		
0.8	1986	1.1634	0.077222	0				
1.336	1987	1.2156	0.044868	0				
1.616	1988	1.2292	0.011188	1	Y	Y		
1.276	1989	1.2814	0.042467	0			Y	1
0.672	1990	1.14	-0.11035	0				
1.554	1991	1.2908	0.132281	0				
0.912	1992	1.206	-0.0657	0			N	
0.989	1993	1.0806	-0.10398	0				
1.598	1994	1.145	0.059597	0				
1.353	1995	1.2812	0.118952	1	Y	Y	y	5
0.879	1996	1.1462	-0.10537	0				
0.627	1997	1.0892	-0.04973	1	y	Y		
0.801	1998	1.0516	-0.03452	1	Y	Y	y	2

Table A5 (Continued).

0.701	1999	0.8722	-0.1706	0				
0.552	2000	0.712	-0.18367	0				
1.403	2001	0.8168	0.147191	1	N			
1.392	2002	0.9698	0.187316	1	N			
1.375	2003	1.0846	0.118375	1	Y			
0.721	2004	1.0886	0.003688	1	y	Y		
0.606	2005	1.0994	0.009921	1	Y	Y	y	4
0.233	2006	0.8654	-0.21284	0				
0.451	2007	0.6772	-0.21747	0				
0.599	2008	0.522	-0.22918	0				
0.605	2009	0.4988	-0.04444	1	N			
0.882	2010	0.554	0.110666	0				
0.821	2011	0.6716	0.212274	0				
1.259	2012	0.8332	0.240619	1	N	N		
1.323	2013	0.978	0.173788	0				
0.62	2014	0.981	0.003067	0				
0.714	2015	0.9474	-0.03425	0				
0.885	2016	0.9602	0.013511	0				
1.039	2017	0.9162	-0.04582	1	Y	Y	y	1
0.785	2018	0.8086	-0.11744					
0.879	2019	0.8604	0.064061					
					67%	77%	80%	2.5

Table A.6

Weeks Bay Statistics: Earlywood

Standard	Year	Avg	Std	Change	Std	Surge	Binary	to Sup	Surge	1 - 5	to Surge	Sup	Recovery
0.187	1950		0.3426		-0.219945		1		Y	Y		Y	2
0.292	1951		0.2814		-0.178634		0						
0.33	1952		0.2552		-0.093106		0						
0.444	1953		0.2876		0.1269592		0						
0.786	1954		0.4078		0.4179416		0						
1.004	1955		0.5712		0.4006866		0						
1.589	1956		0.8306		0.4541317		0						
1.136	1957		0.9918		0.1940766		0						
1.069	1958		1.1168		0.1260335		0						
1.107	1959		1.181		0.0574857		0						
0.9	1960		1.1602		-0.017612		0						
1.051	1961		1.0526		-0.092743		0						
0.705	1962		0.9664		-0.081892		0					N	
0.452	1963		0.843		-0.12769		0						
1.484	1964		0.9184		0.0894425		0						
1.613	1965		1.061		0.15527		0						
1.164	1966		1.0836		0.0213007		0						
0.936	1967		1.1298		0.0426357		0						
0.936	1968		1.2266		0.0856789		0						
1.964	1969		1.3226		0.0782651		1		N	N			
1.967	1970		1.3934		0.0535309		0						
1.203	1971		1.4012		0.0055978		1		Y				
0.895	1972		1.393		-0.005852		1		Y	Y			

Table A6 (continued).

1.429	1973	1.4916	0.0707825	0			Y	3
0.982	1974	1.2952	-0.131671	0				
1.471	1975	1.196	-0.07659	0				
0.988	1976	1.153	-0.035953	0				
1.04	1977	1.182	0.0251518	0				
1.037	1978	1.1036	-0.066328	0				
1.086	1979	1.1244	0.0188474	1	Y	Y	Y	3
0.508	1980	0.9318	-0.171291	0				
0.567	1981	0.8476	-0.090363	0				
0.92	1982	0.8236	-0.028315	0				
1.77	1983	0.9702	0.177999	0				
1.411	1984	1.0352	0.0669965	0				
1.091	1985	1.1518	0.1126352	1	N	N		
1.098	1986	1.258	0.0922035	0				
1.274	1987	1.3288	0.0562798	0				
1.376	1988	1.25	-0.059302	1	Y	Y	Y	1
1.263	1989	1.2204	-0.02368	0				
1.152	1990	1.2326	0.0099967	0				
1.144	1991	1.2418	0.0074639	0				
1.425	1992	1.272	0.0243195	0				
1.525	1993	1.3018	0.0234277	0				
1.043	1994	1.2578	-0.033799	0				
1.196	1995	1.2666	0.0069963	1	Y	Y		
1.021	1996	1.242	-0.019422	0			Y	4
0.647	1997	1.0864	-0.125282	1	Y	Y		
0.86	1998	0.9534	-0.122423	1	N	N		

Table A6 (continued).

0.844	1999	0.9136	-0.041745	0				
0.842	2000	0.8428	-0.077496	0				
1.041	2001	0.8468	0.0047461	1	N			
1.196	2002	0.9566	0.1296646	1	N			
1.101	2003	1.0048	0.0503868	1	Y			
0.802	2004	0.9964	-0.00836	1	Y	Y		
0.75	2005	0.978	-0.018466	1	Y	Y	Y	3
0.335	2006	0.8368	-0.144376	0				
0.644	2007	0.7264	-0.131931	0				
0.76	2008	0.6582	-0.093888	0				
0.793	2009	0.6564	-0.002735	1	N			
0.87	2010	0.6804	0.0365631	0				
0.835	2011	0.7804	0.1469724	0				
0.684	2012	0.7884	0.0102512	1	N	N		
1.029	2013	0.8422	0.0682395	0				
0.844	2014	0.8524	0.0121111	0				
0.834	2015	0.8452	-0.008447	0				
0.856	2016	0.8494	0.0049692	0				
0.765	2017	0.8656	0.0190723	1	Y	Y	Y	2
0.471	2018	0.754	-0.128928					
0.639	2019	0.713	-0.054377					
					61%	69%	88%	2.571429

Table A.7

Weeks Bay Statistics: Latewood

Standard	year	Std Avg	Std Change	Binary Surge	Surge to Sup	1 - 5	Sup to Surge	Recovery
0.315	1950	0.577	-0.169784	1	Y	Y	Y	2
0.263	1951	0.4238	-0.265511	0				
0.145	1952	0.3258	-0.231241	0				
0.719	1953	0.3536	0.0853284	0				
0.283	1954	0.345	-0.024321	0				
1.13	1955	0.508	0.4724638	0				
1.419	1956	0.7392	0.4551181	0				
1.049	1957	0.92	0.2445887	0				
1.089	1958	0.994	0.0804348	0				
1.197	1959	1.1768	0.1839034	0				
0.955	1960	1.1418	-0.029742	0				
1.427	1961	1.1434	0.0014013	0			N	
0.26	1962	0.9856	-0.138009	0				
0.501	1963	0.868	-0.119318	0				
1.438	1964	0.9162	0.05553	0				
1.884	1965	1.102	0.2027941	0				
0.924	1966	1.0014	-0.091289	0				
0.766	1967	1.1026	0.1010585	0				
0.412	1968	1.0848	-0.016144	0				
1.938	1969	1.1848	0.0921829	1	N	N		
2.156	1970	1.2392	0.0459149	0				
0.955	1971	1.2454	0.0050032	1	Y			
0.821	1972	1.2564	0.0088325	1	Y	Y		

Table A7 (continued).

1.097	1973	1.3934	0.1090417	0			Y	3
0.984	1974	1.2026	-0.136931	0				
1.975	1975	1.1664	-0.030101	0				
0.649	1976	1.1052	-0.052469	0				
0.964	1977	1.1338	0.0258777	0				
0.964	1978	1.1072	-0.023461	0				
1.204	1979	1.1512	0.0397399	1	Y	Y	Y	2
0.563	1980	0.8688	-0.245309	0				
0.258	1981	0.7906	-0.090009	0				
1.122	1982	0.8222	0.0399696	0				
1.342	1983	0.8978	0.0919484	0			N	
0.727	1984	0.8024	-0.10626	0				
1.533	1985	0.9964	0.2417747	1	N	N		
0.601	1986	1.065	0.0688479	0				
1.326	1987	1.1058	0.0383099	0				
1.722	1988	1.1818	0.0687285	1	Y	Y		
1.244	1989	1.2852	0.0874937	0			Y	1
0.322	1990	1.043	-0.188453	0				
1.819	1991	1.2866	0.233557	0			N	
0.561	1992	1.1336	-0.118918	0				
0.581	1993	0.9054	-0.201306	0				
1.911	1994	1.0388	0.1473382	0				
1.439	1995	1.2622	0.2150558	1	Y	Y	Y	1
0.795	1996	1.0574	-0.162256	0				
0.591	1997	1.0634	0.0056743	1	Y	Y		
0.753	1998	1.0978	0.0323491	1	Y	Y	Y	2

Table A7 (continued).

0.629	1999	0.8414	-0.233558	0				
0.379	2000	0.6294	-0.251961	0				
1.612	2001	0.7928	0.2596123	1	N			
1.506	2002	0.9758	0.2308274	1	N			
1.528	2003	1.1308	0.158844	1	Y			
0.651	2004	1.1352	0.0038911	1	Y	Y		
0.5	2005	1.1594	0.0213178	1	Y	Y	Y	4
0.174	2006	0.8718	-0.248059	0				
0.308	2007	0.6322	-0.274834	0				
0.502	2008	0.427	-0.324581	0				
0.49	2009	0.3948	-0.07541	1	N			
0.894	2010	0.4736	0.1995947	0				
0.807	2011	0.6002	0.2673142	0				
1.632	2012	0.865	0.4411863	1	N	N		
1.55	2013	1.0746	0.2423121	0				
0.49	2014	1.0746	2.066E-16	0				
0.665	2015	1.0288	-0.042621	0				
0.876	2016	1.0426	0.0134137	0				
1.172	2017	0.9506	-0.088241	1	Y	Y	Y	1
0.962	2018	0.833	-0.123711					
1.024	2019	0.9398	0.1282113		66.7%	76.9%	72.7%	2

06

The Weeks Bay Statistics tables have been provided as an example. Topsail Hill and Gulf State Park have similar tables, and these tables can be provided upon request.

REFERENCES

- Google Earth. 2022. "Gulf State Park, Gulf Shores, Alabama." Satellite Imagery. Accessed June 20, 2022.
- Google Earth. 2022. "Topsail Hill Preserve State Park, Santa Rosa, Florida." Satellite Imagery. Accessed June 20, 2022.
- Google Earth. 2022. "Weeks Bay, Fairhope, Alabama." Satellite Imagery. Accessed June 20, 2022.
- National Oceanic and Atmospheric Association. 1969. "Hurricane Camille." United States Department of Commerce Tropical Cyclone Preliminary Report. Published September 1969. <https://www.nhc.noaa.gov/pdf/TCR-1969Camille.pdf>
- National Oceanic and Atmospheric Association. 2005. *Hurricane Katrina, 12:45Z, August 29, 2005 – About 40 miles southeast of New Orleans Louisiana and about 65 miles southwest of Biloxi Mississippi*. August 29, 2005. GOES Satellite imagery. https://www.ospo.noaa.gov/Organization/History/imagery/Katrina/2005241_1245_RGB.jpg
- National Oceanic and Atmospheric Association. 2020. "2020 Atlantic Hurricane Season Takes Infamous Top Spot for Busiest on Record." Last updated November 10, 2020. <https://www.noaa.gov/news/2020-atlantic-hurricane-season-takes-infamous-top-spot-for-busiest-on-record>
- National Oceanic and Atmospheric Association. 2021. "The Saffir-Simpson Hurricane Wind Scale." Updated May 2021. <https://www.nhc.noaa.gov/pdf/sshws.pdf>

National Oceanic and Atmospheric Association. 2022. “Historical Hurricane Tracks.”

Accessed June 20, 2022. <https://coast.noaa.gov/hurricanes/#map=4/32/-80>

National Oceanic and Atmospheric Association. “HURDAT2 Hurricane Database.”

Hurricane Research Division. Accessed June 19, 2022.

https://www.aoml.noaa.gov/hrd/hurdat/Data_Storm.html

National Oceanic and Atmospheric Association. “International Best Track Archive for Climate Stewardship (IBTrACS).” National Centers for Environmental

Information. Accessed June 19, 2022. <https://www.ncdc.noaa.gov/ibtracs/>

National Oceanic and Atmospheric Association. “Storm Surge Overview.” National Hurricane Center and Central Pacific Hurricane Center. Accessed June 5, 2022.

<https://www.nhc.noaa.gov/surge/>

National Oceanic and Atmospheric Association. “Tropical Cyclone Climatology.”

National Hurricane Center and Central Pacific Hurricane Center. Accessed

June 5, 2022. <https://www.nhc.noaa.gov/climo/>

National Weather Service. “Hurricane Facts.” Accessed June 5, 2022.

https://www.weather.gov/source/zhu/ZHU_Training_Page/tropical_stuff/hurricane_anatomy/hurricane_anatomy.html#:~:text=Typical%20hurricanes%20are%20about%20300,highest%20winds%20in%20the%20storm

National Weather Service. “Introduction to Storm Surge.” Accessed June 21, 2022.

https://www.weather.gov/media/owlie/surge_intro.pdf

Sasaki Associates. 2016. *Alabama’s Gulf State Park Master Plan*. Watertown :Sasaki Associates.

- State of Florida Department of Environmental Protection. 2007. *Topsail Hill Preserve State Park Unit Management Plan*. Tallahassee: State of Florida Department of Environmental Protection Division of Recreation and Parks.
- Southern Climate Impacts Planning Program. 2022. “SURGEDAT Surge Database Console.” Louisiana State University. Accessed June 20, 2022.
<https://surgedat.climate.lsu.edu/surge/>
- United States Department of Agriculture. “Pinus elliottii Engelm. var. elliottii.” Natural Resources Conservation Service. Accessed June 20, 2022.
<https://plants.usda.gov/home/plantProfile?symbol=PIELE2>
- United States Department of Agriculture. “Web Soil Survey.” Natural Resources Conservation Service Soils. Accessed June 5, 2022.
<https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx>
- Weeks Bay National Estuarine Research Reserve System. 2017. *Weeks Bay National Estuarine Research Reserve Management Plan 2017 – 2022*. Washington, D.C.: National Atmospheric and Oceanic Administration.
https://coast.noaa.gov/data/docs/nerrs/Reserves_WKB_MgmtPlan.pdf
- Bacmeister, Julio T., Kevin A. Reed, Cecile Hannay, Peter Lawrence, Susan Bates, John E. Truesdale, Nan Rosenbloom, and Michael Levy. 2018. “Projected Changes in Tropical Cyclone Activity under Future Warming Scenarios using a High-Resolution Climate Model.” *Climatic Change* 146: 547-560. DOI: 10.1007/s10584-016-1750-x
- Barcikowska, Monika, Frauke Feser, Wei Zhang, and Wei Mei. 2017. “Changes in Intense Tropical Cyclone Activity for the Western North Pacific During the last

Decades Derived from a Regional Climate Model Simulation.” *Climate Dynamics* 49: 2,931–2,949. DOI: 10.1007/s00382-016-3420-0

Barrow, W.C. Jr., L.A. Johnson Randall, M.S. Woodrey, J. Cox, E. Ruelas I., C.M. Riley, R.B. Hamilton, and C. Eberly. 2005. “Coastal Forests of the Gulf of Mexico: A description and Some Thoughts on Their Conservation.” In *Bird Conservation Implementation and Integration in the Americas: Proceedings of the Third International Partners in Flight Conference 1*, Edited by Ralph C. John and Terrell D. Rich: 450 – 464.

Blake, Eric S., Christopher W. Landsea, and Ethan J. Gibney. 2011. “The Deadliest Costliest, and Most Intense United States Tropical Cyclones from 1851 to 2010 (and other Frequently Requested Hurricane Facts)”. NOAA, Technical Memorandum NWS NHC-6. <https://www.nhc.noaa.gov/pdf/nws-nhc-6.pdf>

Brunn, Per. 1998. “Dunes—Their Function and Design.” *Journal of Coastal Research* 26: 26 – 31.

Carey, Jennifer H. 1992. “Pinus elliottii. In: Fire Effects Information System”. U.S. Department of Agriculture, Forest Service. Accessed July 3, 2020. <https://www.fs.fed.us/database/feis/plants/tree/pinell/all.html>

Christopherson, Robert W. 2012. *Geosystems: An Introduction to Physical Geography*, 8th Edition. London: Pearson.

Cook, Edward R. 1985. “A Time Series Analysis Approach to Tree Ring Standardization.” PhD thesis, The University of Arizona.

- Cook, Edward R. and Kenneth Peters. 1981. “The Smoothing Spline: A New Approach to Standardizing Forest Interior Tree-Ring Width Series for Dendroclimatic Studies.” *Tree-Ring Bulletin* 41: 45 – 53.
- Cook, E.R., P.J. Krusic., K. Peters, and R.L. Holmes. 2017. Program ARSTAN, Autoregressive tree–ring standardization program. Tree–Ring Laboratory of Lamont–Doherty Earth Observatory.
- Fagherazzi, Sergio, Shimon C. Anisfeld, Linda K. Blum, Emily V. Long, Rusty A. Feagin, Arnold Fernandes, William S. Kearney, and Kimberlyn Williams. 2019. “Sea Level Rise and the Dynamics of the Marsh-Upland Boundary.” *Frontiers in Environmental Science* 7: 25. DOI: 10.3389/fenvs.2019.00025
- Fernandes, Arnold, Christine R. Rollinson, William S. Kearney, Michael C. Dietze, and Sergio Fagherazzi. 2018. “Declining Radial Growth Response of Coastal Forests to Hurricanes and Nor’easters.” *Journal of Geophysical Research: Biogeosciences* 123: 832 – 849. DOI: 10.1002/2017JG004125
- Gigi, Anthony F. and David A. Wert. 1986. “Hurricane Gloria’s Potential Storm Surge.” NOAA, Technical Memorandum NWS ER-70. Published July 1986.
- Gilman, Edward F. and Dennis G. Watson. 1994 “Pinus elliottii Slash Pine.” U.S. Forest Service Department of Agriculture, Fact Sheet ST-463. Published October 1994.
- Gilman Edward F., Dennis G. Watson, Ryan W. Klein, Andrew K. Koeser, Deborah R. Hilbert, and Drew C. McLean. 2019. “Pinus Elliottii: Slash Pine.” University of Florida. Published April 25, 2019. <https://edis.ifas.ufl.edu/publication/ST463>

- Gresham, C. A., T. M. Williams, and D. J. Lipscomb. 1991. "Hurricane Hugo Wind Damage to Southeastern U.S. Coastal Forest Tree Species." *Biotropica* 23 (4): 420 – 426.
- Hardin, James W., Donald J. Leopold, and Fred M. White. 2001. *Harlow & Harrar's Textbook of Dendrology* ninth edition. New York City: McGraw-Hill.
- Harley, Grant L., Justin T. Maxwell, and George T. Raber. 2015. "Elevation Promotes Long-term Survival of *Pinus elliottii* var. *densa*, a Foundation Species of the Endangered Pine Rockland Ecosystem in the Florida Keys." *Endangered Species Research* 29: 117 – 130. DOI: 10.3354/esr00707
- Holmes, Richard L. 1983. "Computer Assisted Quality Control in Tree-Ring Data and Measurement." *Tree-Ring Bulletin* 43: 69 – 78.
- Knapp, Paul A., Justin T. Maxwell, and Peter T. Soulé. 2016. "Tropical Cyclone Rainfall Variability in Coastal North Carolina Derived from Longleaf Pine (*Pinus palustris* Mill.): AD 1771 – 2014." *Climatic Change* 135: 311 – 323. DOI: 10.1007/s10584-015-1560-6
- Larsson, L. 2014. CooRecorder and Cdendro programs of the CooRecorder. Cdendro package version, 7.
- Maxwell, Justin T., Jason T. Ortegren, Paul A. Knapp, and Peter T. Soulé. 2013. "Tropical Cyclones and Drought Amelioration in the Gulf and Southeastern Coastal United States." *Journal of Climate* 26: 8,440 – 8,452. DOI: 10.1175/JCLI-D-12-00824.1
- Maxwell, Stockton. 2019. Coorecorder Tutorial. Youtube. Published Sep 6, 2019. <https://www.youtube.com/watch?v=c-GNKHVUj9I>

- Maxwell, Stockton. 2020. Coorecorder tips- earlywood/latewood, gaps, missing rings, etc. Youtube. Published Aug 26, 2020.
- <https://www.youtube.com/watch?v=xO7Phc93xyM>
- Maxwell, Stockton R. and Lars-Ake Larson. 2021. “Measuring tree-ring widths using the CooRecorder software application.” *Dendrochronologia* 67: 125841. DOI: 10.1016/j.dendro.2021.125841
- Mitchell, Tyler J., Paul A. Knapp, and Jason T. Ortegren. 2019. “Tropical Cyclone Frequency Inferred from Intra-annual Density Fluctuations in Longleaf Pine in Florida, USA.” *Climate Research* 78: 249 – 259. DOI: 10.3354/cr01573
- Mora, Claudia I., Dana L. Miller, and Henri D. Grissino-Mayer. 2006. “Tempest in a Tree Ring: Paleotempestology and the Record of Past Hurricanes.” *The Sedimentary Record* 4 (3): 4 – 8.
- Mori, Nobuhito, Tomoya Shimura, Kohei Yoshida, Ryo Mizuta, Yasuko Okada, Mikiko Fujita, Temur Khujanazarov, and Eiichi Nakakita. 2019. “Future Changes in Extreme Storm Surges based on Mega-Ensemble Projection using 60-km Resolution Atmospheric Global Circulation Model.” *Coastal Engineering Journal* 61 (3): 295-307. DOI: 10.1080/21664250.2019.1586290
- Noss, Reed F., William J. Platt, Bruce A. Sorrie, Alan S. Weakley, D. Bruce Means, Jennifer Costanza, and Robert K. Peet. 2014. “How Global Biodiversity Hotspots May Go Unrecognized: Lessons from the North American Coastal Plain.” *Diversity and Distributions* 21 (2): 236 – 244. DOI: 10.1111/ddi.12278
- Patterson, Thomas. 2019. *Using an Increment Borer*. Photograph. University of Southern Mississippi.

- Patterson, Thomas. 2021. *Topsail Hill State Park*. Photograph. University of Southern Mississippi.
- Pederson, Neil. 2010. "External Characteristics of Old Trees in the Eastern Deciduous Forest." *Natural Areas Journal* 30 (4): 396 – 407.
- Pezeshki, S.R., R.D. Delaune, and W.H. Patrick, JR. 1990. "Flooding and Saltwater Intrusion: Potential Effects on Survival and Productivity of Wetland Forests along the U.S. Gulf Coast." *Forest Ecology and Management* 33/34: 287 – 301.
- Phipps, Richard L. 1985. "Collecting, Preparing, Crossdating, and Measuring Tree Increment Cores." U.S. Geological Survey Water-Resources Investigations Report 85 4148.
<https://play.google.com/books/reader?id=MrnDynR41zMC&pg=GBS.PR8&hl=en>
- Platt, William J., Robert F. Doren, and Thomas V. Amentano. 2000. "Effects of Hurricane Andrew on Stands of Slash Pine (*Pinus elliottii* var. *densa*) in the Everglades Region of South Florida (USA)." *Plant Ecology* 146: 43 – 60.
- Pradtke. 2008. *Hand Increment Borer*. Photograph on Wikipedia.
<https://upload.wikimedia.org/wikipedia/commons/d/d7/IncrementBorer2.JPG>
- Ress, Thomas V. 2016. "Weeks Bay National Estuarine Research Reserve." Encyclopedia of Alabama. Last updated September 22, 2016.
<http://encyclopediaofalabama.org/article/h-3048>
- Rholi, Robert V. and Anthony J. Vega. 2018. *Climatology* 4th edition. Burlington: Jones & Bartlett Learning

- Ross, Michael S. Ross, Danielle E. Ogurcak, Susana Stoffella, Jay P. Sah, Javiera Hernandez, and Hugh E. Willoughby. 2019. "Hurricanes, Storm Surge, and Pine Forest Decline on a Low Limestone Island". *Estuaries and Coasts* 43: 1045 – 1057. DOI: 10.1007/s12237-019-00624-z
- Saha, Sonali, Keith Bradley, and Michael S. Ross. 2011. "Hurricane Effects on Subtropical Pine Rocklands of the Florida Keys." *Climatic Change* 107: 169 – 184. DOI: 10.1007/s10584-011-0081-1
- Sajjad, Muhammad, Ning Lin, and Johnny C.L. Chan. 2020. "Spatial Heterogeneities of Current and Future Hurricane Flood Risk along the U.S. Atlantic and Gulf Coasts." *Science of the Total Environment* 713: 136704. DOI: 10.1016/j.scitotenv.2020.136704
- Speer, James H. 2010. *Fundamentals of Tree Ring Research*. Tucson: The University of Arizona Press.
- Stanturf, John A., Scott L. Goodrick, and Kenneth W. Outcalt. 2007. "Disturbance and Coastal Forests: A Strategic Approach to Forest Management in Hurricane Impact Zones." *Forest Ecology and Management* 250: 119 – 135. DOI: 10.1016/j.foreco.2007.03.015
- Trenberth, Kevin E., Lijing Cheng, Peter Jacobs, Yongxin Zhang, and John Fasullo. 2018. "Hurricane Harvey Links to Ocean Heat Content and Climate Change Adaptation." *Earth's Future* 6: 730-744. DOI: 10.1029/2018EF000825
- Trepanier, Jill C. and Clay S. Tucker. 2018. "Event-Based Climatology of Tropical Cyclone Rainfall in Houston, Texas and Miami, Florida." *Atmosphere* 9 (170): 1-19.

Tucker, Clay S., Jill C. Trepanier, Grant L. Harley, and Kristine L. Delong. 2018.

“Recording Tropical Cyclone Activity from 1909 to 2014 along the Northern Gulf of Mexico using Maritime Slash Pine Trees (*Pinus elliottii*. var. *elliottii* Engelm.)” *Journal of Coastal Research* 34 (2): 328-340. DOI: 10.2112/JCOASTRES-D-16-00177

Zhao, Haikun, Xingyi Duan, G. B. Raga, and Fengpeng Sun. 2018. “Potential Large-scale Forcing Mechanisms Driving Enhanced North Atlantic Tropical Cyclone Activity since the Mid-1990’s.” *Journal of Climate* 31: 1377-1397. DOI: 10.1175/JCLI-D-17-0016.1

Zhou, Yao and Corene J. Matyas. 2018. “Spatial Characteristics of Rain Fields Associated with Tropical Cyclones Landfalling over the Western Gulf of Mexico and Caribbean Sea.” *Journal of Applied Meteorology and Climatology* 57: 1711-1727.