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THE IMPACT OF EXTREME STORM SURGES ON MID-ATLANTIC COASTAL FORESTS

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Disclaimer

Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation.

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ABSTRACT

The Mid-Atlantic coastal forests in Virginia are stressed by episodic disturbance from storms associated with hurricanes and nor'easters. Using annual tree ring data, we adopt a dendroclimatic and statistical modelling approach to understand the response and resilience of a coastal pine forest to slow progressive climate change and extreme storm surge events. Results indicate that radial growth of trees in the study area is influenced by age, vigor, competition, microsite variability, and regional climatic trends, but dominated periodically by disturbance due to storm surges. We evaluated seven local storm surge events to understand the effect of storm surges associated with nor'easters and hurricanes on radial growth. A general decline in radial growth was observed in the year of the storm and three years following it, after which the radial growth starts recovering. Given the projected increase in hurricanes and storm surge severity with changing global climate, this study contributes to understanding declining tree growth response and resilience of coastal forests to past disturbances. This can help predict vegetation response patterns to similar disturbances in the future.

Contents

Abstract **vii**

List of Tables **xi**

List of Figures **xiii**

List of Abbreviations **xvii**

1 Introduction **1**

1.1 Background and Objectives 1

1.2 Thesis Outline 3

2 Methods **4**

2.1 Study Area 4

2.1.1 Geographic Setting 4

2.1.2 Climate 7

2.1.3 Recent Storm History 7

2.1.4 Species Description 9

2.2 Data 10

2.2.1 Tree Ring Data 10

2.2.2 Climate Data 13

2.2.3 Selection of Extreme Storm Surge Events 14

2.3 Statistical Analysis 14

2.3.1 Response Function Analysis 16

2.3.2 Generalised Additive Mixed Model 17

2.3.3 Event Year Analysis 19

2.3.4 Superposed Epoch Analysis 20
2.3.5 Forest Resilience to Storm Surges 21

3 Results **24**

3.1 Tree Growth and Age 24
3.2 Influence of Climate and Extreme Storm Surges on Tree Growth . . . 27
3.2.1 Response Function Analysis 27
3.2.2 Generalized Additive Mixed Model 27
3.2.3 Event Year Analysis 30
3.2.4 Superposed Epoch Analysis 31
3.2.5 Forest Resilience to Storm Surges 35

4 Discussion **40**

4.1 Influence of Age, Individual Tree Variability and Climate 40
4.2 Influence of Storm Surges 42
4.3 Forest Resilience 44

5 Conclusions **47**

A Formulae and Functions Employed in the Study using R Version 3.3.0 **48**

A.1 Response Function Analysis (RFA) 48
A.2 Generalized Additive Mixed Model (GAMM) 49
A.3 Event Year Analysis 50
A.4 Superposed Epoch Analysis (SEA) 50

B Ring Width Statistics for Each Core used in the Study **51**

C Results of Two-Way ANOVA and Tukey's HSD Post Hoc Tests **52**

C.1 Resistance 52
C.2 Recovery 52

C.3 Resilience 53

References **54**

Curriculum Vitae **63**

List of Tables

2.1 Summary of the extreme storm events and low-growth periods analyzed in this study using various methods to characterize the influence of storm surges on tree growth. 16

3.1 Model statistics of radial growth in *Pinus taeda*. The approximate deviance explained by individual predictors and their corresponding F-statistic and p-values are listed. Predictors with p-value <0.05 are considered statistically significant. Mean seasonal temperatures, total annual precipitation, and tree age were modelled as fixed effects using cubic regression splines. Storm surge disturbance and tree group were included as fixed categorical variables and variations among individual trees was modelled as a random effect. Total deviance explained: 49.80%, adjusted R^2: 0.489. 29

3.2 Results of two-way ANOVA for logarithm of ring-width index by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant. 36

3.3 Mean resistance, recovery, and resilience and the corresponding standard deviation (S.D.) for low and high elevation trees for the 1933, 1962, 1998 and 2003 disturbance periods. * Represents indices that are significantly different (p-value <0.05) from the base value 1 as indicated by one-sample t-tests. 38

C.1 Results of two-way ANOVA for resistance by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant. 52
C.2 Results of two-way ANOVA for recovery by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant. 52
C.3 Results of two-way ANOVA for resilience by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant. 53

List of Figures

2·1 Geographic setting and geomorphology of the study area illustrating (A) Satellite imagery displaying areas affected by storm surges during hurricanes (Jelesnianski et al., 1992). Categories 1 through 5 refer to the Saffir-Simpson scale of hurricane wind intensity. Inset shows the study site where *Pinus taeda* trees were sampled. (B) Schematic displaying elevation change along the sampling transect. Distance between trees is not to scale, for illustrative purposes only. 6

2·2 Mean monthly temperature and total monthly precipitation at the study site. The data was obtained from PRISM gridded data products (PRISM, 2015) for a single centrally located point at 37.1280 N, 75.9611 W for the period of 1903 to 2015. 8

2·3 Monthly highest water levels relative to the Monthly Mean Higher High Water (MHHW) recorded at the Chesapeake Bay Bridge Tunnel water level station near the study site (NOAA, 2016). Demarcated extreme spikes in water levels correspond to the occurrence of hurricanes and nor'easters. Black stars indicate high water levels due to an unknown cause. 9

2·4 Illustration of pith year estimation following the method developed by Duncan (1989). Here, (rw5) is the width of 5 adjacent rings to the arc; (h) is the arc height, (L) is the arc length and (d) is its true distance from the pith. 13

2·5 Selection of extreme storm events affecting the study site based on (A) high water levels and (B) long flooding duration obtained from tidal records. The red dashed line represents the threshold criteria. 15

2·6 A representative ring width series illustrating the variables used to calculate percent relative growth change (RGC). $\mathrm{rw_t}$ is the ring width in the year for which RGC is calculated and $\overline{rw}_{t-4}$ is the mean growth in the preceding 4 years. 20

3·1 Mean chronology (solid line) of 25 *Pinus taeda* trees in the study area. Ring-width series of individual tree cores were detrended using a cubic regression spline, averaged per tree and compiled using Tukey's biweight robust mean to build the mean chronology. The grey shaded area indicates the sample size. 25

3·2 Years of establishment of the sampled trees. Pith was observed only in four of the sampled trees. The inferred pith years represent the pith estimated following the method developed by Duncan (1989). Multiple trees shared a common pith year during 1906, 1913, 1938, 1940, 1945, and 1946. 26

3·3 Response coefficients of stand level mean tree-ring chronology to temperature and precipitation from previous April (a) to current September (S) for the period 1904 - 2015. The black solid lines represent 99.9% confidence intervals. 27

3·4 (A-G) Partial predictors of radial growth in *Pinus taeda* estimated using cubic regression splines in GAMM. Dashed lines represent 95% confidence intervals. 30

3·5 Relative growth change and event years for individual trees with the major storm surge event years marked in red. (A) Dot plot showing negative event years for individual trees at the study site. (B) Panels I-V show gradual relative growth change post the 1933, 1962, 1998, 2003 and 2009 storm surge events, for time windows marked I-V in Figure 3·5A. Majority of the trees show a negative event year ($\geq$ 40% decline in growth), three years post-storm. 32

3·6 Percentage of trees showing negative event years among the (A) low elevation trees and (B) high elevation trees at the study site. Grey line indicates the sample size and red markers on the x-axis represent the seven storm surge events considered in this study. 33

3·7 Results of SEA conducted on mean chronology of (a) low elevation trees (b) high elevation trees and (c) all trees, indicating the response of radial tree growth for a 13-year window centred on dates of five major storm surges recorded in Virginia (Refer to section 2.3.4). Individual ring width indices in each key date window were normalized to minimize the chance that a single anomaly may unduly influence the composite analysis. Bars above and below the x-axis indicate above and below average radial growth, respectively for the 13-year window. Declining growth trend across years is indicative of low-growth periods, whereas, a growing trend across years indicates radial growth recovery. Dark grey shading shows statistically significant (at a 95% sample confidence) growth anomalies. (d) Summary of SEA conducted on individual trees. Dark grey shading shows the percentage of trees with statistically significant (at a 95% sample confidence) growth anomalies. 34

3·8 Interaction plot showing the mean ring-width index for low and high elevation trees during disturbance periods associated with extreme storm surge events. Error bars represent one standard deviation of the mean RWI estimate. 36

3·9 Resistance, recovery and resilience of low and high elevation trees for the 1933, 1962, 1998 and 2003 low-growth periods. The band inside each box represents the corresponding median value. Blue regions represent indices that are significantly different (p-value <0.05) from the base value 1 as indicated by one-sample t-tests. 39

4·1 Relationship between resistance, recovery, and resilience of low and high elevation trees during low-growth periods associated with extreme storm events occurring during the growing (1933 and 2003) and dormant (1962 and 1998) seasons. Solid line represents linear regression lines. * indicates significant linear relationship at p-value <0.05. High leverage points were determined using the *influence.measures* function of stats package in R and not included in the regression analysis. . . . 45

List of Abbreviations

ANOVA	…………………	Analysis of Variance
CEP	…………………	Cumulative Eigenvalues Project
DBH	…………………	Diameter at Breast Height
dplR	…………………	Dendrochronology Program Library in R
GAMM	…………………	Generalized Additive Mixed Model
LTER	…………………	Long Term Ecological Research
MHHW	…………………	Mean Higher High Water
PRISM	…………………	Parameter-elevation Regressions on Independent Slopes Model
RFA	…………………	Response Function Analysis
RGC	…………………	Relative Growth Change
RWI	…………………	Ring-Width Index
SEA	…………………	Superposed Epoch Analysis
VCR	…………………	Virginia Coast Reserve

Chapter 1

Introduction

1.1 Background and Objectives

Hurricanes and Nor'easters are short-term disturbance events that frequently affect coastal forests in North America. Damage from storm surges and wind associated with these disturbance forces can influence the structure, development, species composition and diversity of forests (Lugo, 2008). In addition to short-term disturbances, forests are also affected by long-term changes in regional climate (Panayotov et al., 2010) and sea-level (Ross et al., 1994). Decreasing the vulnerability of coastal forests to such disturbances requires that we understand the tree growth response to past disturbances.

The Mid-Atlantic coastal region of the United States, which covers Delaware and parts of New Jersey, Maryland, Virginia, and North Carolina, boasts complex ecosystems comprised of wetland forests, saltwater marshes, freshwater marshes, bays and estuaries (Najjar et al., 2000). Forests account for about 70% of the land cover in this region (Jones et al., 1997). Climate projections indicate that sea level, temperature, storminess, and streamflow will increase in the Mid-Atlantic coastal region in response to global warming (Najjar et al., 2000; Rogers and McCarty, 2000). In addition, Atlantic hurricane activity is projected to increase due to a rise in sea-surface temperatures (Goldenberg et al., 2001; Saunders and Lea, 2008), which may cause an increase in intensity and frequency of storm surges in this region. Therefore, understanding the response and resilience of coastal forests to past environmental changes can help predict their response patterns and manage these forests appropriately in the future.

Coastal and estuarine landscapes form some of the most valuable and vulnerable ecosystems globally.(Barbier et al., 2011; Lotze et al., 2006; Parker and Crichton, 2011). Sea level rise can lead to a progressive landward shoreline displacement along the coast and cause the forest-marsh boundary to migrate inland (Kirwan et al., 2016; Robichaud and Begin, 1997). Forests in these regions can also be dramatically affected by other environmental drivers such as: variation in temperature and precipitation, extreme drought or flooding events (Mickler et al., 2012). These stressors have been reported to cause reduced forest growth, failure in regeneration or dieback events (Kirwan et al., 2016; Mickler et al., 2012). Coastal forests of South Carolina suffered increased mortality in response to salt water infiltration from storm surges and extreme wind damage that accompanied the 1989 Hurricane Hugo (Hook et al., 1991). On the west coast of Florida, regeneration failure is observed in coastal forests due to sea-level rise (Williams et al., 1999). Disturbances often interact with climate and underlying landform characteristics to determine the composition, structure, and function of forests. Given the variability in landform features and disturbances at a local scale, further site-specific investigations are needed to understand how such coastal and estuarine forests respond to environmental changes.

Dendrochronological and statistical techniques have been an effective tool to reconstruct the response of forests to changing environmental conditions over time, including changes in sea level (Kirwan et al., 2007; Robichaud and Begin, 1997), and temperature and precipitation (Byun et al., 2013; Harley et al., 2011; Kirwan et al., 2007; McKenney-Easterling et al., 2000; Samuelson et al., 2013; Schofield et al., 2016; Tipton et al., 2016). Annual tree ring widths are influenced by several factors including the age and species of the tree, competition from neighboring trees, soil conditions, climate, local or stand-wide disturbance pulses and annual variability among individual trees (Cook et al., 1990; Fritts, 1976; Speer, 2010). In coastal environments, tree rings have also been observed to respond to tropical storms and hurricanes (Conner and Inabinette, 2003; Johnson and Young, 1992; Miller et al., 2006; Rodgers III et al., 2006). The effects of these disturbance episodes on tree growth can be studied by analyzing their resilience, i.e., the capacity of the trees to recover after disturbance and regain their pre-disturbance structure and function (Folke et al., 2004; Scheffer et al., 2001).

In this study, we postulate that trees in the Mid-Atlantic coastal forest in Virginia are episodically damaged through the direct influence of flooding and strong winds during storm events. By adopting a dendroclimatic and statistical modelling approach, this paper aims to a) Identify periods of declining tree ring growth following storm surge events and b) to understand the response and resilience of vegetation in the Mid-Atlantic coastal region on the Eastern Shore of Virginia National Wildlife Refuge to slow progressive climate change and extreme storm surge events.

1.2 Thesis Outline

This thesis consists of five chapters including this introductory chapter. All chapters are connected, and together they answer the main objective of this thesis, which is to examine the response and resilience of vegetation at the study site to regional climate trends and extreme storm surges. Chapter 1 provides a general background and introduces the objectives and methodology of the research. Chapter 2 describes the geographic setting, climate and storm history of the study area and outlines the dendrochronological and statistical procedures used. Chapter 3 and 4 present the results and discuss the influence of climate and storm surges on tree growth, and the forest resilience at the study site. Chapter 5 provides a summary of the findings.

Chapter 2

Methods

This chapter describes the methods used to characterize the influence of climate and extreme storm surges on tree growth. It is divided into three subsections. The study area section describes the geographic setting, regional climate trends, storm history and species at the study site. The data section describes the procedures used for preparing the tree-ring data including sampling, chronology preparation and age estimation of the trees. It further outlines the climate data and criteria used to select extreme storm surge events that affected the study site. The third section describes the statistical methods employed to determine the climate-growth relationship of trees and to characterize the response and resilience of trees to extreme storm surge events.

2.1 Study Area

2.1.1 Geographic Setting

The study site is a stand of *Pinus taeda (L.)* (loblolly pine) located on the Eastern Shore of Virginia National Wildlife Refuge. It lies on the southern tip of the Delmarva Peninsula, Virginia, USA, and is bordered by the Atlantic Ocean on the East and the Chesapeake Bay on the West (Figure 2·1A). This site is adjacent to the Virginia Coast Reserve (VCR) that exhibits a rich ecosystem comprising barrier islands, lagoons, tidal marshes, and mainland watersheds (Brinson et al., 1995), and is designated by the National Science Foundation as a Long Term Ecological Research site (LTER). The Delmarva Peninsula formed when rising sea levels during the late Pleistocene and Holocene filled the lower Susquehanna River valley, eventually forming the Chesapeake Bay and isolating the area from the mainland (Colman et al., 1990; Hobbs, 2004; Rice, 2004). Sea level fluctuations, climate, tidal energy, sand supply, and sediment texture control the present-day morphology of the barrier islands and marsh-lagoonal systems along the eastern side of this peninsula (Demarest and Leatherman, 1985). Due to land subsidence and compaction of sediments, the rate of sea-level rise in the Mid-Atlantic region (2.4 mm/yr to 4.4 mm/yr) are significantly higher than the global average (1.7 mm/yr) (Williams et al., 2010). The average rate of sea-level rise at VCR is approximately 4 mm/yr (NOAA, 2010), which is about twice the global rate.

The vegetation in the study area is dominated by *Pinus taeda* (Rice, 2004). Some other species found at this site include *Ilex vomitoria* (yaupon holly), *Iva frutescens* (marsh elder), *Baccharis halimifolia* (groundsel tree), *Myrica cerifera* (bayberry), and *Smilax spp.* (greenbrier). Over the last three decades, 40% of the land cover in Virginia barrier islands, changed from grassland to shrub thicket accompanied by approximately 10 cm rise in sea level and 29% reduction in upland area (Shiflett et al., 2014). Two main factors controlling the vegetation patterns at VCR are the distance from the shoreline and elevation above sea level (Young et al., 2011). The distance from shoreline determines the extent of ecological succession which is controlled by salt spray, burial due to sand, and disturbance, such as storm surges (Ehrenfeld, 1990). The availability of nutrients and groundwater is dependent on the elevation above sea level (Brinson et al., 1995; Ehrenfeld, 1990). In addition to thresholds of disturbance tolerance and landscape position (mainland, barrier island or lagoon), long-term response of marshes to sea-level rise is thought to be related to complex vegetation feedbacks (Erwin et al., 2006).

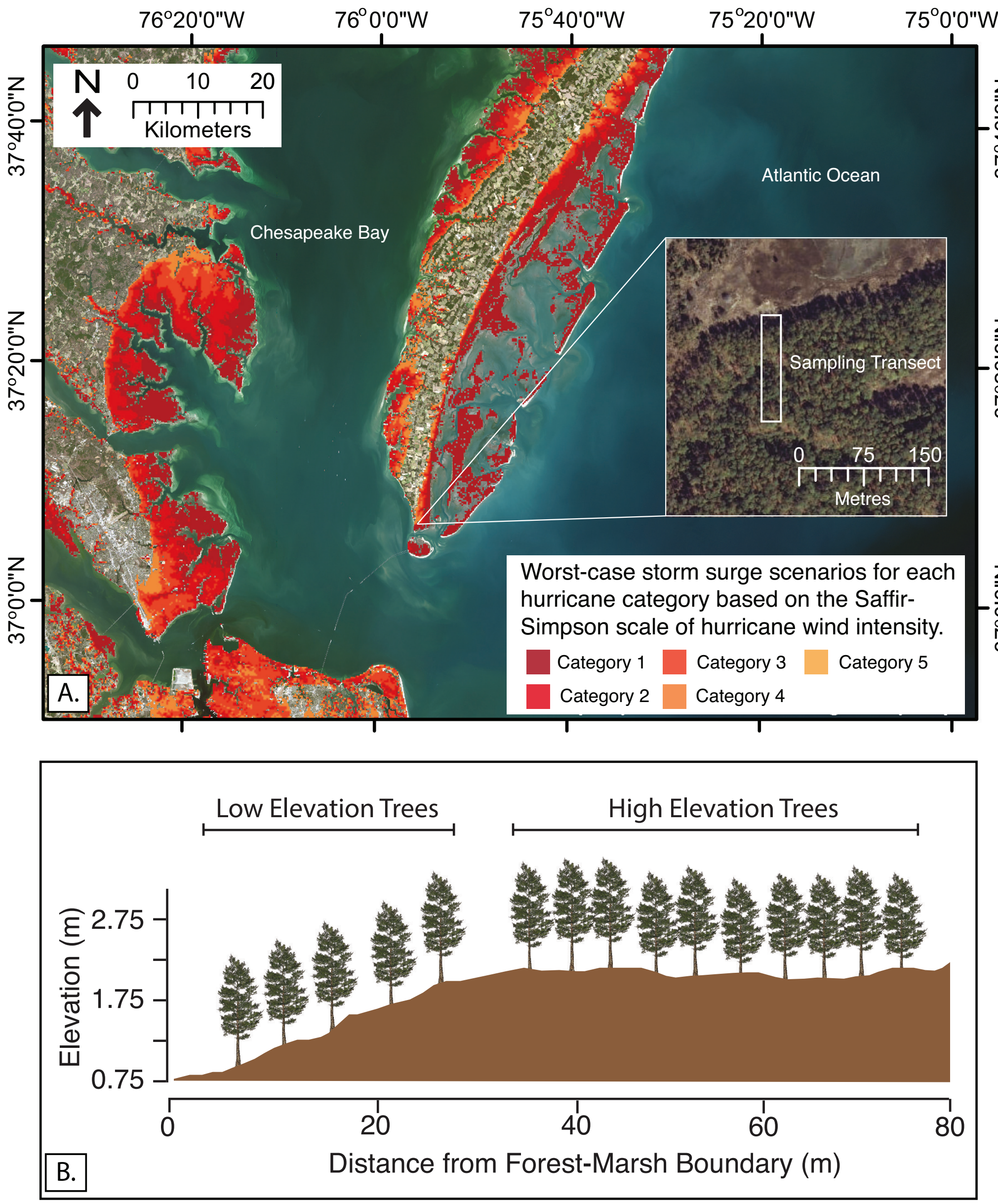

Figure 2·1: Geographic setting and geomorphology of the study area illustrating (A) Satellite imagery displaying areas affected by storm surges during hurricanes (Jelesnianski et al., 1992). Categories 1 through 5 refer to the Saffir-Simpson scale of hurricane wind intensity. Inset shows the study site where *Pinus taeda* trees were sampled. (B) Schematic displaying elevation change along the sampling transect. Distance between trees is not to scale, for illustrative purposes only.

2.1.2 Climate

The climate at the study site is warm during the summer ($\approx 24^{o}$C) with cool winters ($\approx 6^{o}$C) and mean total precipitation of 91 mm per month (1095 mm per year), distributed evenly throughout a year. Figure 2·2 shows the mean monthly temperature and total monthly precipitation at the study site. The data was obtained from PRISM gridded data products (PRISM, 2015) for a single centrally located point at 37.1280 N, 75.9611 W for the period of 1903 to 2015. The mean temperature during fall and spring is about 11 ^{o}C and 18 ^{o}C, respectively. Winter temperatures are more variable than summer temperatures. The highest temperature and precipitation values are found in July and August, although, unlike precipitation, temperature has low variance in these months.

2.1.3 Recent Storm History

A storm surge can be defined as an abnormal rise of water generated by a storm, higher than the predicted astronomical tides (NOAA, 2016). The study site is subject to two major storm types - hurricanes and nor'easters (Parker and Crichton, 2011). Hurricanes, which generally occur during the summer, are of a short-duration and characterized by high wind speeds and large storm surges (Parker and Crichton, 2011). Figure 2·1A shows the regions in VCR that are subject to inundation by storm surges during hurricanes based on its magnitude (Jelesnianski et al., 1992). Unlike hurricanes, nor'easters generally occur during the fall, winter, and early spring, are comparatively slower, have a longer duration, and can produce equally large storm surges (Dolan and Davis, 1992). Figure 2·3 shows the height of extreme water levels above monthly mean higher high water (MHHW) recorded at a nearby tidal station and its association with the occurrence of various hurricanes and nor'easters. The cause of high water levels observed in 1978 and 2000 is unknown, however, they may

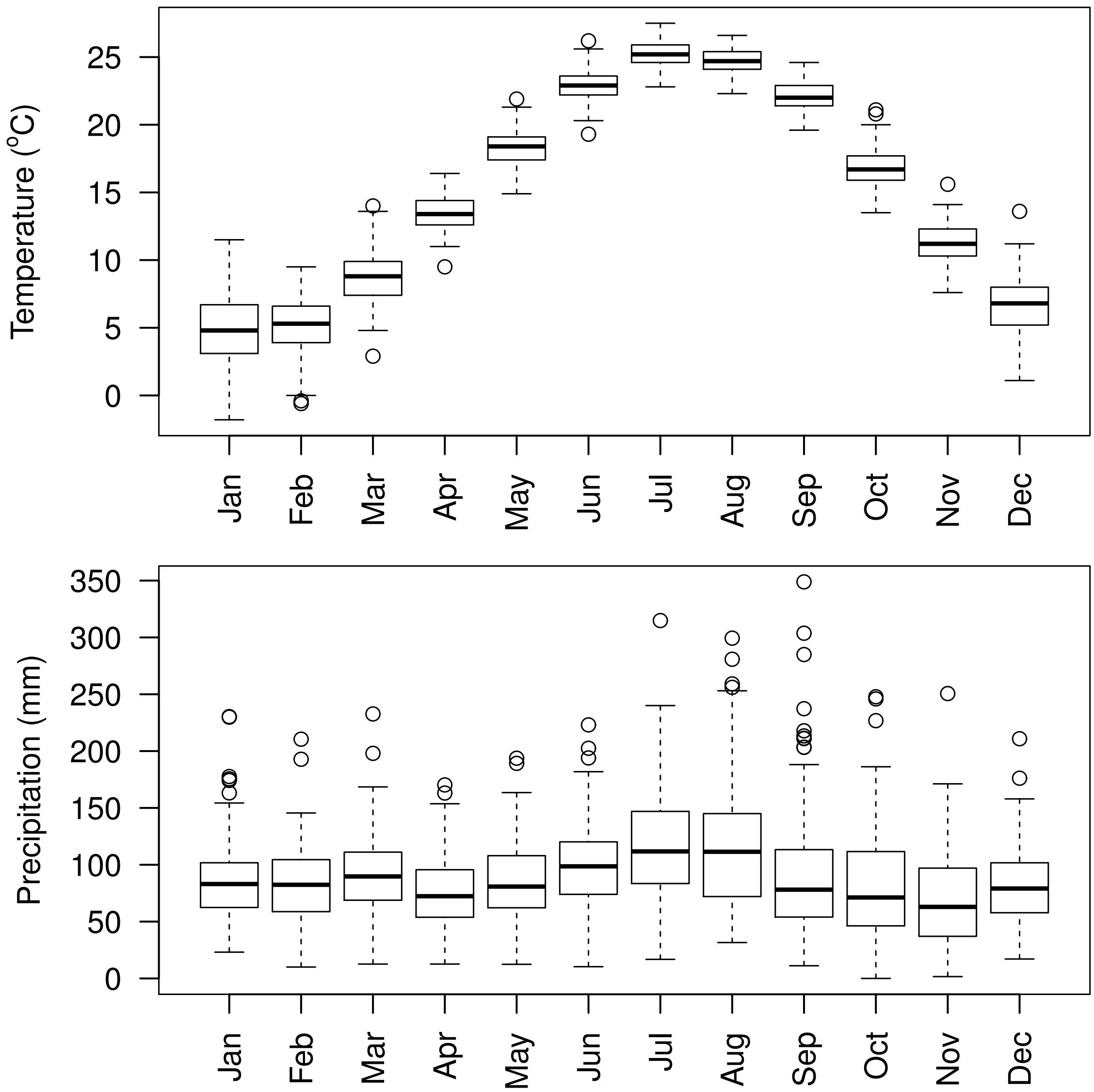

Figure 2·2: Mean monthly temperature and total monthly precipitation at the study site. The data was obtained from PRISM gridded data products (PRISM, 2015) for a single centrally located point at 37.1280 N, 75.9611 W for the period of 1903 to 2015.

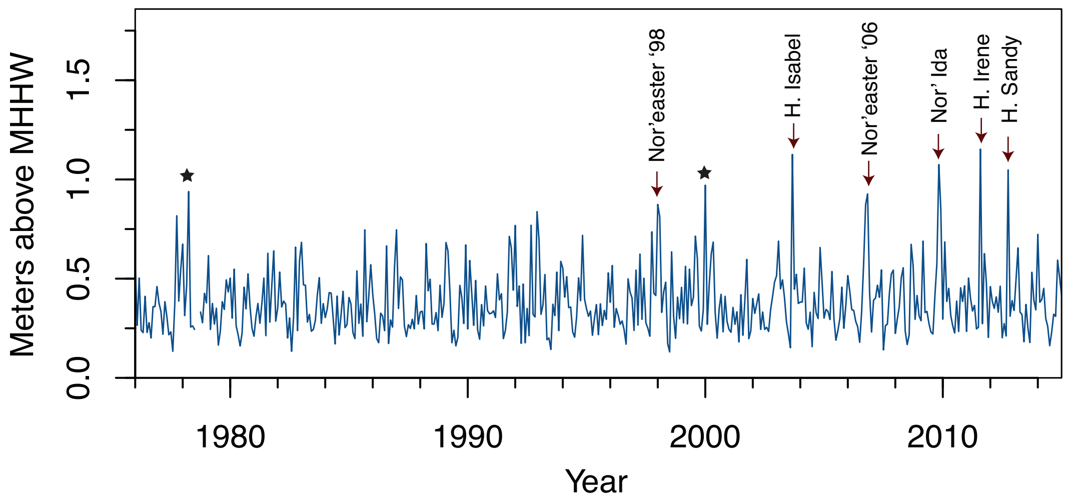

Figure 2·3: Monthly highest water levels relative to the Monthly Mean Higher High Water (MHHW) recorded at the Chesapeake Bay Bridge Tunnel water level station near the study site (NOAA, 2016). Demarcated extreme spikes in water levels correspond to the occurrence of hurricanes and nor'easters. Black stars indicate high water levels due to an unknown cause.

be associated with the 1978 Northeastern United States blizzard and 2000 North American blizzard, respectively.

In addition to the complex storm activity in this region, location and distribution of physical habitats and species on the Eastern Shore of Virginia National Wildlife Refuge can be affected by: changes in sea level, air and water temperatures, and variability in precipitation with changing global climate (Parker and Crichton, 2011). Having a low impact from anthropogenic factors, this site serves as a promising region to study the dynamics of changing vegetation patterns and predict the effects of climate and abrupt disturbance events like storm surges on coastal regimes.

2.1.4 Species Description

Pinus taeda is a medium to large sized evergreen conifer native to North America. It has a generally continuous range extending from Texas eastward to Florida and northward to Delaware (Schultz, 1997). The main distribution of *Pinus taeda*, from latitude 39° 21'N to 28°N, can be well defined by isolines connecting similar rates of annual evapotranspiration (1,050 mm of moisture on the south and 813 mm in the north) (Schultz, 1997). Its northern range and western range are limited by low temperatures and low rainfall, respectively (Wahlenberg, 1960). *Pinus taeda* is also a leading commercial timber species and is useful for site restoration and forest management due to its ability to reproduce and grow rapidly in various environments (Carey, 1992). This tree grows best on moderately acidic soils having a thick, medium textured surface layer and fine textured subsoil, with imperfect to poor surface drainage (Baker and Langdon, 1990). Whereas, its growth is limited on waterlogged sites and shallow, eroded soils (Fowells et al., 1965).

2.2 Data

2.2.1 Tree Ring Data

Sampling

Pinus taeda were sampled along a transect representing an increasing distance from the forest-marsh boundary and elevation above sea level. Core samples were collected from 43 trees with a 5 mm increment borer using standard procedures outlined in Stokes and Smiley (1968). On average, two cores per tree (89 cores in total) were collected at breast height (1.4 m). The cores were then preserved in paper straws for transportation and allowed to air dry under room conditions. To understand the response of trees to storm surges as a function of increasing distance from the forest-marsh boundary, the sampled trees were divided into two groups: trees closer to the marsh ($<$30 m from the forest-marsh boundary, n=16) and those further inland ($\geq$30 m from the forest-marsh boundary, n= 9), hereby referred to as low and high elevation trees, respectively (Figure 2·1B).

Core Preparations

At the Ecological Forecasting Lab, Boston University, general procedures outlined in Stokes and Smiley (1968) were followed for drying, mounting, sanding, and polishing the cores. Increment cores were mounted in grooved wooden holders and sanded using increasingly finer grit sand paper to remove any burred edges and clearly observe and define the cell walls using a dissecting microscope. Digital images at a 1600 DPI resolution of the polished tree cores were acquired using a calibrated Epson Perfection V700 Photo scanner and analyzed using WinDENDRO software for tree-ring analysis (Regent Instruments, 2012).

Chronology Preparation

The tree-rings were visually cross-dated using a variety of methods. First, skeleton plots and marker rings (rings that are consistently narrow or have identifiable characteristics consistent between different trees) were used to visually cross-date ring-width series within trees and then among trees under a microscope. Ring-widths were then measured using WinDENDRO software. The computer program COFECHA (Holmes, 1983) was used to statistically confirm cross-dating. In COFECHA, the ring-width series obtained from WinDENDRO were detrended using a cubic smoothing spline and averaged to build a master chronology. The rigidity of the spline curve was set to 32 years, which has been found to generally result in the highest interseries correlation (Grissino-Mayer, 2001). COFECHA then verified the quality of measurements by correlating each core statistically against the master chronology by dividing them into 50-year segments with an overlap of 25 years (Speer, 2010). Samples that cross-dated poorly upon initial inspection, were re-examined and re-measured. Given the difficulty in cross-dating some of the cores due to very small ring-widths and the color of the wood, the minimum correlation coefficient used in cross-dating was 0.235, which represents a 95% level of confidence when testing 50-year segments of the cores. Cores below this threshold were excluded from further analysis. Thus only 25 trees (46 cores) were used in this study (Refer to Appendix B). These trees were evenly distributed along the sampling transect. The average mean sensitivity, a measure of year-to-year variability in ring-width, and series inter-correlation, a measure of the strength of the common signal between all trees, obtained from COFECHA were 0.342 and 0.394, respectively. The series inter-correlation was within the 0.35-0.6 range, while the mean sensitivity value was slightly higher than the 0.15-0.3 range reported for similar *Pinus taeda* chronologies (Cook et al., 1998), indicating that the trees are highly sensitive to yearly changes in growth-limiting factors.

Using the Dendrochronology Program Library in R (dplR) package (Bunn, 2008), we compiled chronologies for the whole site (stand-level) and the site stratified by distance from the forest-marsh boundary (group-level) as well as retained average detrended ring width indices for each tree for analysis. First, ring-width series of individual tree cores were detrended using a cubic smoothing spline function, having wavelength equal to 2/3rd the length of individual ring-width series and a frequency response of 50% to minimize any age-related trend (Cook and Peters, 1981). This was done using the *detrend* function which divides each raw ring width measurement by the corresponding value estimated by the fitted spline to compute a ring-width index (RWI). The ring-width indices (RWI) of multiple cores of each tree were then averaged using the *treeMean* function to obtain a single time series for individual trees. The RWI of individual trees were then averaged together using the *chron* function that applies a Tukey's biweight robust mean (Cook et al., 1990) to build a mean chronology for 25 trees (stand-level). Group-level mean chronologies for low and high elevation trees were created using the above procedure and the RWI of individual trees were also retained for analysis. The stand-level mean chronology in this study spans the period from 1904 - 2015.

Pith Estimation

Majority of the cores used in this study did not hit the pith. Thus, the pith year was estimated following the method developed by Duncan (1989) to determine the age of all sampled trees. This method assumes concentric ring-growth so that the ring boundaries can be considered arcs of circumferences with pith in the center. First, the length (L) and height (h) of the innermost arc and width of the five adjacent rings to the arc (rw5) were measured as shown in Figure 2·4. The missing radius (d) was then calculated using the following equation (Duncan, 1989; Rozas, 2003):

$$\mathrm{d} = \frac{\mathrm{L}^2 + 4\mathrm{h}^2}{8\mathrm{h}} \tag{2.1}$$

The number of missing rings were estimated by dividing d with the mean rw5.

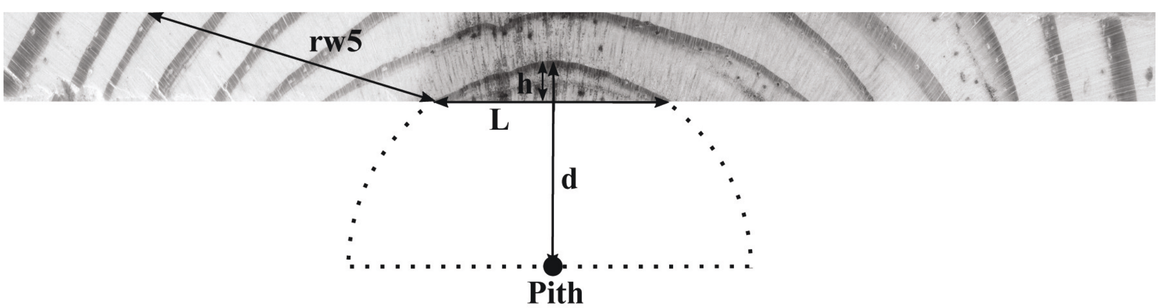

Figure 2·4: Illustration of pith year estimation following the method developed by Duncan (1989). Here, (rw5) is the width of 5 adjacent rings to the arc; (h) is the arc height, (L) is the arc length and (d) is its true distance from the pith.

2.2.2 Climate Data

The climate data used in this study are monthly Parameter-elevation Regressions on Independent Slopes Model (PRISM) AN81m time-series dataset (PRISM, 2015). This dataset is modeled using climatologically-aided interpolation in which the long-term average datasets serve as the predictor grids. It uses all of the station networks and data sources used by the PRISM Climate Group to provide the best possible climate data estimates at a given time. From PRISM, we used mean monthly temperature and total monthly precipitation for a single centrally located point at 37.1280 N, 75.9611 W for the period of 1903 to 2015.

2.2.3 Selection of Extreme Storm Surge Events

The water level data of monthly and hourly resolution were retrieved from the nearest tidal station - 8638863 Chesapeake Bay Bridge Tunnel, Virginia (NOAA, 2016). Based on a combination of storm surge magnitude and duration, events with extremely high water levels ($\geq$ 1m above MHHW) (see Ezer and Atkinson, 2014) and/or long flooding duration ($\geq$ 30 hours above 1m NAVD88) obtained from tidal records were identified as extreme storm surge events (Figure 2·5). Since the water level records are only available from 1975, extreme storm surge events prior to 1975 were identified based on description from historical reports that display maximum impact on Virginia. Only seven storms were identified that met these criteria between 1904-2015 namely, 1933 Chesapeake-Potomac Hurricane, 1962 Ash Wednesday Nor'easter, 1998 Nor'easter, 2003 Hurricane Isabel, 2009 Nor'Ida, 2011 Hurricane Irene, and 2012 Hurricane Sandy.

2.3 Statistical Analysis

In this study various statistical methods were employed to determine the factors that limit tree growth at the study site: (1) Response function analysis: to determine the influence of regional climate trends on stand-level mean chronology (2) Generalized additive mixed modelling: to simultaneously model the effects of regional climate, tree age, individual tree variability, and extreme storm events on radial growth of the trees (3) Event year analysis: to identify low-growth episodes (if any) following the

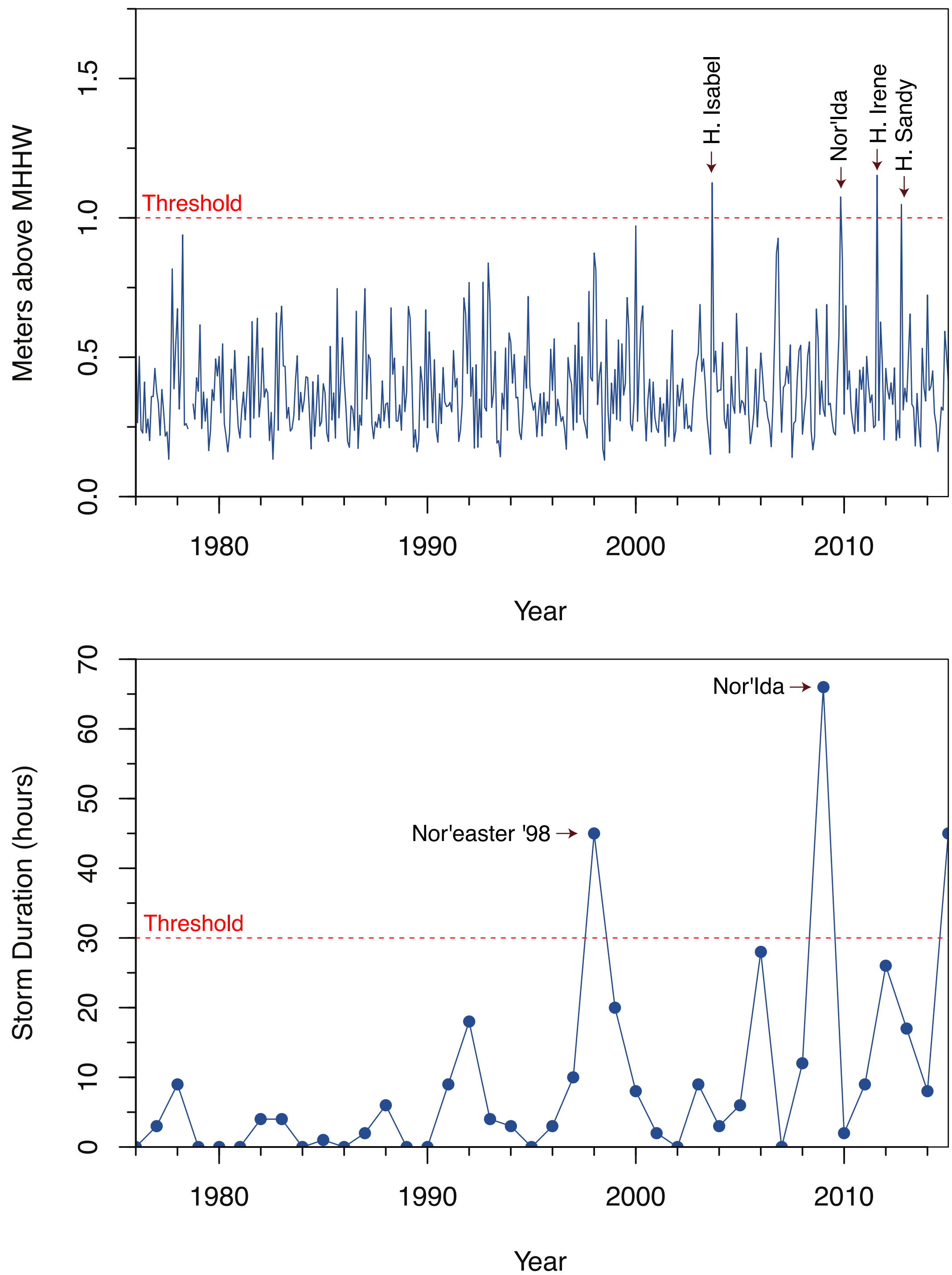

Figure 2·5: Selection of extreme storm events affecting the study site based on (A) high water levels and (B) long flooding duration obtained from tidal records. The red dashed line represents the threshold criteria.

storm surge events (4) Superposed epoch analysis: to isolate growth response signals to key events (in this case, storm surges) which may be difficult to detect in the presence of noise from other competing influences operating at similar time scales, and (5) Resilience analysis: to analyze the resistance, recovery, and resilience of low and high elevation trees towards extreme storm surge events. Due to the underlying statistics of event year analysis, superposed epoch analysis and resilience analysis, the effect of all seven extreme storm surges that affected the study site (Section 2.2.3) could not be analyzed. Table 2.1 summarizes the extreme storm events and low-growth periods analyzed using these methods to characterize the influence of storm surges on tree growth. A detailed description of each method is provided below.

Storms Analyzed	Distinct Low-Growth Period	Influence of Storm Surges on Tree Growth		
		Event Year Analysis	Superposed Epoch Analysis	Resilience Analysis
1933 Chesapeake-Potomac Hurricane	1933-1936	Yes	Yes	Yes
1962 Ash Wednesday Nor'easter	1962-1965	Yes	Yes	Yes
1998 Nor'easter	1998-2001	Yes	Yes	Yes
2003 Hurricane Isabel	2003-2006	Yes	Yes	Yes
2009 Nor'Ida*	No data	Yes	Yes	No data
2011 Hurricane Irene*	No data	Yes	No data	No data
2012 Hurricane Sandy*	No data	Yes	No data	No data

*Limited analysis could be performed due to insufficient tree ring-width data or overlap of low-growth periods between 2009-2015.

Table 2.1: Summary of the extreme storm events and low-growth periods analyzed in this study using various methods to characterize the influence of storm surges on tree growth.

2.3.1 Response Function Analysis

To examine how radial growth of trees in VCR is influenced by regional climate variables, Response Function Analysis (RFA) was performed, using the *dcc* function of bootRes package in R (Zang and Biondi, 2013) (Refer to Appendix A). Response function analysis is a multivariate regression technique, where the mean ring-width chronology is regressed against the principal components of monthly climate data (Fritts et al., 1971). This approach removes the effect of any interdependence amongst climate variables.

Climate variables (mean monthly temperature and total monthly precipitation) covering an 18-month period (April of the previous year to September of the current year of radial growth) were used for RFA. The stand-level mean chronology was used to study the growth response of trees to these climate variables as it is detrended to remove effects of factors like age on radial growth. BootRes performs response function analysis by taking 1000 bootstrap samples from the original distribution. The original climate variables are translated and rotated, and expressed in terms of a new set of coordinates. For climate data containing 18 months of temperature and precipitation each, there are 36 eigenvectors. bootRes then uses the PVP criterion also known as cumulative eigenvalues product (CEP) criterion (Guiot, 1991) to discard the least important eigenvectors. Eigenvectors are first sorted according to descending eigenvalues and only the eigenvectors whose associated eigenvalues have a cumulative product greater than 1 are retained while the rest are discarded. The reduced eigenvectors are then used as predictor variables in an ordinary least squares regression to estimate response functions. Given that RFA tests a large number of variables for significant correlation, the Bonferroni correction was applied to reduce any spurious results. Confidence intervals were thus computed at p-value < 0.001. Coefficients that equaled or exceeded the confidence interval are considered significant.

2.3.2 Generalised Additive Mixed Model

A Generalized Additive Mixed Model (GAMM) allows simultaneous modelling of linear and non-linear relationships between the response and predictor variables using regression splines (Wood, 2006; Zuur et al., 2009; Zuur, 2012). The response of trees to climate, microsite factors, abrupt disturbance events, and age are often non-linear in nature and can be modelled well using a GAMM. An advantage of GAMMs is their ability to incorporate both fixed and random effects to account for repeated measures (e.g. individual trees). A GAMM was built to characterize the effect of climatic variables, age, tree group, storm occurrence and variations among individual trees on their growth. The model was constructed using the *gam* function of mgcv package in R (Wood, 2007) (Refer to Appendix A) using the following equation:

$$\begin{aligned}\mathrm{ln(RW)} = \mathrm{I} + \mathrm{s(temp)} + \mathrm{s(precip)} + \mathrm{tree\,group} + \mathrm{s(age, by{=}\,tree\,group)} + \\ \mathrm{storm\,surge\,disturbance} + \mathrm{treeID_{re}}\end{aligned} \tag{2.2}$$

where (I) is the parametric estimate of the intercept and (s) represents the inclusion of a cubic regression spline that detects and allows non-linear response of raw ring width series of individual tree cores (RW) to each predictor variable. The climate was characterised using mean seasonal temperature (*temp*) and total annual precipitation (*precip*). For each year, monthly temperature was averaged across the following seasons: Spring (April to June), Summer (July to September), Fall (October to December), and Winter (January to March) (see Kirwan et al., 2007). Precipitation was summed across the whole year. A fixed categorical variable (*tree group*) was included in the model to determine the contribution of tree groups (low and high elevation trees) to variance in ring-width. The (*age*) predictor represents the age of the trees estimated by the method developed by Duncan (1989). As the mean age of low (81 years) and high (103 years) elevation trees in 2015 differed by 22 years, a (by = *tree group*) argument was included in the *age* predictor to model potentially different trends over time in low and high elevation trees. The categorical predictor (*storm surge disturbance*) was included as a logical class variable to represent whether or not an extreme storm surge event affected the study site during a given year. The climate variables (temp and precip), tree age (age), tree group and storm occurrence (storm surge disturbance) were included in the model as fixed effects. The variation among individual trees was incorporated as a random effect ($treeID_{re}$) so that the model produces a random coefficient for each tree core, which is modelled as a Gaussian random effect. Smoothing parameters of the spline, knots and rigidity were decided using the generalized cross validation method such that two knots were equally spaced per 3 °C change in seasonal temperature, 400 mm change in precipitation, and 15 years increase in age.

2.3.3 Event Year Analysis

The year to year variation in tree-ring widths contain information about the relationship of the tree with its environment. We define event years as years with a remarkable increase or decrease in radial growth at an individual tree-level. Event years were calculated on raw ring-width series of individual trees using the relative growth change method (Schweingruber et al., 1990) to determine if there were low-growth episodes following the storm surge events listed in Table 2.1. In this method, relative growth change is measured as the ratio of ring width in the current year ($\mathrm{rw_t}$) and the average growth in 4 preceding years ($\overline{rw}_{t-4}$) for individual trees. Figure 2·6 shows a representative ring width series to illustrate the variables used to calculate the relative growth change. The percent relative growth change (RGC) was calculated using the following equation:

$$\mathrm{RGC}\,(\%) = \frac{\mathrm{rw_t} - \overline{\mathrm{rw}}_{\mathrm{t-4}}}{\overline{\mathrm{rw}}_{\mathrm{t-4}}} \times 100 \tag{2.3}$$

The resulting relative growth changes were then used to identify event years for the trees. A positive event year was defined as the year with at least 60% increase in growth, whereas a negative event year was defined as the year with at least 40%

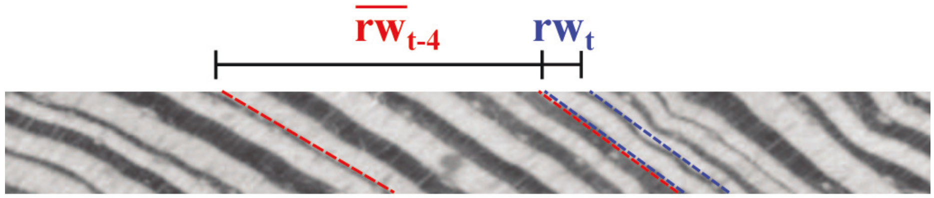

Figure 2·6: A representative ring width series illustrating the variables used to calculate percent relative growth change (RGC). rw_t is the ring width in the year for which RGC is calculated and $\overline{rw}_{t-4}$ is the mean growth in the preceding 4 years.

decrease in growth as compared to the average growth in the preceding four years following Schweingruber et al. (1990). The event year analysis was performed using the *pointer.rgc* function of pointRes package in R (van der Maaten-Theunissen et al., 2015) (Refer to Appendix A).

2.3.4 Superposed Epoch Analysis

Superposed Epoch Analysis (SEA) is a statistical method used to isolate response signals to key events (in this case, storm surges) which may be difficult to detect in the presence of noise from other competing influences operating at similar time scales. The SEA method applies simple compositing to sort data into categories dependent on 'key events' for synchronization and then compares the means of those categories. Theoretically, a causal response to a disturbance event should emerge in the mean (composite), while the noise from other sources in the data should cancel.

SEA was performed using the *sea* function of dplR package in R (Bunn, 2008) to isolate growth response signals to extreme storm surge events (Refer to Appendix A). SEA was conducted on RWI of individual trees, as well as, group and stand-level mean chronologies. The ring-width index was averaged at 13 temporal lags centered on the key dates thereby creating a composite of the tree-ring response in the year of disturbance (lag year 0), and in each of the six years preceding and following the disturbance. Our study involves five key dates representing a combination of highest storm surge magnitude and duration: 1933 Chesapeake-Potomac Hurricane, 1962 Ash Wednesday Nor'easter, 1998 Nor'easter, 2003 Hurricane Isabel, and 2009 Nor'Ida. Individual ring width indices in each key date window were normalized to minimize the chance that a single anomaly may unduly influence the composite analysis. Ten thousand bootstrap samples were used to compute 95% confidence intervals for the scaled RWI for each year in the superposed epoch. The 2011 Hurricane Irene and 2012 Hurricane Sandy could not be included as a key date in SEA as ring-width data for six years post-storm was not available.

2.3.5 Forest Resilience to Storm Surges

From the results of the superposed epoch analysis and event year analysis, a 4-year low-growth (disturbance) period was identified beginning at the year of the storm surge events (Table 2.1) and three years following it. The characteristics of each storm event differ in terms of proximity to the site, wind speeds, storm surge height, and duration of flooding, and may thereby affect tree growth differently. To characterize this effect, a two-way analysis of variance (ANOVA) was performed on ring-width indices as a function of tree group, storm effect, and their interaction using the *aov* function of stats package in R. The tree group factor was categorized into two classes: low and high elevation trees. The storm effect factor was categorized into seven classes: disturbance period associated with the 1933, 1962, 1998, 2003, 2009, and 2011 storms, and no storm (the remaining years during the 1904-2015 period when no extreme storm surge event affected the study site). In order to meet the assumptions of normality and homogeneity of variances, the ring-width indices of individual trees were log transformed. The two-way ANOVA was followed by Tukey's HSD post hoc test using the *TukeyHSD* function to localize the significant differences among tree groups and storms, and view the pairwise comparisons at p-value <0.05.

Having concentrated solely on ring-width growth in the above mentioned method, we analyzed the resilience of the stand during disturbance periods associated with four extreme storm surge events: 1933 Chesapeake-Potomac Hurricane, 1962 Ash Wednesday Nor'easter, 1998 Nor'easter, and 2003 Hurricane Isabel. The resilience of a system is defined as the extent of perturbation it can experience before it undergoes a shift to an alternative state (Holling, 1973; Scheffer et al., 2001). In simpler terms, it is the capacity of forests to reorganize while undergoing changes so as to retain their original function, structure, identity and feedbacks (Folke et al., 2004). We computed three metrics: resistance, recovery, and resilience, according to the definitions described in Lloret et al. (2011) to characterize how the trees respond to and recover from disturbance due to the storm. These metrics were compared between trees belonging to the low and high elevation groups to determine if the resilience of the trees varied as a function of distance from the forest-marsh boundary.

Resistance can be defined as the inverse of radial growth reduction during disturbance and was estimated as:

$$\text{Resistance} = \frac{\overline{RWI}_{Dr}}{\overline{RWI}_{PreDr}} \tag{2.4}$$

Recovery corresponds to the ability of the trees to recover relative to the damage experienced by them during the disturbance, and was estimated as follows:

$$\text{Recovery} = \frac{\overline{RWI}_{PostDr}}{\overline{RWI}_{Dr}} \tag{2.5}$$

Resilience corresponds to the capacity of the trees to reach their pre-disturbance performance levels, and was estimated as follows:

$$\text{Resilience} = \frac{\overline{RWI}_{PostDr}}{\overline{RWI}_{PreDr}} \tag{2.6}$$

Where, $\overline{RWI}_{Dr}$, $\overline{RWI}_{PreDr}$ and $\overline{RWI}_{PostDr}$, represent the mean ring-width indices of each tree during the low-growth period, four years before the low-growth period and four years after the low-growth period, respectively. The selected low growth periods (*Dr*) were 1933-1936, 1962-1965, 1998-2001, 2003-2006. Hereafter we refer to each of these according to the first year: 1933, 1962, 1998 and 2003, respectively. Since the tree-ring record used in this study is only until 2015, the *PostDr* period corresponding to the 2009 Nor'Ida, 2011 Hurricane Irene, and 2012 Hurricane Sandy could not be defined and were therefore not used in this analysis.

Furthermore, one sample t-tests were performed to determine if the resistance, recovery and resilience of low and high elevation trees were significantly different from the base value 1 indicating a significant change in growth patterns at a 95% confidence level. A two-way ANOVA was then performed on each of the three metrics (resistance, recovery, and resilience) as a function of tree group, storm effect, and their interaction to determine if there were significant differences in these indices between the two tree groups and between different disturbance periods associated with extreme storm surge events. The tree group factor was categorized into two classes: low and high elevation trees. The storm effect factor was categorized into four classes: disturbance period associated with 1933, 1962, 1998 and 2003 storms. Any significant results from the two-way ANOVA were investigated further using Tukey's HSD post hoc test to localize the significant differences in resistance, recovery and resilience among tree groups and storms, and view the pairwise comparisons at p-value <0.05.

Chapter 3

Results

This chapter presents the results showing the relationship of radial growth to climate and extreme storm surge events on the Eastern Shore of Virginia National Wildlife Refuge. This chapter is divided into two subsections. The first section describes the variations in radial growth of the sampled trees over time, their age and lists any growth suppressions observed. The second section describes the results of statistical analysis used to determine the influence of climate and extreme storm surge events on tree growth and to understand the overall forest dynamics.

3.1 Tree Growth and Age

Radial growth of the trees was found to be consistent over time with a few strong growth suppressions. Figure 3·1 shows the stand-level mean chronology. Strong growth suppressions were observed post-1917, 1933, 1955, 1963, 1979, 1999, 2002, 2009 and 2012. Similar growth suppressions were also seen in the group-level mean chronologies (low and high elevation trees). The high variance at the start of the chronology (Figure 3·1) may be due to low sample size prior to 1920.

Pith was present only in four of the sampled trees. The pith years for the remaining trees were estimated as described in Section 2.2.1 to determine the age of the trees. Figure 3·2 shows the results of pith estimation. The mean age of the stand, low, and high elevation tree groups in 2015 were 89, 81, and 103 years, respectively. Overall, the age of the 25 sampled trees ranged between 60 and 113 years, of which 11 trees were older than 100 years.

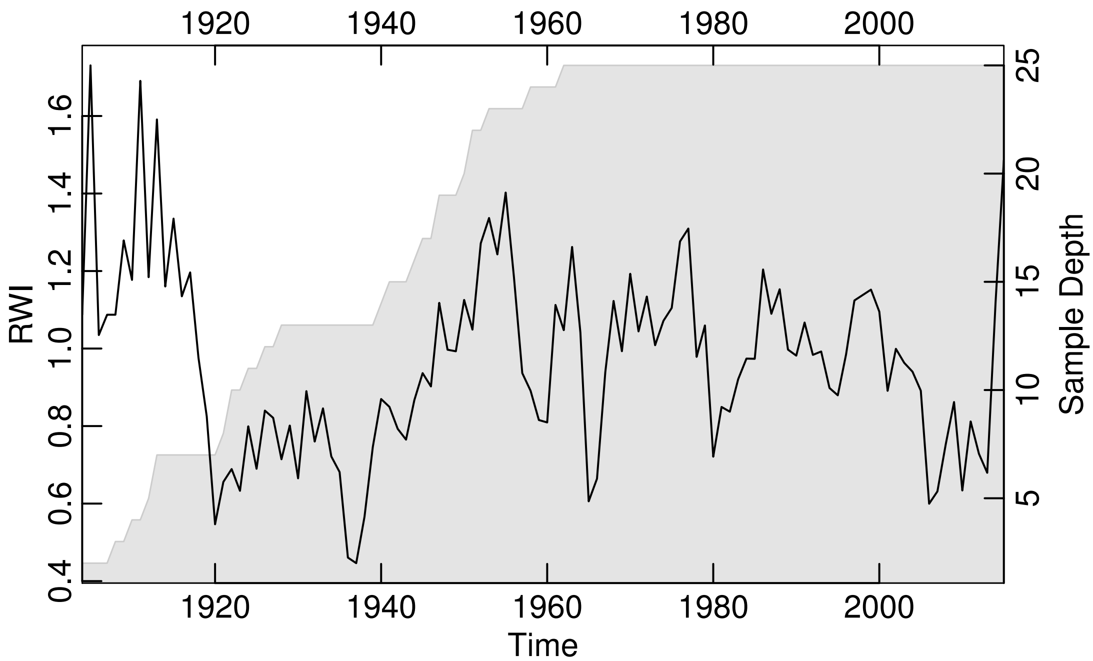

Figure 3·1: Mean chronology (solid line) of 25 *Pinus taeda* trees in the study area. Ring-width series of individual tree cores were detrended using a cubic regression spline, averaged per tree and compiled using Tukey's biweight robust mean to build the mean chronology. The grey shaded area indicates the sample size.

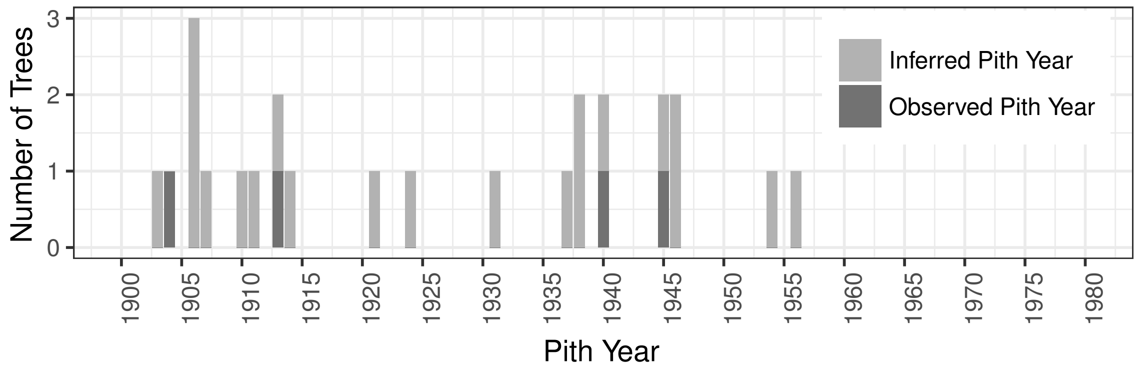

Figure 3·2: Years of establishment of the sampled trees. Pith was observed only in four of the sampled trees. The inferred pith years represent the pith estimated following the method developed by Duncan (1989). Multiple trees shared a common pith year during 1906, 1913, 1938, 1940, 1945, and 1946.

3.2 Influence of Climate and Extreme Storm Surges on Tree Growth

3.2.1 Response Function Analysis

Response function analysis showed no significant correlation between the stand-level mean chronology and temperature and precipitation at p-value < 0.001 (Figure 3·3).

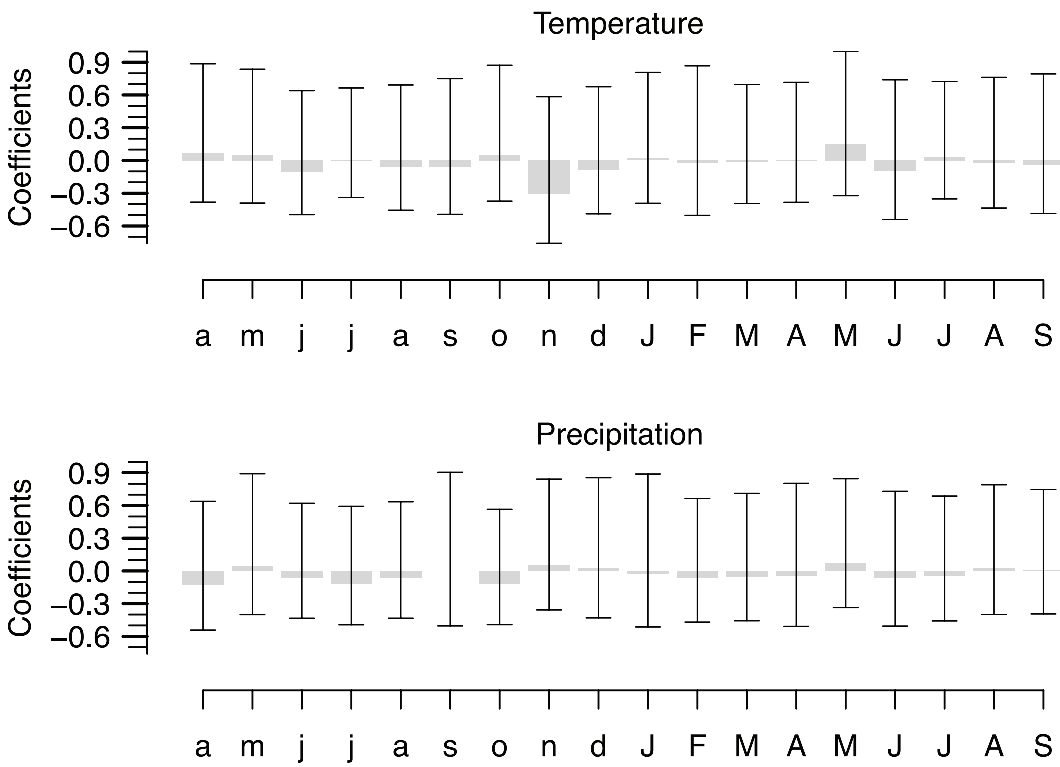

Figure 3·3: Response coefficients of stand level mean tree-ring chronology to temperature and precipitation from previous April (a) to current September (S) for the period 1904 - 2015. The black solid lines represent 99.9% confidence intervals.

3.2.2 Generalized Additive Mixed Model

Variations in radial growth of the trees was modeled by climate, age, storm surge disturbance and individual tree variations, with the final GAMM explaining 49.80% of deviance in radial growth. Spring, summer, fall, and winter temperature, total precipitation, tree age, storm surge disturbance and variation among individual trees were found to be significant predictors of radial growth (p-value < 0.05) (Table 3.1). Tree groups based on distance from the forest-marsh boundary was found to be a non-significant predictor at a 95% confidence level. Overall, variation among individual trees explained the highest proportion of deviance in radial growth (18.96%) followed by tree age (14.54%). Total annual precipitation (1.65%) explained slightly more deviance in radial growth as compared to the mean temperatures in spring (0.45%), summer (0.38%), fall (0.35%), and winter (0.16%). Total annual precipitation and mean seasonal temperature show variable influences on radial growth.The standardized partial predictors of radial growth are shown in Figure 3·4. High precipitation influenced radial growth negatively. High radial growth was observed in both low and high elevation trees at a young age ($<$ 20 years old) and a decline in radial growth was observed as the trees grow older ($>$ 90 years old).

Predictors	F-statistic	Deviance Explained (%)	p-value
Winter temperature	3.117	0.16	0.020
Fall temperature	12.468	0.35	< 0.001
Summer temperature	14.533	0.38	< 0.001
Spring temperature	10.715	0.45	< 0.001
Precipitation	32.270	1.65	< 0.001
Tree age (High)	128.828	14.54	< 0.001
Tree age (Low)	70.002		< 0.001
Individual tree effects	31.215	18.96	< 0.001
Storm surge disturbance	58.701	NA	< 0.001
Tree group (Low or high trees)	0.098	NA	0.754

Table 3.1: Model statistics of radial growth in *Pinus taeda*. The approximate deviance explained by individual predictors and their corresponding F-statistic and p-values are listed. Predictors with p-value <0.05 are considered statistically significant. Mean seasonal temperatures, total annual precipitation, and tree age were modelled as fixed effects using cubic regression splines. Storm surge disturbance and tree group were included as fixed categorical variables and variations among individual trees was modelled as a random effect. Total deviance explained: 49.80%, adjusted R^2: 0.489.

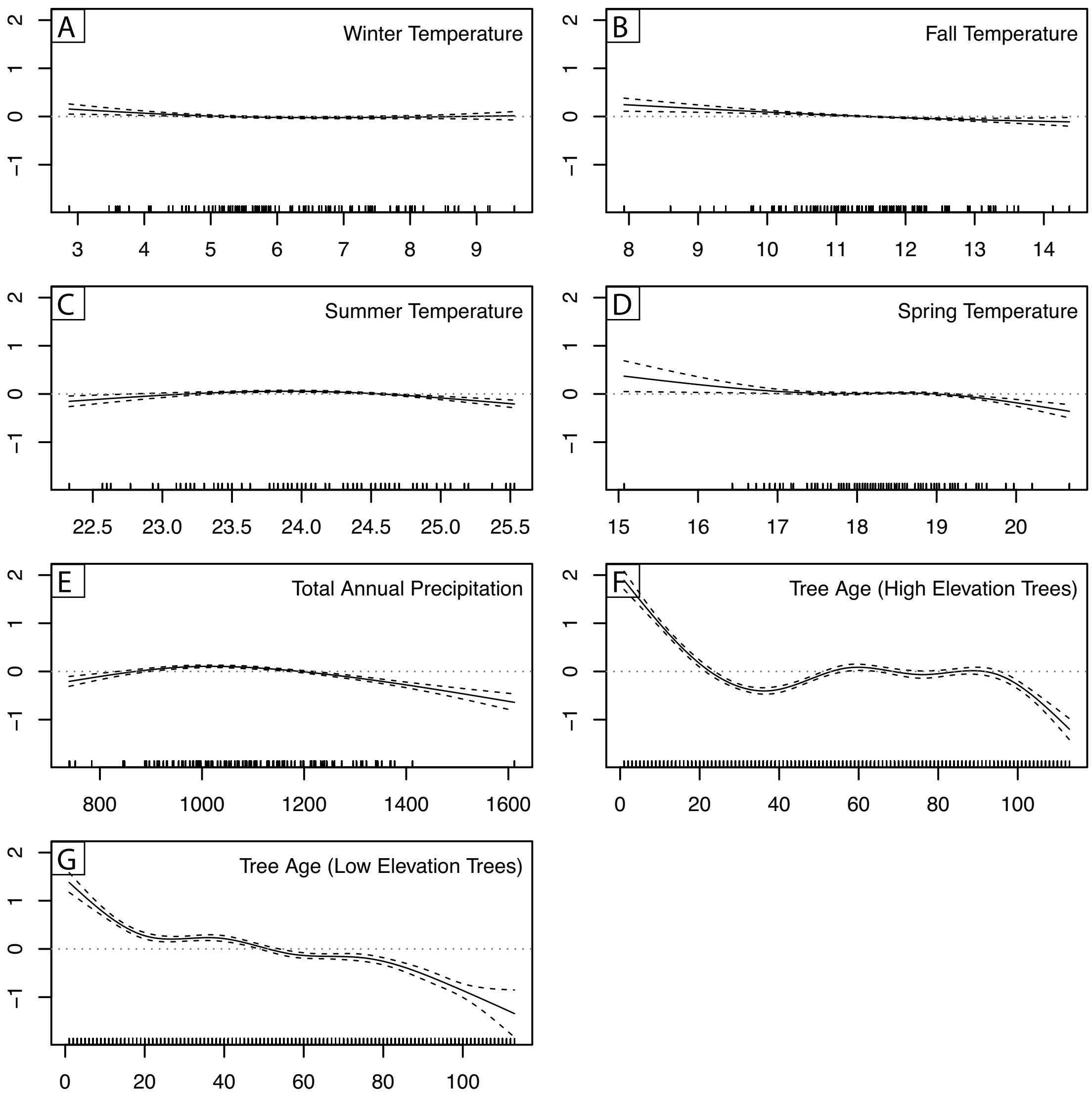

Figure 3·4: (A-G) Partial predictors of radial growth in *Pinus taeda* estimated using cubic regression splines in GAMM. Dashed lines represent 95% confidence intervals.

3.2.3 Event Year Analysis

A relationship between decline in radial growth and storm surge events was observed at an individual tree level. Almost all trees show a negative event year ($\geq$ 40% decline in growth compared to average growth in preceding four years) following the major storm surge events of 1933, 1962, 1998, 2003, 2009, 2011, and 2012 in Virginia

(Figure 3·5A). A relatively higher number of low elevation trees exhibit a decline in growth as compared to high elevation trees, following the 1933, 1962 and 1998 storms (Figure 3·5B and Figure 3·6).

An increase in the number of trees showing a negative event year was observed for up to three years following the extreme storm surge events. Following the 1933 storm surge event, about 60% of low elevation trees and 50% of high elevation trees showed a negative event year by 1936 (Figure 3·6). After the 1962 storm surge event, about 70% of the low elevation trees and only 10% of the high elevation trees showed a negative event year by 1965 (Figure 3·6). After the 1998 storm surge event, about 55% of the low elevation trees showed a negative event year by 2001 (Figure 3·6). For the 2003, 2009, 2011 and 2012 storm surge events the percentage of trees showing negative event years in three years post-storm is variable. Growth suppressions were also observed between 1955-1957 and 1978-1980 (Figure 3·6).

3.2.4 Superposed Epoch Analysis

Superposed epoch analysis revealed a common growth response signal of declining ring-width indices (RWI) to the five major storm surge events analyzed (Figure 3·7). The decline in RWI starts in the year of the storm surge and a relatively large decrease in RWI is observed 3-4 years after the storm. At a stand level (i.e., using the mean chronology of all trees), a declining trend in RWI is observed for up to three years following the storm surge event, after which the RWI starts recovering. A similar response is observed in high elevation trees. However, low elevation trees show a decline in RWI for up to four years after the storm surge event, after which it begins to recover. Because of the occurrence of storm surges associated with the 1998 Nor'easter, 2003 Hurricane Isabel, and 2009 Nor'Ida, within short intervals (¡ 13 years) there is a bias introduced in the pre-storm lag years (-6 to -1).

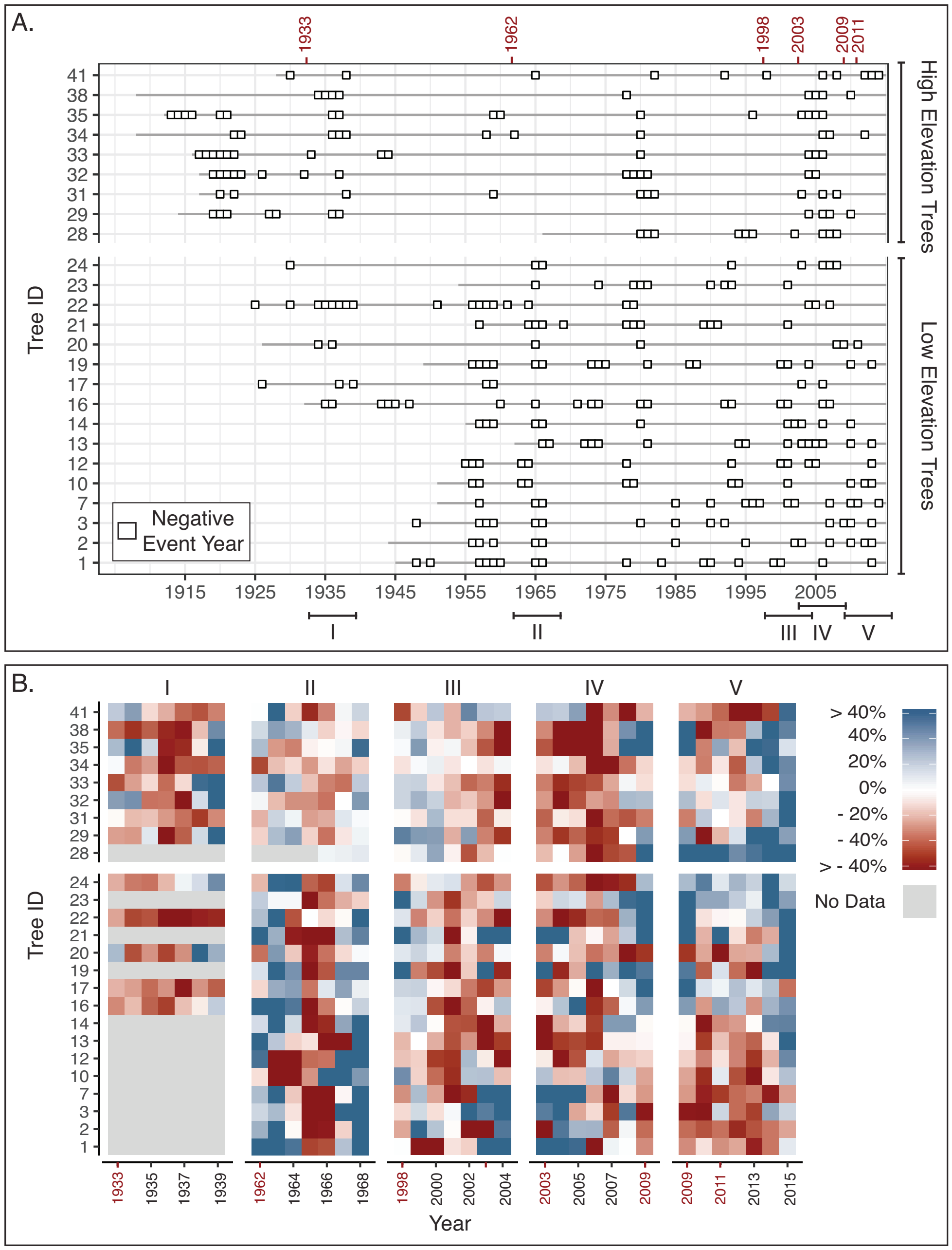

Figure 3·5: Relative growth change and event years for individual trees with the major storm surge event years marked in red. (A) Dot plot showing negative event years for individual trees at the study site. (B) Panels I-V show gradual relative growth change post the 1933, 1962, 1998, 2003 and 2009 storm surge events, for time windows marked I-V in Figure 3·5A. Majority of the trees show a negative event year (≥ 40% decline in growth), three years post-storm.

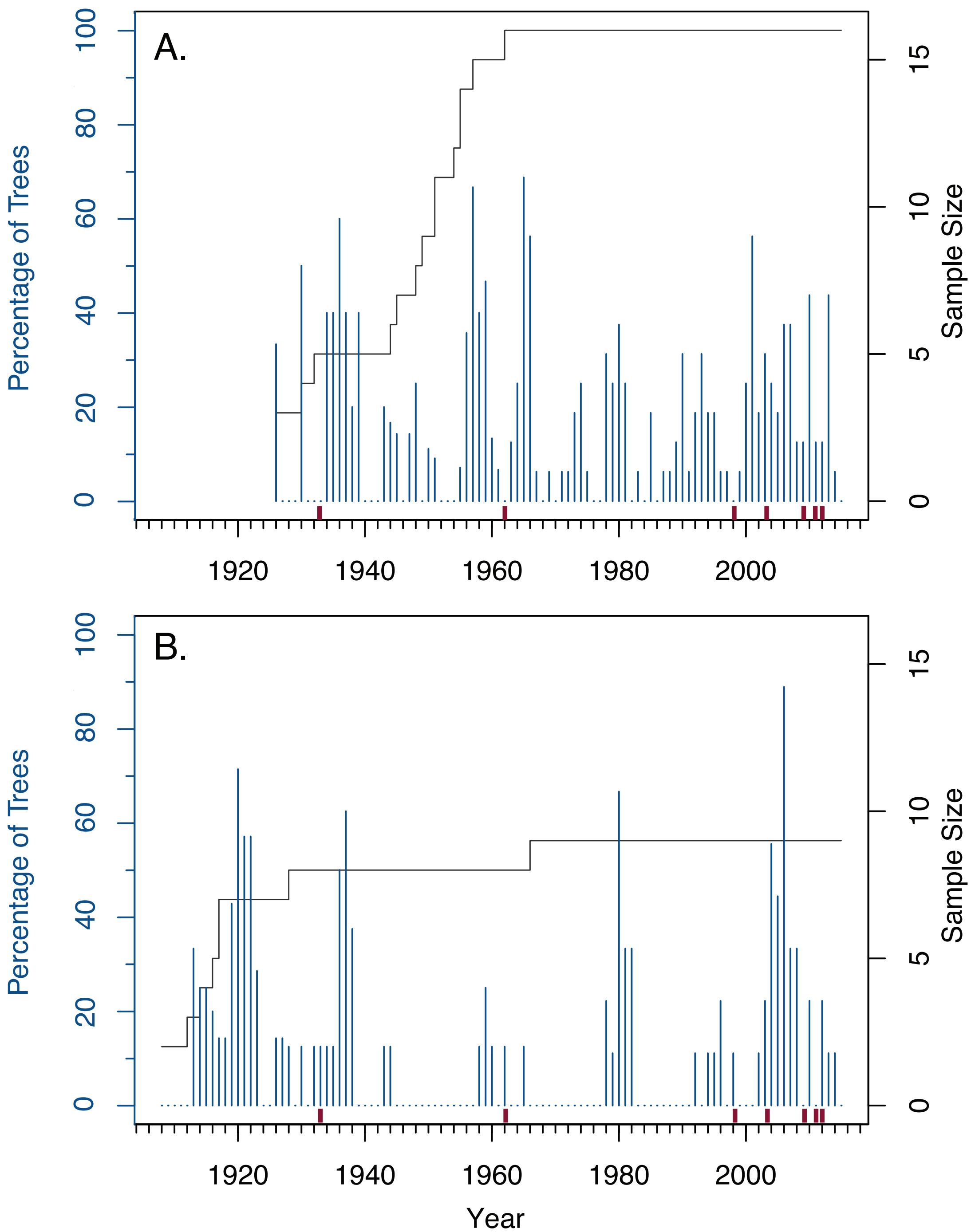

Figure 3·6: Percentage of trees showing negative event years among the (A) low elevation trees and (B) high elevation trees at the study site. Grey line indicates the sample size and red markers on the x-axis represent the seven storm surge events considered in this study.

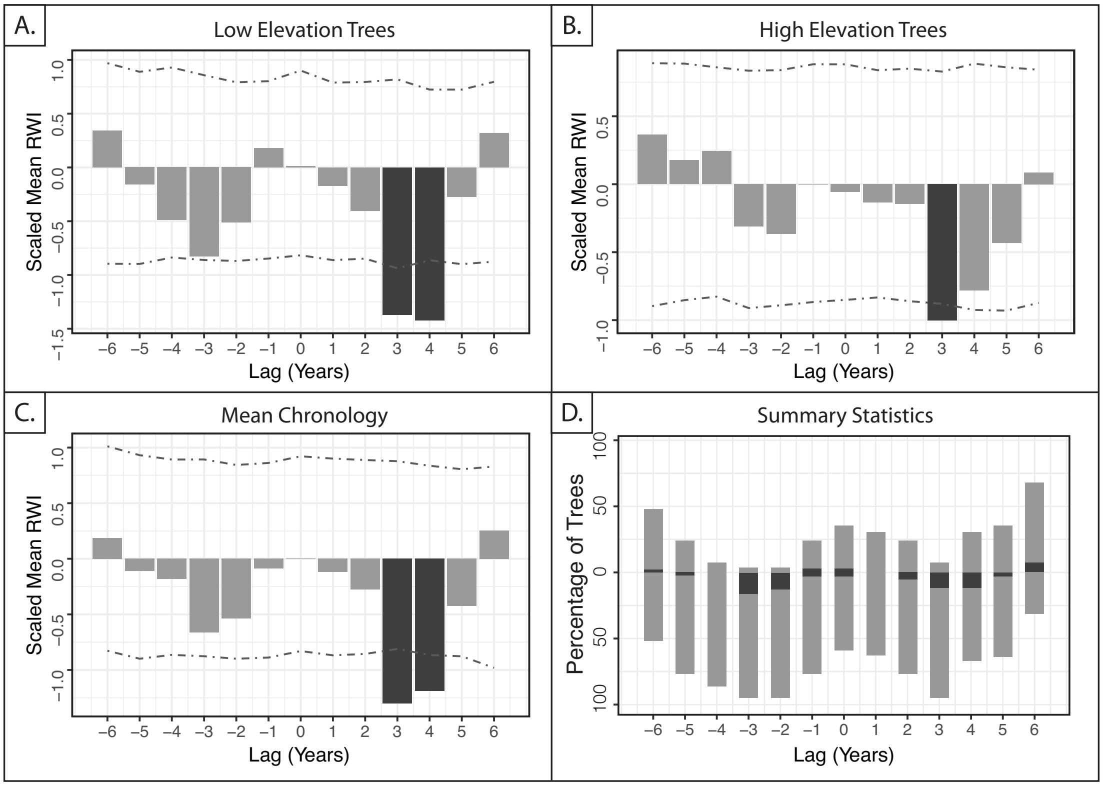

Figure 3·7: Results of SEA conducted on mean chronology of (a) low elevation trees (b) high elevation trees and (c) all trees, indicating the response of radial tree growth for a 13-year window centred on dates of five major storm surges recorded in Virginia (Refer to section 2.3.4). Individual ring width indices in each key date window were normalized to minimize the chance that a single anomaly may unduly influence the composite analysis. Bars above and below the x-axis indicate above and below average radial growth, respectively for the 13-year window. Declining growth trend across years is indicative of low-growth periods, whereas, a growing trend across years indicates radial growth recovery. Dark grey shading shows statistically significant (at a 95% sample confidence) growth anomalies. (d) Summary of SEA conducted on individual trees. Dark grey shading shows the percentage of trees with statistically significant (at a 95% sample confidence) growth anomalies.

3.2.5 Forest Resilience to Storm Surges

The mean RWI of low and high elevation trees during the low-growth (disturbance) period corresponding to the 1933, 1962, 1998, 2003, 2009, and 2011 storm surge events is shown in Figure 3·8. To determine if the mean RWI significantly differed between the two tree groups and between disturbance periods associated with extreme storm events, a two-way ANOVA was performed, the results of which are listed in table 3.2. A statistically significant effect of storm surge events and the interaction between tree groups and storm surge events on RWI was observed. Pairwise comparison using Tukey's HSD post hoc test indicated that mean growth of high elevation trees was significantly lower (p-value <0.05) during the disturbance period associated with the 1933, 2003, and 2009 storm surge events than that during the 1962 and 1998 storms. In addition, mean growth of high elevation trees during the disturbance period associated with the 2011 storm surge event was significantly (p-value <0.05) lower than that during the 1998 storm only. No significant differences in mean growth of low elevation trees were observed between the analyzed storm surge events at 95% confidence level. In addition, no significant consistent difference was observed between low and high elevation trees during all the disturbance periods.

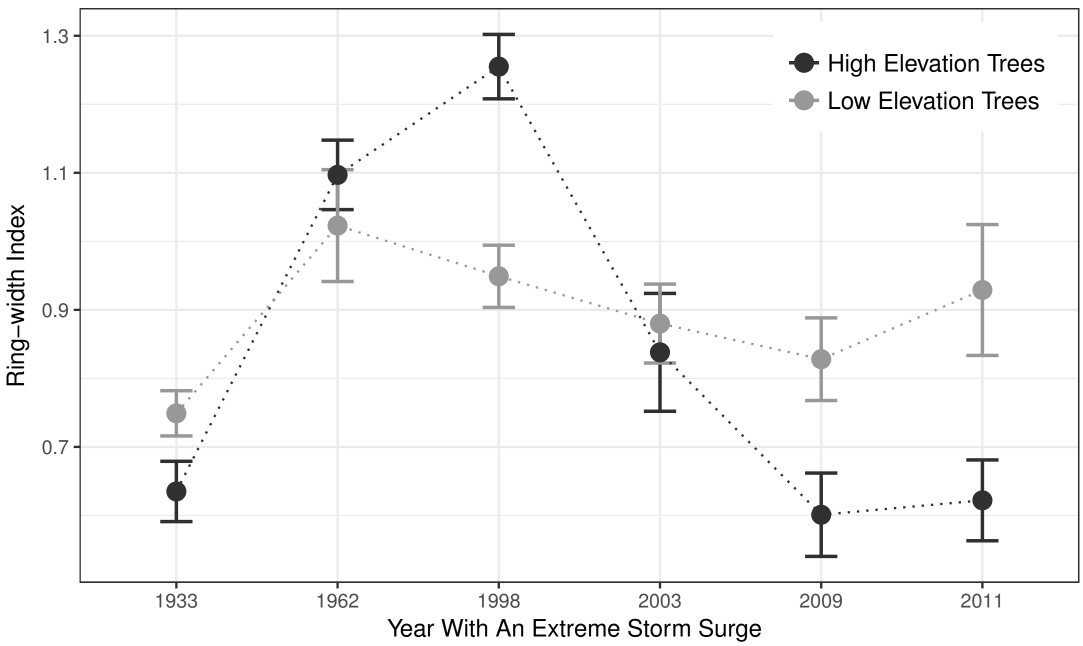

Figure 3·8: Interaction plot showing the mean ring-width index for low and high elevation trees during disturbance periods associated with extreme storm surge events. Error bars represent one standard deviation of the mean RWI estimate.

Factors	df	Sum Sq	Mean Sq	F-value	p-value
Tree Group	1	0.0	0.038	0.157	0.692
Storm Event	7	19.3	2.764	11.358	<0.001
Interaction	7	6.8	0.965	3.966	<0.001

Table 3.2: Results of two-way ANOVA for logarithm of ring-width index by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant.

The radial growth of low and high elevation trees showed a mixed response to storm surges in terms of resistance, recovery and resilience (Figure 3·9). Low elevation trees showed a significantly (p-value <0.05) low resistance and resilience towards the 1933 storm surge event. During the 1962 storm surge event, high elevation trees showed a significantly (p-value <0.05) low mean recovery and resilience. Both tree groups had good resistance to this storm surge event (mean ≈ 1 or higher). Both tree groups also had good resistance and resilience towards the 1998 storm surge event (mean ≈ 1 or higher). A significantly low (p-value <0.05) mean resistance and resilience towards the 2003 storm surge was observed in high elevation trees. Except for the difference in resilience of low and high elevation trees during the 2003 disturbance period, the two-way ANOVA and Tukey's HSD post hoc tests indicated no statistically significant differences in resistance, recovery and resilience between the two tree groups, between the different disturbance periods analyzed or their interaction at a 95% confidence level (Refer to Appendix C). Further details on the magnitude of mean resistance, recovery, and resilience of low and high elevation trees can be found in Table 3.3.

Index	Tree Group	1933		1962		1998		2003	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Resistance	Low	0.72*	0.07	1.31*	0.52	1.04	0.24	1.17	0.87
	High	0.98	0.25	0.97	0.21	1.25*	0.31	0.66*	0.33
Recovery	Low	0.85	0.34	1.05	0.30	1.07	0.64	1.03	0.31
	High	1.08	0.51	0.87*	0.14	0.89	0.44	0.80	0.39
Resilience	Low	0.63*	0.29	1.33*	0.59	1.04	0.46	1.11	0.67
	High	1.05	0.50	0.83*	0.16	1.09	0.57	0.45*	0.16

Table 3.3: Mean resistance, recovery, and resilience and the corresponding standard deviation (S.D.) for low and high elevation trees for the 1933, 1962, 1998 and 2003 disturbance periods. * Represents indices that are significantly different (p-value <0.05) from the base value 1 as indicated by one-sample t-tests.

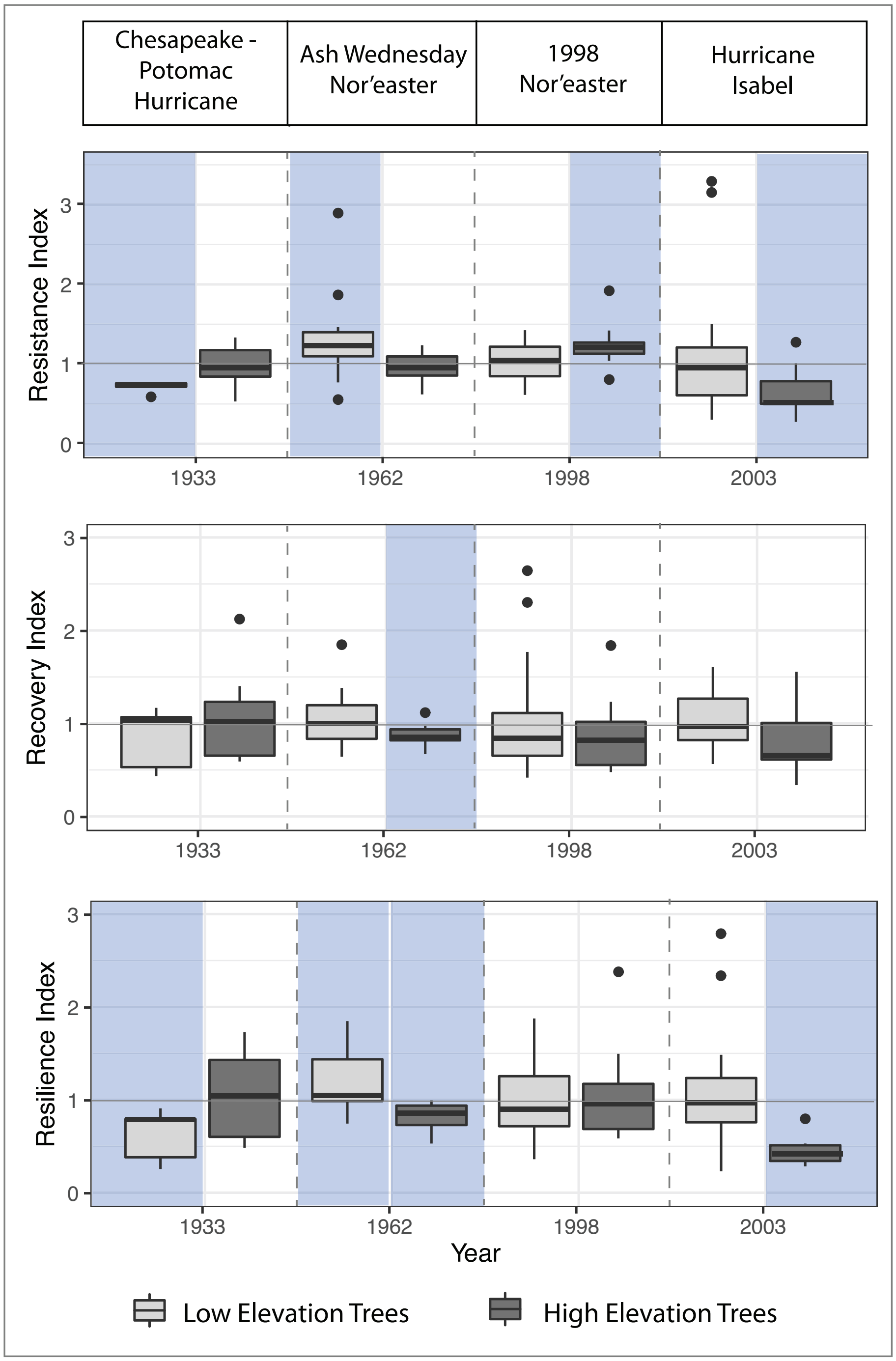

Figure 3·9: Resistance, recovery and resilience of low and high elevation trees for the 1933, 1962, 1998 and 2003 low-growth periods. The band inside each box represents the corresponding median value. Blue regions represent indices that are significantly different (p-value <0.05) from the base value 1 as indicated by one-sample t-tests.

Chapter 4

Discussion

Numerous studies have analyzed the effect of long-term trends in climate and sea-level (Barber et al., 2000; Byun et al., 2013; Douglass, 1920; Kirwan et al., 2007) and shown the potential association between low-growth episodes and disturbances from storm events (Johnson and Young, 1992; Samuelson et al., 2013). In addition, given the complex interaction between climate, disturbances, local landform characteristics, and tree physiology, there is a need to better understand the factors affecting tree growth in coastal forests at a site-specific level. In this study, dendrochronological and statistical methods were employed to achieve two main objectives:

1. Identify periods of declining tree ring growth following storm surges.

2. To understand the response and resilience of vegetation in the Mid-Atlantic coastal region, on the Eastern Shore of Virginia National Wildlife Refuge, to extreme storm surge events.

The interpretation of the results presented in Chapter 3 are discussed below, in the context of the two main objectives mentioned above.

4.1 Influence of Age, Individual Tree Variability and Climate

Tree age is an important variable that influences radial growth (Table 3.1). Initially, the low and high elevation trees show a reverse-J growth pattern, typical of trees growing in an increasingly competitive environment. Both tree groups display high radial growth prior to age 20 and lower radial growth after 90 years (Figure 3·4).

A possible scenario is that rapid radial growth occurred until canopy closure at the age of 20 years, after which growth begin to decline due to increasing competition, structural changes and shifts in carbon allocation associated with canopy closure and maximum foliage (Smith and Long, 2001). This is consistent with the growth pattern observed by Reams (1996) in *Pinus taeda* from the Virginia Coastal Plain. Bendtsen and Senft (1986) also observed decline in radial growth of *Pinus taeda* from North Carolina until the age of 12 years after which the ring-width remained relatively constant till the age of 30 years. The drop in radial growth of both low and high elevation trees post-90 years may be associated with the beginning of senescence.

Furthermore, variations among individual trees was found to be a significant predictor that explained the highest proportion of deviance in radial growth (18.96%) (Table 3.1). This could be attributed to microsite variability, competition, and variations in tree vigor (Amateis and Burkhart, 2016; Bullock and Burkhart, 2005; Ryu et al., 2013). Microsite effects include the heterogeneity in soil moisture levels and nutrient availability across relatively small distances within the study site which can affect the competition among trees (Amateis and Burkhart, 2016; Bullock and Burkhart, 2005; Fajardo and McIntire, 2007). Competition involves the struggle between individual trees to acquire limiting resources like light, water, and nutrients that together determine rates of carbon acquisition (Grimes, 2001).

Radial growth was also found to be influenced by mean seasonal temperature and total annual precipitation, although the deviance explained by these predictors were relatively low as compared to tree age and individual tree variability (Table 3.1). Radial growth was found to be negatively associated with high precipitation (Figure 3·4). A plausible explanation to this could be water stress associated with an increase in saturation of the soil and associated low aeration (Fowells et al., 1965; Schultz, 1997).

4.2 Influence of Storm Surges

A strong association is observed between the decline in radial growth and storm surge events associated with hurricanes and nor'easters on the Eastern Shore of Virginia National Wildlife Refuge (Figure 3·5 and Figure 3·7). This decline in radial growth of *Pinus taeda* was observed for up to four years following the seven extreme storm surge events analyzed in this study (Figure 3·5 and Figure 3·7). Growth suppression observed in both low and high elevation trees during the 1978-1980 period (Figure 3·6) may be associated with the 1978 Northeastern United States blizzard. While the cause of a strong growth suppression during the 1955-1957 period (Figure 3·6A) could not be analyzed as no local tidal records are available for that period, we hypothesize this low-growth period to be associated with the 1954 Hurricane Hazel and 1955 tropical storms Connie and Diane. The growth suppression following storms observed from our study are in accord with several other works. Johnson and Young (1992) observed a similar association between decline in ring-width of *Pinus taeda* and occurrence of hurricanes and nor'easters on the Delmarva barrier islands. Samuelson et al. (2013) and Robichaud and Begin (1997) also reported a similar 3 to 4 year growth decline in ring-width following storm events.

We associate the growth reduction observed in *Pinus taeda* with flooding and/or storm wind effects. Flooding affects the soil structure, salinity, decreases or eliminates soil O_2, accumulates CO_2, produces potentially toxic compounds, reduces Fe and Mn, and induces anaerobic decomposition of organic matter (Kozlowski, 1997; Ponnamperuma, 1984). These changes in soil properties can affect the physiological functions of *Pinus taeda*. Soil salinization due to flooding has been reported to cause browning and loss of needles or leaves in *Pinus taeda* along with decrease in nutrient use efficiency, nitrogen retention and physiochemical retention mechanisms (Blood et al., 1991). Soil inundation can also reduce root growth of *Pinus taeda* (DeBell et al., 1984). The reduced supply of oxygen to tree roots and sedimentation during flooding can further damage or injure the roots (Bratkovich et al., 1993; Kozlowski, 1985). Wind associated with the hurricanes and nor'easters have been reported to affect the growth of *Pinus taeda* by increased salt spray (Levy, 1983), damage or loss of branches and defoliation (Gresham et al., 1991; Negrón-Juárez et al., 2010; Brokaw and Walker, 1991).

Major losses in leaf surface area due to the storm would result in reduced radial growth of *Pinus taeda* until the leaf surface is replaced (Kuprionis, 1970). Wiley and Zeide (1991) observed a reduction in diameter growth of *Pinus taeda* for 8 years after the 1974 ice storm in southeast Arkansas that caused severe crown damage, bending and breakage of stems; the following 6 years however showed similar or increased diameter growth of broken trees relative to undamaged trees (See also Bragg and Shelton (2010)). Belanger et al. (1996) also reported lack of recovery in diameter growth of *Pinus taeda* with severe crown damage for a 5-year period following the 1983 storm in central Georgia. Similar effects resulting in reduced radial growth of *Pinus taeda* were observed in our study for up to four years following the storms. The decline in radial growth during the disturbance period can be further explained by the allocation of carbohydrates to dormant buds, branch formation, and to add roots, thereby giving precedence to the demands for restoring crown components and roots in damaged trees over lower stem growth (Belanger et al., 1996; Bragg and Shelton, 2010; Shelburne et al., 1993; Waring and Pitman, 1985).

Radial growth usually begins to recover after the disturbance period depending on the frequency of storms in the immediate future. High frequency of disturbances is expected to accelerate environmental change and deplete individual tree reserves needed to withstand and overcome stressful episodes, thereby reducing their resilience (Lloret et al., 2011). One disturbance can increase the susceptibility of the forest to another disturbance (Oliver and Larson, 1996). The combined effect of successive disturbances of different nature can lead to negative responses and slow forest-canopy recovery (Díaz-Delgado et al., 2002; Payette and Delwaide, 2003). Low elevation trees, which lie closer to the marsh, are subject to low magnitude storm surges more often compared to the high elevation trees, which are further inland. The increased exposure of low elevation trees to storm surges, could be the reason for the relatively higher number of low elevation trees exhibiting a decline in growth as compared to high elevation trees, following the 1933, 1962 and 1998 storms as seen in the results of event year analysis (Figure 3·5B and Figure 3·6). However, considering that decline in growth of both low and high elevation trees was variable following the 2009, 2011, and 2012 storm surge events, no definite conclusion about the impact of storm surge events as a function of distance from the forest-marsh boundary can be made.

4.3 Forest Resilience

The resistance, recovery, and resilience to storm surges varied between low and high elevation trees (Table 3.3). The forest resilience towards storm surge events was found to be partially related to the timing of the storm, i.e., whether the storm occurred during the growing season or the dormancy period. Flooding during the growing season, especially in late spring, is found to be more detrimental to the immediate tree growth than flooding during the dormant season (Bratkovich et al., 1993). This is consistent with the results of two-way ANOVA on ring-width indices as a function of tree group and disturbance period associated with storms which indicated a significantly lower (p-value <0.05) mean growth in high elevation trees during the disturbance period associated with the 1933 Chesapeake-Potomac Hurricane and 2003 Hurricane Isabel which occurred in the growing season than those occurring in the dormancy period (1962 Ash-Wednesday Nor'easter and 1998 Nor'easter).

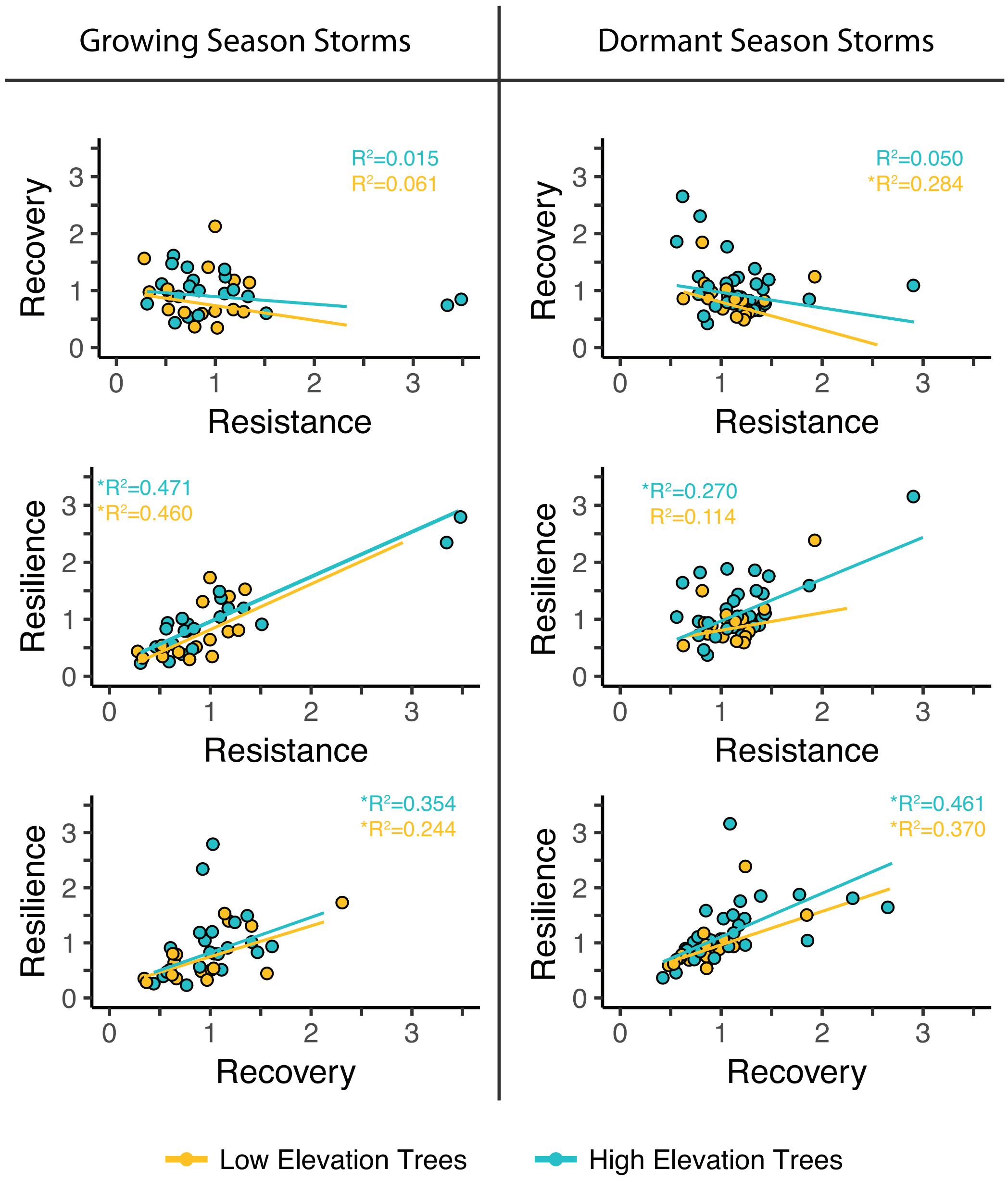

Figure 4·1: Relationship between resistance, recovery, and resilience of low and high elevation trees during low-growth periods associated with extreme storm events occurring during the growing (1933 and 2003) and dormant (1962 and 1998) seasons. Solid line represents linear regression lines. * indicates significant linear relationship at p-value <0.05. High leverage points were determined using the *influence.measures* function of stats package in R and not included in the regression analysis.

Recovery of the trees is a function of the impact of the event inducing the disturbance (Lloret et al., 2011). In our case, this impact which can be defined by the magnitude of decline in ring-width during the disturbance period would be a function of storm characteristics (proximity to the site, wind speeds, storm surge height, and duration of flooding) as well as resistance of individual trees and overall stand dynamics. Comparison of resistance versus recovery points towards an inverse relationship as we expected (Figure 4·1). Strong resistance would indicate very low decline in ring-width during the disturbance period. This can be interpreted as a low damage fast recovery situation. This tradeoff between resistance and recovery after extreme storm surge events could occur if both these components at least partially depend on the amount of stored carbon reserves needed to withstand and overcome the stress (Galiano et al., 2011). More resilient trees showed higher recovery (Figure 4·1) which could be attributed to either high amount of stored reserves or increased availability of resources due to a decrease in competition. In addition, we observe a very gentle but positive linear trend between resistance and resilience for low elevation trees during storms which occurred in the dormant season (Figure 4·1). This indicates that if the impact during the storm events was large (low resistance), the trees do not return to their original pre-disturbance state (low resilience). These could be signs of a progressive decrease in resilience over time on account of constant exposure to coastal inundation due to its proximity to the forest-marsh boundary.

Although multiple factors (tree age, competition, microsite factors, and to some extent macroclimate) provide an explanation for variation in growth of *Pinus taeda* over time, the focus of our study points towards how discrete occurrences like extreme storm surge events could influence the growth pattern periodically. Carefully controlled experimental data would be necessary to prove the cause and effect relationship with storm surge.

Chapter 5

Conclusions

The projected increase in frequency and intensity of storm surges with changing global climate is likely to affect the Mid-Atlantic coastal forests adversely in the foreseeable future. This study aimed at identifying periods of declining tree ring growth following storm surge events and understanding the response and resilience of vegetation in this region following these disturbances. Results indicated episodic suppressions in radial growth for up to four years after the storm surge events, after which the radial growth starts recovering. The impact of these disturbance events on tree growth was found to be at least partially associated with the timing, intensity, and frequency of the storms. An inverse relationship was observed between resistance of trees to storm surge events and their recovery. In addition, we also observe low resilience in trees closer to the forest-marsh boundary during storms occurring in the dormant season pointing towards failure to successfully recover to its original pre-disturbance state. We hypothesize this decrease in resilience to be associated with constant flooding in low lying regions. Although the growth at our site was found to be influenced by age, vigor, microsite factors, competition, and regional climate trends, episodic disturbances due to storm surges appear to control radial growth trend from time to time. Carefully controlled experimental data is required to identify concrete thresholds for impact parameters which in turn would help in better managing storm affected coastal forests.

Appendix A: Formulae and Functions Employed in the Study using R Version 3.3.0

A.1 Response Function Analysis (RFA)

RFA implemented in R using the *bootRes* package was conducted with the following function:

```
library(bootRes)
library(dplR)
dcc(chrono, clim, method = "response", start = -4, end = 9,
      boot = TRUE, ci = 0.05)
```

Where *chrono* is the stand-level mean chronology. *clim* is the dataset containing climate variables (monthly mean temperature and total monthly precipitation). *method* is a string specifying the calculation method, i.e., response or correlation. The *start* and *end* represent, the the first and last month to be used as a predictor in the response function. *boot* is a logical flag indicating whether bootstrap resampling is to be performed. *ci* is the numerical value to set the test level for significance test according to which the confidence intervals are adapted. The Bonferroni Correction was then applied and confidence intervals were recalculated at a p-value of 0.001, manually.

A.2 Generalized Additive Mixed Model (GAMM)

The GAMM implemented in R using the *mgcv* package was computed with the following function:

```
library(mgcv)
library(dplR)
gam(ln(chrono) ~ s(WinterTemp, bs='cr', k=5) +
                  s(FallTemp, bs='cr', k=4) +
                  s(SummerTemp, bs='cr', k=3) +
                  s(SpringTemp, bs='cr', k=4) +
                  s(Precipitation_mm, bs='cr', k=5) + Tree Group +
                  s(Age, by=Tree Group, bs='cr', k=7) +
                  Storm Surge Disturbance +
                  s(TreeID, bs='re'), method = "GCV.Cp")
```

Where *chrono* is the ring-width series of individual tree cores. *WinterTemp*, *FallTemp*, *SummerTemp* and *SpringTemp* are the mean seasonal temperatures. *Precipitation* is the total annual precipitation. *Age* is the age of the trees estimated as described in Section 2.2.1. *Tree Group* is a categorical variable for the two tree groups - low and high elevation trees. *Storm Surge Disturbance* is a categorical variable representing whether an extreme storm surge event affected the study site during a given year. *TreeID* accounts for variations among individual trees. *bs='cr'* represents predictors modeled using a penalized cubic regression spline. *bs='re'* represents predictors modeled as a random effect. *k* represents the number of knots used to control the smoothness of the spline. *GCV.Cp* is the method used for estimating the smoothing parameters.

A.3 Event Year Analysis

Event year analysis implemented in R using the *pointRes* package was conducted with the following function:

```
library(pointRes)
library(dplR)
pointer.rgc(chrono, nb.yrs = 4, rgc.thresh.pos = 60,
            rgc.thresh.neg = 40)
```

Where *chrono* is the ring-width series of individual trees. *nb.yrs* is the number of preceding years used in calculating relative growth changes. *rgc.thresh.pos* is the threshold above which the percentage relative growth change of a tree and year is considered a positive event year. *rgc.thresh.neg* represents the threshold below which the percentage relative growth change of a specific tree and year is considered a negative event year.

A.4 Superposed Epoch Analysis (SEA)

SEA implemented in R using the *dplR* package was conducted with the following function:

```
library(dplR)
keyevents<-c(1933,1962,1998,2003,2009)
sea(chrono, keyevents, lag=6, resample = 10000)
```

Where *chrono* is the ring-width chronology. *keyevents* is a vector that specifies the key event years (in this case, storm surges) for the superposed epoch. *lag* specifies the number of lagged years. *resample* specifies the number of bootstrap sample for computing the confidence intervals. SEA was performed using stand-level mean chronology (all trees), group-level mean chronology (low and high elevation trees) and ring-width indices of individual trees.

Appendix B: Ring Width Statistics for Each Core used in the Study

Core	First year*	Last year	Total years	Mean ring-width (mm)	Standard deviation
VCR201B	1940	2015	76	0.78	0.458
VCR202A	1943	2015	73	1.45	0.784
VCR202B	1939	2015	77	1.99	1.067
VCR203A	1962	2015	54	0.89	0.505
VCR203B	1943	2015	73	1.12	0.663
VCR207A	1956	2015	60	1.67	1.304
VCR207B	1946	2015	70	1.91	1.468
VCR210A	1949	2015	67	1.58	1.328
VCR210B	1944	2015	72	2.15	0.976
VCR212B	1950	2015	66	2.09	1.112
VCR213A	1967	2015	49	1.21	1.163
VCR213B	1957	2015	59	1.73	1.262
VCR214A	1950	2015	66	1.28	0.711
VCR214B	1949	2015	67	1.5	1.155
VCR216A	1927	2015	89	1.04	1.229
VCR216B	1931	2015	85	0.82	0.888
VCR217A	1920	2015	96	1.7	1.091
VCR217B	1927	2015	89	1.99	1.359
VCR219B	1944	2015	72	0.91	0.794
VCR220A	1920	2015	96	1.74	1.153
VCR220B	1921	2015	95	1.69	0.952
VCR221C	1952	2015	64	0.7	0.538
VCR222B	1920	2015	96	1.13	1.14
VCR223A	1949	2015	67	1.27	1.12
VCR223B	1953	2015	63	0.99	0.878
VCR224A	1931	2015	85	1.47	0.787
VCR224B	1924	2015	92	1.72	0.998
VCR228A	1962	2015	54	1.35	1.318
VCR228B	1961	2015	55	1.22	0.91
VCR229A	1910	2015	106	1.66	2.269
VCR229B	1911	2015	105	1.24	2.499
VCR229C	1910	2015	106	1.3	1.694
VCR231A	1913	2015	103	1.56	1.547
VCR231B	1914	2015	102	1.67	1.361
VCR232A	1913	2015	103	0.85	0.684
VCR232B	1951	2015	65	1.56	0.681
VCR233A	1912	2015	104	0.85	0.948
VCR233B	1912	2015	104	0.85	0.877
VCR233C	1914	2015	102	0.73	0.5
VCR234A	1905	2015	111	2.28	3.543
VCR234B	1904	2015	112	2.35	2.764
VCR235A	1910	2015	106	1.34	0.913
VCR235B	1908	2015	108	1.25	1.16
VCR238A	1904	2015	112	1.9	1.959
VCR238B	1915	2015	101	1.37	0.958
VCR241A	1924	2015	92	0.8	0.402

*First year is indicative of the measured ring year and does not necessarily represent the pith year. Pith years were estimated using the method described in Section 2.2.1.

Appendix C: Results of Two-Way ANOVA and Tukey's HSD Post Hoc Tests

C.1 Resistance

Factors	df	Sum Sq	Mean Sq	F-value	p-value
Tree Group	1	0.555	0.555	2.349	0.129
Storm Event	3	0.881	0.294	1.243	0.300
Interaction	3	2.188	0.729	3.086	0.032

Table C.1: Results of two-way ANOVA for resistance by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant.

Although, a statistically significant effect of interaction between tree group and storm surge events on resistance was observed, pairwise comparison using Tukey's HSD post hoc test indicated this significant relationship to be associated with non-relevant combination of explanatory variables.

C.2 Recovery

Factors	df	Sum Sq	Mean Sq	F-value	p-value
Tree Group	1	0.329	0.329	1.862	0.176
Storm Event	3	0.066	0.022	0.124	0.946
Interaction	3	0.488	0.163	0.922	0.434

Table C.2: Results of two-way ANOVA for recovery by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant.

No statistically significant effect of tree group, storm surge event, or their interaction on recovery was observed at a 95% confidence level.

C.3 Resilience

Factors	df	Sum Sq	Mean Sq	F-value	p-value
Tree Group	1	1.412	1.412	5.574	0.021
Storm Event	3	1.077	0.359	1.418	0.244
Interaction	3	3.204	1.068	4.217	0.008

Table C.3: Results of two-way ANOVA for resilience by tree group, storm event, and their interaction. df: degrees of freedom, Sum Sq: Sums of Squares and Mean Sq: Mean squares. Factors with p-value <0.05 are considered significant.

A statistically significant effect of tree group and interaction between tree group and storm surge events on resilience was observed. Except for the difference in resilience of low and high elevation trees during the 2003 disturbance period, the Tukey's HSD post hoc test indicated no other significant relationship between relevant combination of explanatory variables at a 95% confidence level.

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