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Evaluation of Tidal Fresh Forest Distributions and Tropical Storm Impacts Using Sentinel-2 MSI Imagery

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EVALUATION OF TIDAL FRESH FOREST DISTRIBUTIONS AND TROPICAL STORM IMPACTS USING SENTINEL-2 MSI IMAGERY

by

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(Under the Direction of Christine M. Hladik)

ABSTRACT

Situated in the transitional zone between non-tidal forests upstream and tidal fresh marshes downstream, tidal fresh forests occupy a unique and increasingly precarious habitat. The threat of intensifying anthropogenic climate change, compounded by the effects of historical logging and drainage alterations, could reduce the extent of this valuable ecosystem. The overall goals of this project were to identify forest communities present in the Altamaha tidal fresh forest; develop satellite imagery-based classifications of tidal fresh forest and tidal marsh vegetation along the Altamaha River, Georgia; and to quantify changes in vegetation distribution in the aftermath of hurricanes Matthew and Irma. Based on vegetation data gathered during our field survey, we identified at least eight distinct forest communities with hierarchical clustering methods. Using Sentinel-2 Multispectral Imager (MSI) satellite imagery and a balanced random forest classifier, we mapped land cover for six anniversary images from 2016 to 2021 to examine changes in vegetation distributions. Overall classification accuracies ranged from 80 to 86%, and we were able to accurately discriminate between several classes at the species level. Over our six year study period we did not observe any substantial changes in land cover, including the forest-marsh transition, suggesting resilience to tropical weather impacts. We postulate that this stasis may be due to the large volume of freshwater delivered by the Altamaha River and the extensive tidal marshes of the Altamaha estuary, which protect freshwater wetlands from the short-term effects of saltwater intrusion by reducing salinity and buffering them from acute pulse events such as hurricane storm surges.

INDEX WORDS: Altamaha River, community analysis, climate change, habitat mapping, hurricanes, plant ecology, remote sensing, satellite imagery, tidal freshwater forests, temporal change

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CHAPTER 1

INTRODUCTION

1.1 Overview of Tidal Fresh Forests

Tidal fresh forests are freshwater riparian ecosystems located between the upstream extent of tidal flooding and tidal fresh marshes downstream, where the effects of salinity are moderated by freshwater river discharge (Doyle et al. 2007). They are flooded at high tide by freshwater delivered by tidal forcing, the temporary displacement of fresh river water by the tidal pulse (Doyle et al. 2007). The effects of salinity are moderated by freshwater river discharge, and under normal conditions salinity remains below 0.5 parts per thousand (ppt) (seawater is ~35 ppt) (Doyle et al. 2007). Due to their low elevation, tidal influence, and limited tolerance for salinity, these species-rich ecosystems are threatened by climate change (Grieger et al. 2020). If tidal fresh forests cannot maintain their elevation relative to sea level, rising sea levels can cause them to transgress inland or permanently replace tidal fresh forests with herbaceous brackish or salt marsh vegetation if accommodation space is not available (Carr et al. 2020).Moreover, even intermittent pulses of salinity can have adverse long-term effects on forest health (Anderson et al. 2013). Mortality from windthrow (treefall due to wind) and saltwater intrusion will likely increase with more frequent and intense tropical storms linked to anthropogenic global warming (Sharma et al. 2021).

The importance of tidal fresh forest ecosystems is widely recognized (Barendregt and Swarth 2013; Duberstein and Kitchens 2007; Grieger et al. 2020; Smart et al. 2020), but numerous researchers have characterized tidal fresh forests as understudied compared to salt marshes or non-tidal riparian ecosystems (Anderson et al. 2013; Craft 2012; Doyle et al. 2007;

Duberstein et al. 2014; Grieger et al. 2020; Huylenbroeck et al. 2020). Doyle *et al*. (2007) suggest that tidal fresh forests are understudied because they were altered or destroyed by human activities such as logging and drainage prior to scientific study, and because large areas remain under active management. The remaining tidal fresh forests are valuable ecosystems. Tidal fresh forests are more productive than upland forests, and sequester more than three times the amount of carbon per hectare: 22 to 75 g C m^{-2} yr^{-1} for tidal fresh forests (Craft 2012) compared to 0.7 to 13.1 g C m^{-2} yr^{-1} for temperate upland forest (Mcleod et al. 2011). In addition, tidal fresh forests are highly biodiverse, providing habitat to many protected species (Stevenson and Chandler 2017). Tidal fresh forests provide many valuable ecosystem services, from nutrient removal through water filtration to flood protection to buffering coastal areas against the impact of tropical storms. While most research on coastal ecosystems and climate change has focused on saline tidal marsh ecosystems (Grieger et al. 2020), tidal fresh forest vegetation patterns are equally dependent on species salinity tolerances (Krauss et al. 2007). Prior studies have explored the physiological and ecological responses of tidal fresh forests to saltwater intrusion and sea level rise at localized study areas (Anderson et al. 2013; Duberstein et al. 2020; Pivovaroff et al. 2015; Sharitz and Lee 1985). To date, however, relatively few have taken advantage of the potential of synoptic remote sensing to map tidal fresh forest extent and vegetation species distributions (McCarthy et al. 2021; Riegel et al. 2013; Shaffer et al. 2009; Smart et al. 2020; Ury et al. 2021; White Jr and Kaplan 2021).

The Georgia coast is home to approximately 38,445 hectares of tidal fresh forest (U.S. Fish and Wildlife Service 2014). On tidal fresh forests of the lower Altamaha River, Georgia, where this study is focused, the effects of climate change are compounded by an extensive network of dikes and drainage ditches constructed for logging and rice cultivation, which enable salt water to penetrate further inland (Poulter et al. 2008). Several previous studies have explored the community composition of Georgia's tidal fresh forest (Duberstein et al. 2014) and their response to climate change (Craft 2012) at select sampling locations but have yet to undertake large-scale vegetation mapping and monitoring of the effects of sea level rise and tropical storms. Remote sensing-based studies, such as this project, can have significant advantages over conventional field studies for scaling and assessing the impacts of extreme events by allowing rapid, comprehensive coverage of large areas. (Ury et al. 2021).

1.1.1 Tidal Fresh Forest Ecology

Tidal fresh forests can be found at the terminus of many rivers but are most abundant where large rivers flow across relatively flat coastal plains and meet coasts with high tidal ranges (Doyle et al. 2007). These conditions can be found throughout the Southeastern United States, where there are more than 200,000 hectares of tidal fresh forest (Doyle et al. 2007). Inundation and salinity are the two main drivers of community composition within tidal fresh forests (Doyle et al. 2007). The mixture of fresh and brackish water creates an ecosystem characterized by a mix of plant species typical of both freshwater and estuarine wetlands (Craft 2012). Within this transition zone, the distribution of tidal fresh forest species is highly dependent on fresh water delivered by the river to buffer against tidal action. In drainages with lower volumes of river discharge, estuarine wetlands are more abundant (Mitsch and Gosselink 1993). Tidal fresh forests exist on a continuum from relict forests at the margins of tidal marsh to healthy forests upstream flooded by fresh water delivered by tidal forcing (Doyle et al. 2007). Coastal ecosystem distributions are dependent on elevation and river distance, as these determine the frequency and depth of inundation (Flitcroft *et al*. 2018). The effects of global warming on tidal fresh forest (e.g., sea level rise, saltwater intrusion, storm frequency and strength) are expected to be the most severe at the downstream margin at the forest-marsh interface where elevations are lowest and tidal influence strongest (Carr et al. 2020).

Tidal fresh forest tree species are poorly adapted to salinity. Chronic exposure to 3-4 practical salinity units (psu) is enough to cause mortality in mature trees, and seedlings are even more sensitive (Duberstein et al. 2020; Shaffer et al. 2009). Salinity-induced osmotic stress reduces leaf area (Duberstein et al. 2020) and inhibits germination (Tully et al. 2019). Anderson et al. (2013) found that tidal forests had a higher density of small trees and increased mortality due to saltwater intrusion compared to non-tidal forests. Reduced leaf area and competition from tree seedlings create opportunities for salt-tolerant understory vegetation to become established, initiating the process of forest-marsh transition (Smart et al. 2020). Climate change will also cause changes in precipitation patterns (Arias et al. 2021), affecting the overland delivery of freshwater (Grieger et al. 2020). Given that many tidal fresh forest tree species depend on consistent seasonal flooding for seed dispersal and dry periods for germination, altered precipitation patterns could have a significant impact on sapling recruitment and regeneration (Sharitz and Lee 1985).

1.1.2 Threats to Tidal Fresh Forests

Tidal fresh forests are hydrologically complex, affected by the dynamics of river flooding, tidal pulses, precipitation, and groundwater. Because of their low tolerance for salinity, low elevation, and proximity to the ocean, exposure to salt water is the main threat to tidal fresh forest health (Anderson et al. 2013). Under ideal conditions, porewater salinity in tidal fresh forests remains below 5 psu, but most tidal forests are regularly exposed to pulses of higher salinity (Anderson and Lockaby 2007). Several interacting drivers contribute to the salinization of tidal fresh forests, including sea level rise, wind-driven overwash, drought, and hydrologic connectivity (Anderson and Lockaby 2007; Duberstein et al. 2020; Tully et al. 2019).

Globally, eustatic sea levels are rising due to melting ice sheets and thermal expansion of ocean waters, but local rates of sea level rise vary due to differences in vertical land motion, ocean circulation, and gravitational deformation (Arias et al. 2021; Sweet et al. 2022). The 3.25 mm yr^{-1} historical local rate of sea level rise in Georgia is slower than the current global rate of 3.7 mm yr^{-1} (Arias et al. 2021; Langston et al. 2021). While this rate is slower than the local rate of sea level rise at other tidal freshwater forests in the Southeastern U.S. (Doyle et al. 2010; Doyle et al. 2007), the outlook for tidal fresh forests in Georgia is not optimistic. One model of sea level rise on the Altamaha River projected that 24% of Georgia's tidal fresh forest could be converted to tidal freshwater and brackish marsh by 2100 (Craft et al. 2009). Even modest increases in sea level can have substantial effects on coastal wetlands by intensifying the effects of storm surges, tides, and erosion (Sweet et al. 2022).

The Georgia coast is regularly impacted by tropical weather systems (Bossak et al. 2014), and their strong winds, high precipitation, and storm surges can cause substantial ecological disruption (Svejkovsky et al. 2020). While increased precipitation can be beneficial, particularly in times of drought (Sharma et al. 2021), windthrow and saltwater overwash due to storm surges can be substantial sources of mortality in the short to medium term (Middleton and Souter 2016). Healthy bald cypress (*Taxodium distichum* [L] Rich.) -water tupelo (*Nyssa aquatica* L.) swamps are highly resistant to mortality from windthrow and flooding (Shaffer *et al*. 2009). However, mortality is much higher at salt-stressed sites (greater than 5.0 psu) where weakened root systems and a more open canopy increase the risk of windthrow (Doyle et al. 2007; Shaffer et al. 2009). Since 1851 when records began, 197 hurricanes have passed within 200 km of our study site, 14 of which made landfall in Georgia (Bossak et al. 2014; Landsea et al. 2015). Even storms which do not make landfall can still cause damage, as wind-driven tides and waves can extend more than 100 km from the storms center (Jackson 2010). At our study site, hurricane storm surges have caused short-term (days) spikes in salinity as high as 22 psu, far in excess of tidal fresh forest tolerance (Di Iorio 2018). The combination of high winds and astronomical tides can cause flooding events comparable to hurricane storm surges (Manda et al. 2014). Freshwater flushing from river flow or rainfall can ameliorate the effects of these pulses (Shaffer et al. 2009). However, repeated storm impacts can lead to chronically elevated soil salinity, ultimately causing tree mortality and forest-marsh transition (Doyle et al. 2007).

Droughts compound the stresses induced by all of these mechanisms. Georgia experienced six periods of drought between 1930 and 2000 (Jackson 2010), and climate modeling suggests that droughts are likely to increase in frequency and duration in the future (Ardón et al. 2013). In the estuaries of large rivers with high discharge, such as the Altamaha, river water is often stratified, with fresh water at the surface and a saltwater wedge beneath (Day et al. 2007). In periods of low river flow, this salt wedge penetrates further upstream, exposing freshwater ecosystems to increased salinity (Duberstein and Kitchens 2007). In areas that have already been exposed to some salinity, lower precipitation and river discharge reduce freshwater flushing, causing salts to concentrate in the soil (Langston et al. 2017). This process has been linked to tidal forest dieback and forest-marsh transition (Desantis et al. 2007).

The combination of punctuated extreme events (storm surges and wind tides) and chronic stress (droughts and sea level rise) can accelerate rates of forest retreat in the ‘ecological ratchet’ model (Carr et al. 2020). Kearney et al. (2019) found that saltwater intrusion due to sea level rise creates chronically stressful conditions, reducing the health of mature trees and preventing seedling recruitment. This creates “zones of persistence” in which mature trees can survive, but the forest is unable to regenerate (Kearney et al. 2019). Subsequent extreme events can cause mortality of both mature trees and saplings within this zone via windthrow and flooding (Kearney et al. 2019). Thus, tree mortality from extreme events can lead to forest retreat in advance of substantial increases in sea level (Kearney et al. 2019). It is essential, therefore, to develop an understanding of the impacts of tropical storms on tidal fresh forest in addition to the role of sea level rise. As hurricane storm surges and wind tides can cause increased inundation and salinity, shifts in vegetation may occur within transition zones following a storm event (Raabe and Stumpf 2015). Few studies have explored whether remote sensing using moderate resolution sensors such as Sentinel-2’s Multispectral Instrument (MSI) and Landsat Operational Land Imager (OLI) or Enhanced Thematic Mapper + (ETM+) can detect whether these pulses of salinity lead to a permanent shift from tidal fresh forest to tidal marsh habitat (Ury et al. 2021).

The threat to the Altamaha’s tidal fresh forest from climate change is compounded by centuries of environmental alteration. In Georgia and the Carolinas, rice cultivation in the 18th and 19th centuries involved the construction of complex systems of dikes and ditches to control water flow (Wharton et al. 1982). Decades or centuries after being abandoned, these anthropogenic features continue to have effects. In coastal areas with little topographic relief, water flow is dominated by wind and tidal forces (Poulter et al. 2008). Because of their linear form, canals and ditches have greater fetch (the maximum continuous distance of water surface over which wind can blow) than more sinuous natural tidal channels, which amplifies the effect of wind tides (Doyle et al. 2007; Manda et al. 2014). Ditches and canals also increase flow during regular tidal pulses and extreme weather events (Kirwan and Gedan 2019). Finally, beginning in the earliest stages of European colonization, large areas of Eastern North America’s tidal forests were logged for their valuable timber, especially bald cypress (Wharton et al. 1982). Of the estimated 21 million hectares of both tidal and non-tidal riparian forests extant before European colonization, only 4.9 million hectares survived by 1991 (Mitsch and Gosselink 1993). In Georgia, less than 40,000 hectares remain, including salt-stressed areas transitioning to marsh (U.S. Fish and Wildlife Service 2014).

Forest to marsh transition is often irreversible. As trees die and their roots decompose, erosion and subsidence increase, exposing previously forested sites to flooding and salinity regimes that prevent tree seed germination and sapling recruitment (Baldwin 2007; Desantis et al. 2007; Krauss et al. 2007). Damage to this ecosystem is especially concerning given tidal fresh forest's disproportionately high carbon sequestration capacity (Smart et al. 2020). Loss of carbon-sequestering coastal ecosystems (blue carbon) is of global concern, because as tidal fresh forests decline, they can become net producers of greenhouse gasses, including carbon, methane, and nitrous oxide (Martinez and Ardon 2021; Mcleod et al. 2011). Considering the ecological effects of the loss of tidal forests, it is essential to effectively monitor these habitats at multiple spatial and temporal scales.

1.1.3 Remote Sensing Approaches

Remote sensing-based classification of forests is commonplace, and methodologies are diverse and well-developed (Boyd and Danson 2005). The details of plant classification techniques vary but typically rely on exploiting differences in spectral reflectance. Physical properties such as pigmentation, cell structure, and canopy structure create distinct spectral absorption and reflectance features for each species (Asner 1998). Additionally, spectral band ratios (vegetation indices) using specific wavelengths can be used as proxy measures of plant health and biomass, with the Normalized Difference Vegetation Index (NDVI) being one of the most common metrics (Svejkovsky et al. 2020). Numerous other vegetation indices have been developed that highlight different characteristics of vegetation or compensate for certain atmospheric and environmental conditions (Lillesand et al. 2015). Historically, high-spatial and low-spectral resolution aerial orthophotography has been used for land cover mapping on an annual or biennial (or less frequent) basis, but the deployment of satellite sensors with moderate to high-spatial-resolution multispectral sensors offers a potent tool for large-spatial scale studies (Boyd and Danson 2005). The use of drone (unmanned aerial vehicle (UAV)) technology is increasingly widespread in forestry and ecological research, offering centimeter-scale spatial resolution and, depending on the sensor used, between 3 and 8 spectral bands (Nezami et al. 2020). However, area coverage is low compared to satellites, and temporal resolution is dependent on revisit frequency to the study site (Takahashi Miyoshi et al. 2020).Light detection and ranging (LiDAR) elevation data are widely used in combination with data from optical sensors (Huylenbroeck et al. 2020). Because wetland plant community distributions are so closely correlated with elevation (Flitcroft et al. 2018), digital elevation models (DEM) can be used as input for vegetation classification (Alexander and Hladik 2015; Hladik et al. 2013). In addition, canopy height and structure derived from topographic LiDAR point clouds can be used to discriminate between vegetation types (Smart et al. 2020) and, in some cases, species (Brandtberg et al. 2003). Among the vegetation remote sensing literature reviewed, Random Forest (Breiman 2001) was one of the most common classification techniques used to map vegetation communities (Immitzer et al. 2012; Immitzer et al. 2016; Persson et al. 2018; Smart et al. 2020; Sunde et al. 2020; Takahashi Miyoshi et al. 2020; Ury et al. 2021). Random Forest is a machine learning classifier that is relatively easy to set up, produces high accuracy classifications, and performs well with small training data sample sizes (Immitzer et al. 2016).

Thirty-meter spatial resolution Landsat satellite data (Landsat 7, 8, and 9 are currently operational) provided at no cost by the U.S. Geologic Survey has been the standard for small-scale vegetation mapping for decades (Reese et al. 2002), but the launch in recent years of satellites with higher spatial and spectral resolution sensors such as the European Space Agency's (ESA) Sentinel-2 Multispectral Imager (MSI) and Maxar's Worldview-2 WV110 camera have enabled researchers to map forests with greater detail and accuracy (Immitzer et al. 2012; Immitzer et al. 2016; Persson et al. 2018). When Reese et al. (2002) mapped Wisconsin statewide vegetation cover using Landsat 4/5 Thematic Mapper (TM) data, they were only able to discriminate between broad vegetation classes containing multiple species (e.g., "coniferous forested/deciduous shrub wetland" or "upland coniferous forest") (Reese et al. 2002). The 10 m spatial resolution of Sentinel-2 MSI imagery allows species-level classification by reducing variation within each pixel (Persson et al. 2018). An additional advantage of Sentinel-2 MSI over Landsat 8/9 Operational Land Imager (OLI) is its improved spectral resolution. The MSI includes three additional bands in the red edge and near-infrared (NIR) spectral regions (720-790 nm), which have been shown to be important in vegetation mapping (Immitzer et al. 2016; Persson et al. 2018). Spectral reflectance for healthy vegetation typically peaks in the red edge/NIR due to leaf cellular structure and canopy density; thus, anatomical differences between species maximize spectral separability in this region of the electromagnetic spectrum (Lillesand et al. 2015). Because of its wider swath and two-satellite configuration (Sentinel-2A and 2B), Sentinel-2 has a five-day revisit time compared to 16 days for Landsat 8 (now eight days with the recent launch of Landsat 9 in 2021). This increases the number of cloud-free images available at a given location and facilitates time-change analyses (Svejkovsky et al. 2020). In combination, higher spatial and spectral resolution and a shorter revisit time make Sentinel-2 MSI ideal for moderate to large-scale vegetation mapping, and well-suited to this project.

While the literature for the remote sensing of non-tidal forests is extensive, tidal fresh forests are generally understudied; thus, remote sensing-based studies of these ecosystems are few. Most research to date has focused on the forest-marsh transition zone where the impacts of salinization are most apparent rather than looking at the entire extent of tidal forests (McCarthy et al. 2021; Riegel et al. 2013; Shaffer et al. 2009; Smart et al. 2020; Ury et al. 2021; White Jr and Kaplan 2021) Additionally, most studies focus either on biomass derived from LiDAR data or vegetation indices without classifying vegetation, or separate vegetation into broad classes composed of many species. Riegel *et al*. (2013)combined LiDAR data with four spectral band (visible to NIR) National Agricultural Imagery Program (NAIP) aerial photography to measure coastal forest biomass, but did not classify forest species. Smart *et al.* (2020) mapped dead (ghost) forests in North Carolina using LiDAR to quantify above-ground carbon storage. They classified ghost forests using Landsat 7 Enhanced Thematic Mapper + (ETM+) and Landsat 8 (OLI) data, but mapped only three general vegetation classes: forest, transition-ghost forest, and marsh. Shaffer *et al.* (2009) took a similar approach using a single Landsat 7 ETM+ scene to map broad ecological categories (e.g., “natural marsh” or “bottomland forest”). Through subsequent fieldwork, they determined the species compositions of each of these classes, but their data does not describe or map the distribution of each species within the forest.

Other studies have quantified biomass based on NDVI values. White and Kaplan (2021) used NDVI derived from low spatial resolution (250 m) MODIS data to study the effects of saltwater intrusion in coastal forests. Similarly, McCarthy *et al.* (2021) used NDVI in conjunction with a DEM and Landsat 5 (TM) and 8 (OLI) imagery to track forest dieback, but did not discriminate between vegetation communities beyond broad marsh and forest classes. The general ecological trends established by these studies are significant and noteworthy, but they do not fully exploit the potential of synoptic remote sensing. A moderate to high spatial resolution, species-level classification of tidal forests would help to bridge the gap between high spatial resolution studies of plant physiology and the existing low spatial resolution remote-sensing-based studies. Such a classification would give more detailed insights into forest-marsh successional dynamics, the potential impacts of tropical storms, and improve our ability to forecast ecological change. Different tree species have varying tolerance for inundation and salinity, meaning certain forest types may be more vulnerable to salinization (Field et al. 2016). Therefore, accurately mapping the full extent of tidal fresh forests at the species- or community-level is important to predicting future transgression and loss.

1.2 Study Site

Our study site is located on the central Georgia coast, near the mouth of the Altamaha River (81°28'49"W 31°21'39"N). The South Atlantic coast of the U.S. is composed of barrier islands of Holocene and Pleistocene origin, backed by estuaries with extensive tidal marshes (Anderson and Lockaby 2007; Jackson Jr 2010). In the estuaries of larger rivers, tidal fresh marshes and tidal fresh forests can be found upriver of brackish marshes (Anderson and Lockaby 2007). The Altamaha River is the longest undammed river in the eastern U.S., and the largest in the state of Georgia (Jackson Jr 2010; Stevenson and Chandler 2017). In total, the Altamaha watershed drains 3.6 million hectares, 23% of the state of Georgia (Stevenson and Chandler 2017). The main tributaries of the Altamaha, the Oconee and Ocmulgee rivers, originate in the foothills of the Appalachian mountains (Higinbotham et al. 2004). From the confluence of these two rivers, the main stem of the Altamaha runs 220 km through the coastal plain to its mouth on the Georgia Bight (Higinbotham et al. 2004). The Altamaha estuary has a semi-diurnal tide cycle with an amplitude of approximately 2 m (Higinbotham et al. 2004). Head of tide is 54 km from the river mouth, but the large volume of freshwater discharge (393 $m^3 s^{-1}$) typically prevents salinity from reaching further than 20 km upstream (Doyle et al. 2007; Higinbotham et al. 2004; White and Alber 2009).

The soils of tidal fresh forests vary with elevation, hydrology, and vegetation cover, but are less well characterized than upland soils (Anderson and Lockaby 2007)., The most common soil type in our study area is described only as “Swamp”, a type of fluvaquent, which covers 34.8% of the study area (NRCS 2021). In general, tidal fresh forest soils are anaerobic and high in organic matter (up to 15.5% carbon) (Anderson and Lockaby 2007; Craft 2012). Inorganic soil components are mainly sand and silt (Craft 2012). Fulton Ridge, a feature formed by remnants of Pleistocene-era aeolian dunes, extends into the northern part of our study area (Wharton et al. 1982). Its soils are infrequently flooded sands, sandy loams, and clay loams (NRCS 2021).

Our study site encompasses a variety of ecosystems, ranging from scrub oak sandhill communities to tidally flooded mesohaline marsh (Figure 1.1). Brackish and tidal fresh marsh vegetation are primarily giant cutgrass (*Zizaniopsis miliacea* Michx.), black needlerush (*Juncus roemerianus* Scheele), and big cordgrass (*Spartina cynosuroides* [L.] Roth) (Higinbotham et al. 2004). This project focuses on the tidal fresh forest ecosystem. Tidal fresh forest vegetation in Georgia are dominated by water tupelo, swamp tupelo (*N. biflora* Walt.), and bald cypress, interspersed with sweetgum (*Liquidambar styraciflua* L.), red maple (*Acer rubrum* L.) and water oak (*Quercus nigra* L.) (Craft 2012; Duberstein and Kitchens 2007; Duberstein et al. 2014).

Flood-tolerant tree species are largely excluded from upland areas due to competition from more vigorous upland vegetation (Beane 2020). Within the floodplain forest, changes from one plant community to another are driven by small local changes in elevation (Wharton et al. 1982), which strongly impacts flooding frequency and duration. All these species have some degree of flood tolerance, but bald cypress is the best adapted to inundation, with established trees capable of growing in permanently flooded conditions (Beane 2020). Bald cypress, together with water tupelo and swamp tupelo, are generally restricted to near-permanently inundated floodplain habitats (Sharitz and Lee 1985). Water oak and sweetgum can tolerate intermittent flooding and are found at the margins of the floodplain or suitably high-elevation microsites within it (Sharitz and Lee 1985).

Species salinity tolerance is variable as well. Mature bald cypress trees can tolerate chronic salinity of 3-4 psu but may experience mortality in times of drought when salinity increases (Duberstein et al. 2020). Tupelo are more sensitive. Duberstein *et al.* (2020) found that water tupelo were completely absent at sites exceeding 2.2 psu. Red maple and oak species have even lower salinity tolerance (Middleton and Souter 2016). Saplings of all species are less robust than mature trees, and even infrequent pulse-type salinization events, such as a storm surge, can cause sapling mortality (Tully et al. 2019). Upland areas are predominantly managed forests of pine (*Pinus* spp.) and oak (*Quercus* spp.). The entire Altamaha River study area was logged at one time in its history, and active forest management continues in upland areas (Wharton et al. 1982). Selective logging of bald cypress for its rot-resistant wood has changed the makeup of the tidal forests, increasing the abundance of water tupelo, as it occupies a similar elevation range (Wharton et al. 1982). Large areas on the lower Altamaha River were developed for rice cultivation between the late 17th and mid-19th centuries (Odum et al. 1984). Some of these fields are still under cultivation, while others have been abandoned, reverting to a mixture of marsh and forest vegetation. However, the drainage ditches constructed to enable logging and rice cultivation remain and increase hydrologic connectivity, thus increasing the rate and extent of saltwater intrusion and nutrient leaching (Tully et al. 2019). At the same time, dikes around disused rice fields reduce drainage, which can concentrate and increase salinity (Herbert et al. 2015).

1.3 Hurricanes

Hurricane Matthew passed just off the Georgia coast on October 7, 2016, as a Category 2 hurricane, with sustained winds of 65 knots (kt) and gusts to 83 kt (Stewart 2017) (Figure 1.2). Matthew delivered 43 cm of rain and record-setting flooding of 1.5 m above mean high high water (MHHW) level at the Fort Pulaski, Georgia, National Ocean Service (NOS) gauge (Station ID: 8670870) (Stewart 2017). The Fernandina Beach, Florida NOS gauge (Station ID: 8720030) recorded inundation 1.3 m above MHHW (Stewart 2017). One year later, Hurricane Irma, by then downgraded to a tropical storm, passed through southwest Georgia on October 17, 2017, bringing sustained winds of 41 kt, gusts to 61 kt, 12-25 cm of rain, and flooding of 1.4 m above MHHW at the Fort Pulaski NOS gauge (Cangialosi et al. 2018), and 1.2 m to the Fernandina Beach gauge (Cangialosi et al. 2018)(Figure 1.3). Although Hurricane Irma's wind speeds were lower Hurricane Matthew's, higher tides and onshore winds during the storm resulted in the highest storm surge recorded for the central Georgia coast (Alber et al. 2019). A Georgia Coastal Ecosystems Long Term Ecological Research (GCE LTER) water monitoring station on the Altamaha River recorded high water levels for two days, and salt water penetrated over 30 km upstream into the tidal fresh forest (Figure 1.3) (Di Iorio 2018).

1.4 Overview of Thesis

The overall goal of this project is to map the species distribution of tidal fresh forest on the Altamaha River, GA, and examine the effects of hurricanes Matthew (10/2016) and Irma (10/2017) on vegetation by conducting a time change analysis focused on the forest-marsh transition zone. Classification of multiple image dates before and after these hurricanes will enable us to assess the nature and extent of changes in tidal fresh forest health and distribution. These goals are summarized by the following objectives:

Chapter 2 focuses on the characterization of tidal fresh forest plant communities and species associations using hierarchical clustering of ground reference data to categorize training data for image classification.

Chapter 3 describes the classification of current tidal fresh forest distributions using recent Sentinel-2 MSI satellite imagery and the Random Forest classifier and assesses the importance of variables (spectral reflectance, elevation, vegetation indices) in mapping plant community distributions.

Chapter 4 uses classified time-series imagery and applies temporal change analysis to quantify the effects of hurricanes Matthew and Irma on habitat distributions.

Under the imminent threat of sea level rise, large-scale monitoring of coastal ecosystems is of paramount importance. Remote sensing-based approaches offer the ability to survey large study areas at low cost. This project will fill significant gaps in the literature and understanding of how tidal forests respond to sea level rise and extreme weather events. The development of an accurate remote-sensing classification methodology for tidal fresh forests that could be applied to the entire Georgia coast would greatly improve our ability to monitor this sensitive ecosystem. Additionally, this classification could be used to estimate biophysical parameters (e.g., biomass) and model the impacts of sea level rise, thus permitting large geographic-scale studies of forest productivity and carbon storage, factors which are both expected to be negatively impacted by climate change (Smart et al. 2020).

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1.6 Tables and Figures

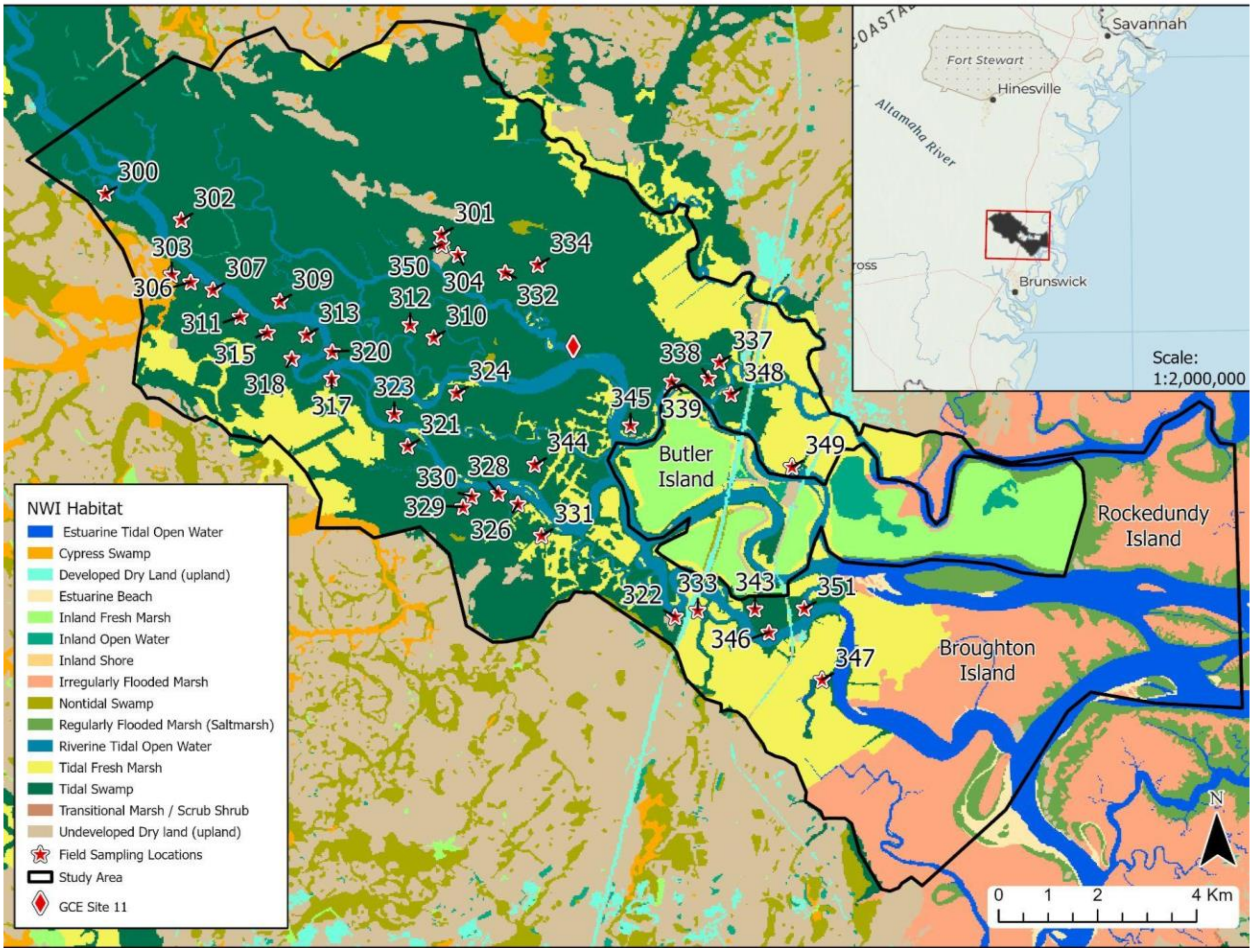

Figure 1.1 Study area (black outline) and field sampling plot locations (stars) on the Altamaha River, Georgia. National Wetlands Inventory (NWI) habitat classes are shown, which represent the best existing map of vegetation distributions for our study area. Also shown is the location of the Georgia Coastal Ecosystems (GCE) Long Term Ecological Research (LTER)Site 11 (diamond), where the water depth and salinity instruments referenced in Figure 1.3 are located, and it is the site of some prior research on tidal fresh forests.

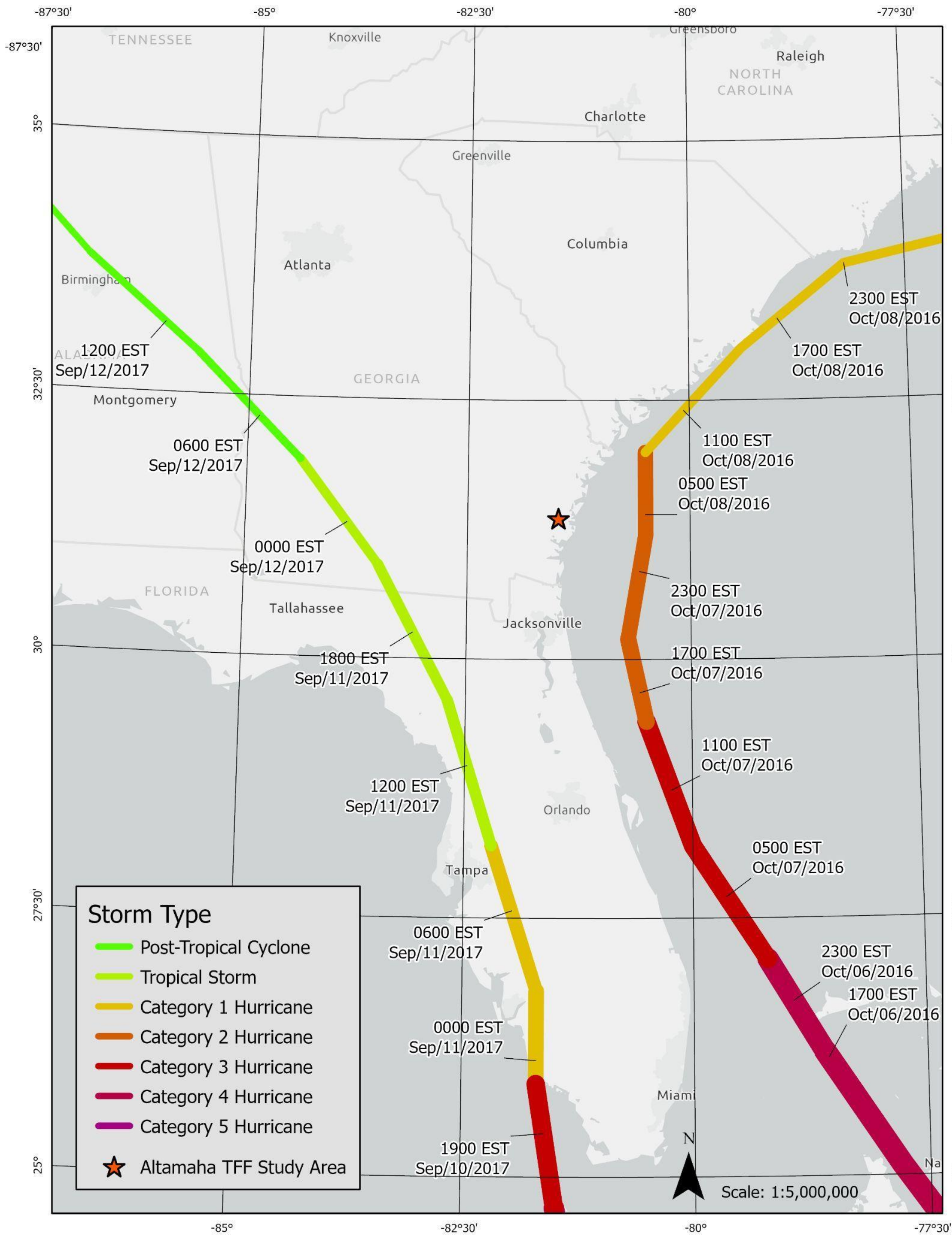

Figure 1.2 Hurricane track positions obtained from the National Hurricane Center of Hurricane Matthew (2016) and Hurricane Irma (2017) relative to our study site on the Altamaha River, GA (star).

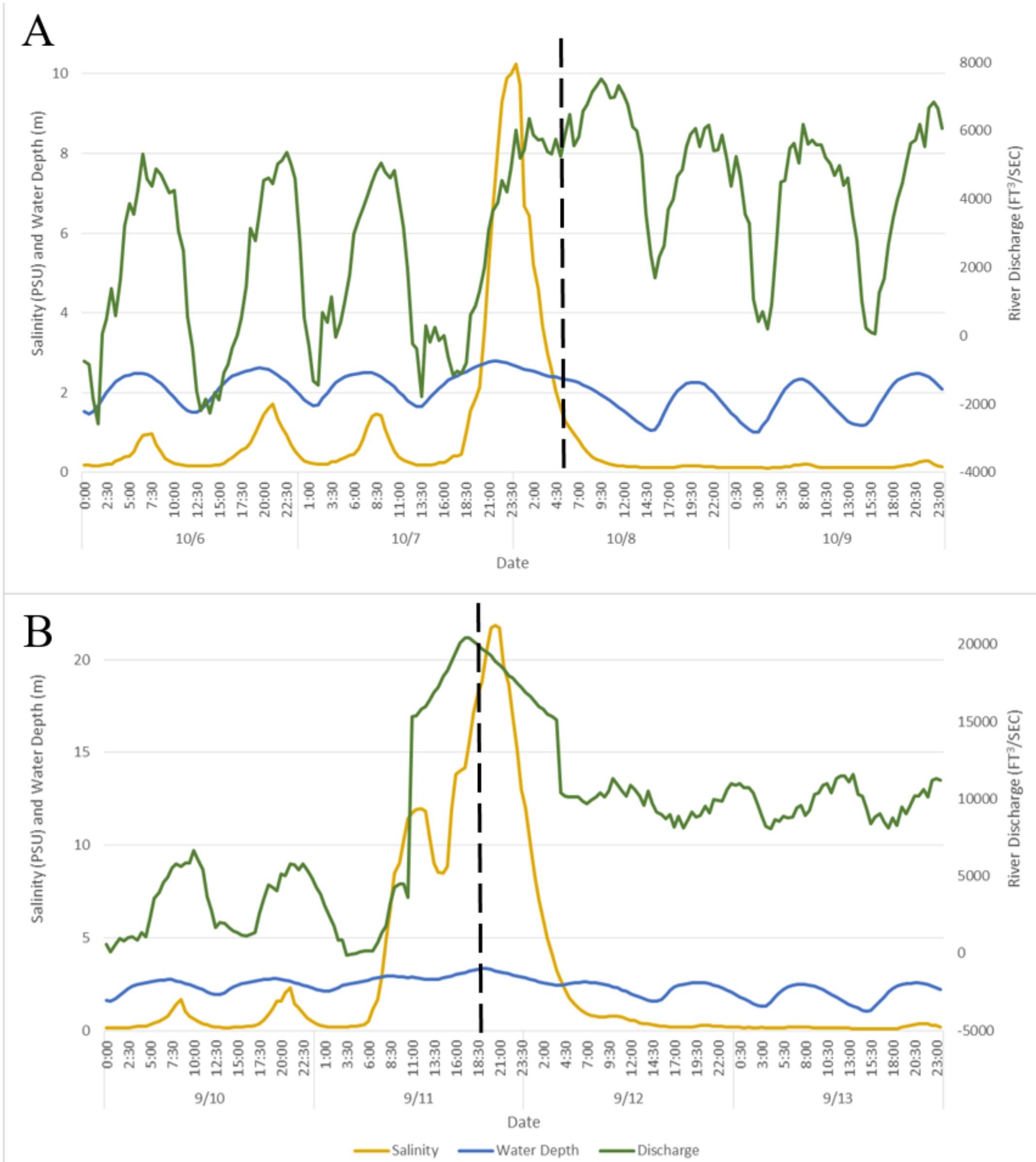

Figure 1.3 Water depth (blue line), volume of river discharge (green line), and salinity (orange line) at GCE Site 11 in the Altamaha tidal fresh forest before and after Hurricane Matthew (2016, A) and Hurricane Irma (2017, B). Salinity and water depth data are from a GCE sonde located at GCE Site 11 (Figure 1.1) (Di Iorio 2018). River discharge data is from the USGS gauge at Everett City, GA (Station ID 02226160), approximately ten river miles upstream of GCE Site 11 (U.S. Geological Survey 2022). The vertical dashed lines indicate the storm's nearest point of approach to our study site (see Fig. 1.2). Hurricane Matthew came within 93.5 km, and Hurricane Irma within 195 km.

CHAPTER 2

FIELD DATA AND PLANT COMMUNITY ANALYSIS

2.1 Introduction

Tidal fresh forests are widely recognized as important but understudied ecosystems (Anderson et al. 2013; Doyle et al. 2007; Duberstein et al. 2014). Because most tidal fresh forests have already been extensively altered and degraded (Conner et al. 2007), the relatively intact nature of the Altamaha tidal fresh forest makes it an ideal site. Although the lower Altamaha River has been subjected to the anthropogenic modifications typical for these areas (logging, drainage, diking, and rice farming) (Barendregt and Swarth 2013; Wharton et al. 1982), today, the Altamaha River tidal fresh forests are located within numerous United States Fish and Wildlife Service Wildlife Management Areas (WMA) and the domain of the Georgia Coastal Ecosystems Long Term Ecological Research (GCE LTER) site.

While the tidal marsh vegetation of the Altamaha is well studied (Higinbotham et al. 2004; White and Alber 2009), its tidal fresh forests are less well documented. Prior studies have examined Altamaha tidal fresh forest community composition (Duberstein et al. 2014; Stahl et al. 2018), soil properties (Craft 2012), and aboveground productivity (Stahl et al. 2018). However, these studies were limited in spatial extent, confined to areas at or upstream of GCE LTER Site 11 (31.378508 N, -81.496112 W), the only tidal fresh forest site examined by the GCE LTER (Figure 1.1). No prior studies have attempted to map the full extent of tidal fresh forest on the Altamaha River across the full range of tidal influence, brackish to fresh. The objective of this chapter is to document the composition of the Altamaha tidal fresh forest and to identify forest communities that can be applied to subsequent remote sensing analyses. Tidal fresh forest plant communities and species associations were identified through hierarchical clustering and additional multivariate statistical analyses of ground reference data.

2.2 Field data collection

Ground reference data were collected at thirty-eight 500 m^2 circular vegetation plots between 15 May and 12 June 2021 (Figure 2.2). Plots were distributed using a stratified random technique based on a preliminary classification of Sentinel-2 Multispectral Imagery (MSI) satellite imagery with five major forest classes: tupelo, pine, bald cypress, bald cypress/tupelo, and salt-stressed transitional forest (described in Section 2.3.1). Fifty potential plot locations were generated using ArcGIS Pro 2.9.2 (www.esri.com), of which only 38 were sampled due to time and logistical constraints. We navigated to each plot using a Garmin eTrex 30 GPS (www.garmin.com), which was used to record plot location accurately to within +/- four meters. At each plot center, we recorded a general site description, took photographs, and measured percent canopy coverage using a canopy densiometer (Forest Densiometers, Marianna, FL). Following the methodology of Anderson et al. (2013), for all trees greater than 2.5 cm in diameter at breast height (DBH), we measured height using a laser hypsometer (Nikon Inc., Melville, NY) and DBH with a diameter tape, identified them to species where possible, and assessed their height and whether their crown reached the canopy. Additionally, general vegetation health was noted (e.g., healthy, stressed, dead).

2.3 Forest Community Analysis

2.3.1 Plot-level Vegetation Composition

Plot-level species diversity and abundance were initially described by computing species importance values (IV) following the method used by Duberstein et al. (2014). IV ranges from 0 to 1 and was calculated as$[(Relative\ Density\ +\ Relative\ Dominance)/2]$, where relative density is the sum of species density (trees/ha) divided by the sum of total density, and relative dominance is the sum of species basal area (m^2/ha) divided by the sum of total basal area. IV provides a good summary of the relative influence of each species on the overall composition of a plot (Curtis and McIntosh 1951).

Prior to hierarchical clustering, raw plot data were summarized by calculating the total basal area for each species per plot. Due to difficulty distinguishing between species in the field, all ash trees (*Fraxinus*) were combined at the genus level (Duberstein et al. 2014). Likewise, laurel oak (Quercus laurifolia Michx.) and water oak (Quercus nigra L.) were grouped into a single class, as they are commonly found together and are capable of hybridizing (Tobe 1998). Subsequent analyses can be sensitive to outliers, so tree species which occurred in fewer than 5% of plots were excluded (McCune and Grace 2002). Based on this criteria, 11 species were eliminated: water hickory (*Carya pallida* Ashe), swamp dogwood (*Cornus foemina* Mill.), American holly (*Ilex opaca* Aiton var. *opaca*), Yaupon holly (*Ilex vomitoria* Aiton), Southern magnolia (*Magnolia grandiflora* L.), white mulberry (*Morus alba* L.), Southern wax myrtle (*Morella cerifera* [L.] Small), Ogeechee tupelo (*Nyssa ogeche* W. Bartram ex Marshall), swamp chestnut oak (*Quercus michauxii* Nutt.), winged elm (*Ulmus alata* Michx.), and farkleberry (*Vaccinium arboreum* Marshall). Species abundance data (based on basal area) for the remaining trees were standardized using a Hellinger transformation, which consists of taking the square root of the row-standardized abundances. This transformation performs two important functions: it reduces the influence of rare species and is not susceptible to the double-zero problem, in which a species' absence from two sites erroneously increases their similarity (Legendre and Gallagher 2001).

In addition to tree species abundance data, an additional binomial variable was introduced to distinguish sites suffering from salinization, as assessed in the field based on tree morphology and herbaceous vegetation cover. Trees growing in soils with elevated salinity typically have reduced leaf and crown area due to osmotic stress, and this open canopy permits marsh vegetation to colonize the area(Duberstein et al. 2020). As this variable is based on a subjective assessment (we did not measure porewater salinity at our plots), we conducted all subsequent statistical analyses in parallel, one including the "stressed" variable and one based on relative abundance data alone.

2.3.2 Community Analysis

Distinct tidal fresh forest communities were identified and described using a variety of multivariate statistical analyses implemented in R version 4.1.0(R Core Team 2021). Initial grouping was performed via hierarchical clustering based on relative species abundance. Following clustering, specific plant communities were identified and described based on indicator species analysis following the method of Duberstein et al. (2014). Multi-response permutation procedures (MRPP) were used to test the significance of differences between these communities as an external validation of our clustering methodology. Finally, sample plot groupings were visualized in relation to environmental variables (elevation and longitude) using nonmetric multidimensional scaling ordination (NMDS). Each of these analyses is described in more detail below.

Hierarchical clustering is an agglomerative clustering technique. Each observation (in this case, each plot) starts as an individual cluster. It is then joined with the most similar plot with the goal of minimizing variation within groups and maximizing the differences between groups. Hierarchical clustering groups inputs based on similarity but permits the user to select the number of clusters after classification, a step called pruning. The overall strength of clustering produced by different distance metrics and linkage methods was evaluated using the *agnes* function from the R package *cluster* (Maechler et al. 2021). *Agnes* calculates the agglomerative coefficient (AC), the mean of the normalized distances at which each observation joins its cluster (Maechler et al. 2021). Higher values indicate stronger, more compact clustering. Distance measures and linkage methods were chosen which were most appropriate for the data, maximized AC, and gave the most reasonable ecological interpretation.

First, a Hellinger distance matrix was calculated for the transformed plot data using the *vegdist* function in the R *vegan* package (Oksanen et al. 2020). Using these distances, hierarchical clustering was performed using the *eclust* function in the package *factoextra* (Kassambara and Mundt 2020). Ward's minimum variance linkage was used, which groups clusters based on minimizing their Analysis of Variance (ANOVA) sum of squares (Milligan and Cooper 1985). In addition to clustering results, *eclust* computes several other informative statistics. The gap statistic estimates the optimal number of clusters by comparing the total intra-cluster variation for different numbers of clusters, *k*, with the expected values from a null reference distribution of the data (Tibshirani et al. 2001). The optimal number of clusters is generally that which maximizes the difference between the observed and expected variances.

The silhouette statistic assesses the overall quality of the clustering by measuring how well each observation fits into its assigned cluster. Values range from -1 to 1, with positive values indicating a good fit and negative values suggesting that the observation has been incorrectly classified. Finally, like *agnes*, *eclust* calculates the agglomerative coefficient (AC).

Following clustering, the resulting dendrogram was pruned at a range of pruning levels from 2-10. Following Duberstein *et al.* (2014), these cluster identities were used as categorical variables, and indicator species analysis was implemented independently for each clustering level with the *multipatt* function from the package *indicspecies* (De Câceres and Legendre 2009). This function calculates the indicator value index (IVI) for each species, which measures the strength of association between a species and each cluster or combination of clusters (Dufrêne and Legendre 1997). The IVI ranges from zero to one and is the product of two components: Component A (specificity) and Component B (fidelity) (Dufrêne and Legendre 1997). A species' specificity value is the probability that a particular plot belongs to a cluster, given that the species is found there (Dufrêne and Legendre 1997). Component A will equal one if a species is found only in sites belonging to a particular group. Fidelity is the probability of finding a species at plots belonging to that cluster (Dufrêne and Legendre 1997). Component B will equal one if a species is found at all plots belonging to a particular group. Together, these two statistics determine how diagnostic a species is of each group. The maximum IVI for each species in any group was taken as its value for all groups (Dufrêne and Legendre 1997). Significance was assessed by comparing actual values to randomized data produced by a Monte Carlo simulation with 1,000 iterations. Total *p* values for all species and the number of significant indicator species ($p<0.05$) were recorded for all clustering levels.

MRPP testing functions as a nonparametric alternative to ANOVA and tests for significant differences between plot groupings (McCune and Grace 2002). The test was implemented using the function *mrpp* from the *vegan* package (Oksanen et al. 2020). MRPP uses as input the transformed species abundance data and the cluster identities for each plot produced by hierarchical clustering. MRPP first calculates the mean within-group distance (δ) for each cluster, weighted by the number of plots in each cluster. As with hierarchical clustering, Hellinger distance was used. δ is then calculated for every possible partition of plots into clusters of the same size. The proportion of partitions for which the expected δ is less than the observed δ is calculated; this gives the *p*-value for the test. In addition to the overall probability, MRPP calculates within-group agreement (A), a measure of group homogeneity equal to$1 - \delta/E(\delta)$, where $E(\delta)$ is the expected mean within-group distance if species were grouped randomly. A will equal zero if there is no difference from a random distribution and one if all plots in a cluster have an identical species composition.

NMDS was performed with the *metaMDS* function from the *vegan* package (Oksanen et al. 2020) to determine the strength of the relationship between plot species composition and environmental variables. Each species is an axis in n-dimensional species space. *metaMDS* automatically finds the optimal number of dimensions by making multiple runs from randomized starts and selecting the result with the lowest stress. The function *envfit* (*vegan* package) was used to test the correlation between NMDS axes and two external environmental variables: longitude and elevation. Both elevation and longitude as a measure of river distance are environmental gradients that can influence plant species distribution (Anderson et al. 2013). Mean elevation for each plot relative to the NAVD88 vertical datum was calculated from a LiDAR-derived digital elevation model (DEM) of the study area with a horizontal spatial resolution of 2 m. The DEM was not corrected for vegetation bias. Longitude was based on the plot center coordinates recorded in the field with GPS and serves as a proxy for river distance. Ordination results were plotted in two dimensions, and environmental variables were visualized as surfaces using the function *ordisurf* (*vegan* package).

2.4 Results

2.4.1 Plot-Level Species Composition

Plot-level species composition varied considerably across our 38 plots. No single species occurred at every plot (Figure 2.3). Ash was the most widely distributed, occurring at 32 plots, followed by bald cypress (30 plots) and swamp tupelo (29 plots) (Figure 2.3). Pine was the least widely distributed of the eight most dominant species shown, occurring at just four plots. In two of those plots, however, it represented the majority of that plot's IV (Figure 2.3). Dominant species (the species with the highest IV in each plot) were also variable (Figure 2.3). Bald cypress was the most common dominant species (9 plots), followed by water tupelo, swamp tupelo, and Laurel Oak/Water Oak (6 plots each) (Figure 2.3).

2.4.2 Salt-Stressed Variable Parallel Analyses

Hierarchical clustering and indicator species analysis, both with and without the salt-stressed variable, produced similar results. Only results without the salt-stressed variable are included in this chapter. Salt-stressed results can be found in Appendix A. The community identities of 26 out of the 38 plots were unchanged in the salt-stressed analyses. Four communities (Oak/Hornbeam, Pine, Alder/Magnolia, and Live Oak) retained all the same plots (Table 2.1, Figure 2.4, and Table A1, Figure A1). The main difference with the inclusion of salt-stress was the loss of the Bald Cypress/Tupelo class and the emergence of distinct Stressed Cypress and Stressed Tupelo communities. Plots in these communities had previously been assigned to the Water Tupelo, Bald Cypress/Tupelo, Bald Cypress, and Swamp Tupelo communities. Reassignment of the salt-stressed plots, which were lower in diversity and overall abundance, generally increased mean basal area and density and decreased mean importance values for the communities they left. For instance, the mean IV of bald cypress decreased from 0.54 in the relative abundance only analysis to 0.45 in the salt-stressed analysis, while the mean basal area increased from 37.3 $m^2 \cdot ha^{-1}$ to 66.2 $m^2 \cdot ha^{-1}$. These differences lend credence to the salt-stressed analysis. Further changes are detailed in the community descriptions below.

2.4.3 Relative Abundance Only

Hierarchical clustering based on relative abundance alone, excluding the salt stress variable, produced a dendrogram with an AC of 0.83 (scale of 0 - 1), indicating relatively strong clustering (Figure 2.4). The average silhouette width was 0.24 (Figure 3). Following Duberstein *et al.* (2014), based on indicator species analysis, we plotted the number of significant indicator species and the total *p*-value for all species at each clustering level (Figure 2.5). Clustering levels with low total *p*-values and a high number of indicator species represent optimal pruning levels (McCune and Grace 2002). Based on these criteria, either six or eight clusters are possible. We chose to prune at eight clusters, as this gave the most reasonable ecological interpretation and agreed with the gap statistic (Figure 2.6). Subsequent MRPP and NMDS analyses provided additional support for this decision (Figure 2.7). Cophenetic distance measures how closely the dendrogram preserves pairwise distances compared to the original distance matrix. Our value is 0.68 (on a scale of 0 - 1), which indicates moderately high fidelity to the original distances.

Inspection of the dendrogram reveals clear ecological stratification based on species composition (Figure 2.4). The two highest-level clusters separate continuously or frequently flooded plots from seasonally flooded or upland plots. The former are occupied primarily by flood-tolerant species such as tupelo and bald cypress, while the latter have varying compositions of oak (*Quercus* spp.) and pine (*Pinus* spp.). Within these two broad categories, many species are widely distributed (Table 2.1), so subsequent groupings are dependent on relative abundance rather than presence-absence.

MRPP results indicated that these eight communities have significantly different species compositions, A=0.428, p=0.001, meaning that more than 40% of the variation in species composition could be explained by cluster identity. Mean within-group distance was 0.349, and mean between-group distance was 0.666.

NMDS ordination showed clear separation between groups of plots and strong environmental gradients (Figure 2.7). A two-dimensional solution was chosen as it provided an acceptably low stress score of 0.15 and optimal ecological interpretation (Clarke 1993). Both longitude and elevation were strongly correlated with both axes (Table 2.2).

Community descriptions of the eight groups determined based on hierarchical clustering and field descriptions of the study sites are described below.

1. Oak/Hornbeam

   Plots in this community were concentrated at the upstream extent of our study area (Figure 2.2). When we visited them in May 2021, some showed signs of having been recently flooded: the soil was muddy but drying, and pools of standing water remained in low areas. Various compositions of oaks (*Q. nigra, Q. lyrata* Walter, *Q. laurifolia* Michx.) are the dominant canopy tree, accounting for

34% of IV (Table 2.1). Canopy coverage was 96%, among the highest of all our communities. Hornbeam (*Carpinus caroliniana* Walter) is abundant in the understory, along with sweetgum, which occasionally emerges as a canopy tree. Plots in this community had the third highest average elevation, at 1.82 m above NAVD88, based on a DEM (Table 2.1). The abundance of large oak trees in this community gives it the greatest basal area of any community: 68 $m^2 \cdot ha^{-1}$ (Table 2.1).

2. Water Tupelo

   This community was prevalent in the backswamp further from the river banks (Figure 2.2). When we visited in May of 2021, they were flooded to depths of 2 - 10 cm. The canopy is almost exclusively water tupelo (36% of IV), with some bald cypress (13% of IV) (Table 2.1). Individuals of both species are generally mature and large in stature, with a maximum height of 35 m. Canopy coverage is complete (97%). The understory is sparse but mainly ash and sweetgum. Herbaceous ground cover is variable. In less deeply flooded areas, lizard's tail (*Saururus cernuus* L.) proliferates.

3. Bald Cypress/Tupelo

   This community was a mixture of bald cypress (25% of IV), water tupelo (16% of IV), and swamp tupelo (16% of IV), and was intermediate between the two tupelo and Bald Cypress communities in many respects (Table 2.1). These plots were located further upstream than those in the Bald Cypress Community (Figure 2.2). The greater abundance of tupelo resulted in a less open canopy (93% vs. 86% canopy cover) and greater stem density than the Bald Cypress community (1268 stems·ha^{-1} vs. 680 stems·ha^{-1})(Table 2.1). Understory and herbaceous vegetation were most similar to the Swamp Tupelo community. Ash (12% of IV) and sweetgum (7% of IV) were the most common understory trees, and lizard's tail was abundant in all plots (Table 2.1). Site flooding conditions were similar to those in the Swamp Tupelo and Bald Cypress communities, as all three of these communities were found within 1.0 to 1.1 m above NAVD88 (Table 2.1).

4. Pine

This community contains stands of pine trees in managed forests or, in one case, on a hill of earth left over from highway construction (Figure X). With 84% of IV, pine trees dominate almost to the exclusion of all other species, although sweetgum occurs as an understory tree or rarely in the canopy (Table 2.1). The pine trees are homogeneous in height and girth. Canopy coverage is complete (99%), and the underbrush is sparse, with occasional yaupon holly being the most common shrubs. Herbaceous ground cover is minimal. This community had the second-highest average elevation, at 2.17 m above NAVD88 (Table 2.1).

5. Swamp Tupelo

This was the most abundant community in our study area, typically occupying areas adjacent to the main channel of the river (Figure 2.2). The canopy is dominated by swamp tupelo (38% of IV), with sweetgum (10% of IV) and ash (23% of IV) occasionally emerging from the understory (Table 2.1). The abundance of these trees in the understory contributes to this community having the highest average density, at 1500 stems·ha^{-1}. A dense network of surface roots creates low hummocks where less flood-tolerant vegetation, such as dwarf palmetto or oaks, can establish. Ground cover is abundant, typically a mixture of lizard's tail and pickerelweed.

6. Bald Cypress

   These plots represent almost homogeneous stands of bald cypress (45% of IV). This community had one of the widest distributions along the tidal gradient and therefore included plots subjected to a wide range of salinity regimes. The presence of some salt-stressed plots in this community depresses values for basal area, density, and canopy coverage (see 2.4.2 and Appendix A). At most sites, swamp tupelo is sparsely present in the understory or canopy (17% of IV) (Table 2.1). Where trees are not subject to salt stress, the uniformly tall canopy and complete canopy closure largely exclude understory and underbrush species, but sweetgum and red maple are sometimes present. Ground cover is mainly lizard's tail, dwarf palmetto (*Sabal minor* [Jacq.] Pers.), and pickerelweed (*Pontederia cordata* L.).

7. Alder/Magnolia

   This community was represented by only one plot (Plot 331) (Figure 2.2), but we encountered several similar sites en route to other plots. The plot was on the margin of an abandoned rice field, now colonized by giant cutgrass and bisected by a tidal creek (Figure 2.2). Hazel alder (*Alnus serrulata* [Aiton] Willd.) and ash are the most common species, but sweetbay (*Magnolia virginiana* L.) was more abundant here than in any other community (16% of IV) (Table 2.1). The growth form of all species is small, branching, and shrub-like. Where trees grow, the canopy is dense, but the community is fragmented by stands of *Z. miliacea*, resulting in a mean canopy coverage of just 59%. This community had the lowest elevation at just 0.46 m above NAVD88 (Table 2.1).

8. Live Oak

   This community is present on several islands on the north bank of the Altamaha River and Lewis Creek (Figure 2.2). These islands are the remnants of Pleistocene sand dunes, and these soil conditions support a unique xeric plant community within the swamp (Wharton et al. 1982). This community had the highest elevation, at 6.5 m above NAVD88 (Table 2.1). The canopy is almost exclusively live oak (*Q. virginianus*), with 96% of IV (Table 2.1). The understory is a mixture of saw palmetto (*Serenoa repens* [W. Bartram] Small) and yaupon holly. Only one plot occurred in this community, but based on other reports and interpretation of aerial imagery, we believe it to be a valid community.

2.5 Discussion

This study examined the species composition of the Altamaha tidal fresh forest based on a field survey of 38 plots. Using hierarchical clustering and indicator species analysis, we identified eight distinct forest communities (Table 2.1). Species composition differed significantly from community to community based on MRPP analysis (A=0.428, p=0.001). Plot-level species composition was significantly correlated with elevation and longitudinal river distance (Figure 2.7, Table 2.2).

The tree species and ecological gradients we observed (Table 2.2, Figure 2.7) are consistent with existing descriptions of tidal fresh forests in the Southeastern United States (Anderson et al. 2013; Conner et al. 2011; Duberstein and Kitchens 2007; Duberstein et al. 2014;

Krauss et al. 2009). Bald cypress, swamp tupelo, and water tupelo are the dominant species at low-elevation sites (Table 2.1), a pattern documented in prior studies (Duberstein and Kitchens 2007; Duberstein et al. 2014; Krauss et al. 2009; Tiner 2013; Wharton et al. 1982). At higher elevations within the floodplain, oak, sweetgum, and other less flood-tolerant species increase in importance (Table 2.1, Figure 2.2) (Wharton et al. 1982). On uplands adjacent to the floodplain, forests are composed of flood-intolerant species such as pines and live oak (Table 2.1, Figure 2.2).

Additionally, the forest communities we identified through hierarchical clustering (Figure 2.4, Table 2.1) correspond in part with prior studies of tidal fresh forests in Georgia (Duberstein and Kitchens 2007; Duberstein et al. 2014). For example, our Water Tupelo and Swamp Tupelo communities appear to be homologous with classes of the same name identified by Duberstein *et al.* (2014), with similar species compositions and distributions of importance values. Water tupelo was the dominant species in our Water Tupelo community (IV of 0.43 on a scale of 0-1), followed by ash (IV of 0.16) (Table 2.1). In Duberstein et al.'s (2014) study, within their Water Tupelo community, water tupelo and ash are also the two most dominant species, with IV of 34.3 and 14.1, respectively (scale of 0-100) (Duberstein et al. 2014, Table 3). Basal area is also comparable, with our Water Tupelo community having 73 m^2/ha (Table 2.1) and theirs 70 m^2/ha (Duberstein et al. 2014, Table 3). This level of agreement gives us high confidence in our results for these classes. Stem densities for all of our communities are significantly lower than those observed by Duberstein and Kitchens (2014), but this is likely the consequence of different sampling methodologies and locations detailed below.

Unlike prior surveys of tidal fresh forests in the Southeast (Anderson and Lockaby 2011; Duberstein and Kitchens 2007; Duberstein et al. 2014), we identified two bald cypress-dominated communities: Bald Cypress and Bald Cypress/Tupelo (Table 2.1, Figure 2.4). Bald cypress is widely described as codominant with water tupelo in frequently or continuously flooded swamps throughout the Southeast (Larson et al. 1981; Tiner 2013; Wharton et al. 1982). In our fieldwork, we encountered numerous sites where bald cypress grows in nearly monospecific stands, but these areas were patchily distributed, possibly reflecting natural gradients and disturbance history (Wharton et al. 1982). Previous studies of tidal fresh forest communities on the Altamaha River sampled areas of the forest where bald cypress is less abundant (Duberstein et al. 2014; Stahl et al. 2018). Our field sampling sites were more widely distributed within the extent of tidal fresh forests in comparison to prior studies on the Altamaha River, and our use of stratified random sampling based on a preliminary classification enabled us to deliberately target bald cypress-dominated areas. Finally, because our field plots included upland areas adjacent to the tidal fresh forest, our community analysis identified several upland communities (Live Oak, Pine) not documented in previous studies (See Appendix B).

Some differences between our results and those of Duberstein et al. (2014) are likely due to differences in sampling methodology. Because our focus was on identifying communities detectable via remote sensing (canopy down view), vines, herbaceous vegetation, and other ground cover were excluded. For instance, the palms *Sabal minor* and *Serenoa repens* were abundant in some plots. However, unlike Duberstein et al. (2014), we grouped them with herbaceous ground cover, noting their presence and estimating their relative abundance without measuring individuals. Additionally, we only measured trees larger than 2.5 cm DBH, while Duberstein et al. measured all trees and shrubs greater than 1.4 m tall. These choices likely account for the disparity in stem density for otherwise similar communities.

As a result of the study design and purpose, our classification represents tree species communities with a focus on canopy and understory vegetation. While prior studies have placed greater emphasis on taxonomic detail across all strata (Duberstein et al. 2014), our classification's focus on dominant canopy species may lend itself better to long-term monitoring via remote sensing. The species and species associations identified in this study will be evaluated as habitat classes in subsequent analyses using remote sensing imagery. As noted by Duberstein et al. (2014), this type of community classification can be a valuable first step prior to remote sensing classification. Ideally, this community classification will enable us to produce a remote sensing-based classification that better reflects actual ecological gradients than a classification based only on spectral separability. One of the challenges of this approach, however, is that closely related taxa or communities (especially those with different ratios of the same species) may not be spectrally distinct enough to classify accurately (Schriever and Congalton 1995). In the next chapter, we will detail the process of applying this community classification to satellite remote sensing data to produce a detailed map of forest cover.

2.6 Conclusion

In conclusion, this study successfully identified eight tidal fresh forest communities using hierarchical clustering and supported by additional multivariate statistical analysis. These communities correspond well with prior characterizations of tidal fresh forests throughout the Southeastern U.S. Overall species distributions and the influence of environmental variables (elevation and river distance) were also consistent with existing studies. Compared to prior studies, our more widely distributed sample plots better represented the diversity of the Altamaha River tidal fresh forest and adjacent upland areas. The results of this study contribute to our understanding of the community and structure of the Altamaha River tidal fresh forests, a relatively understudied ecosystem. These results represent an important first step in anticipating and managing future threats from tropical storms and sea level rise.

2.7 References

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2.8 Tables and Figures

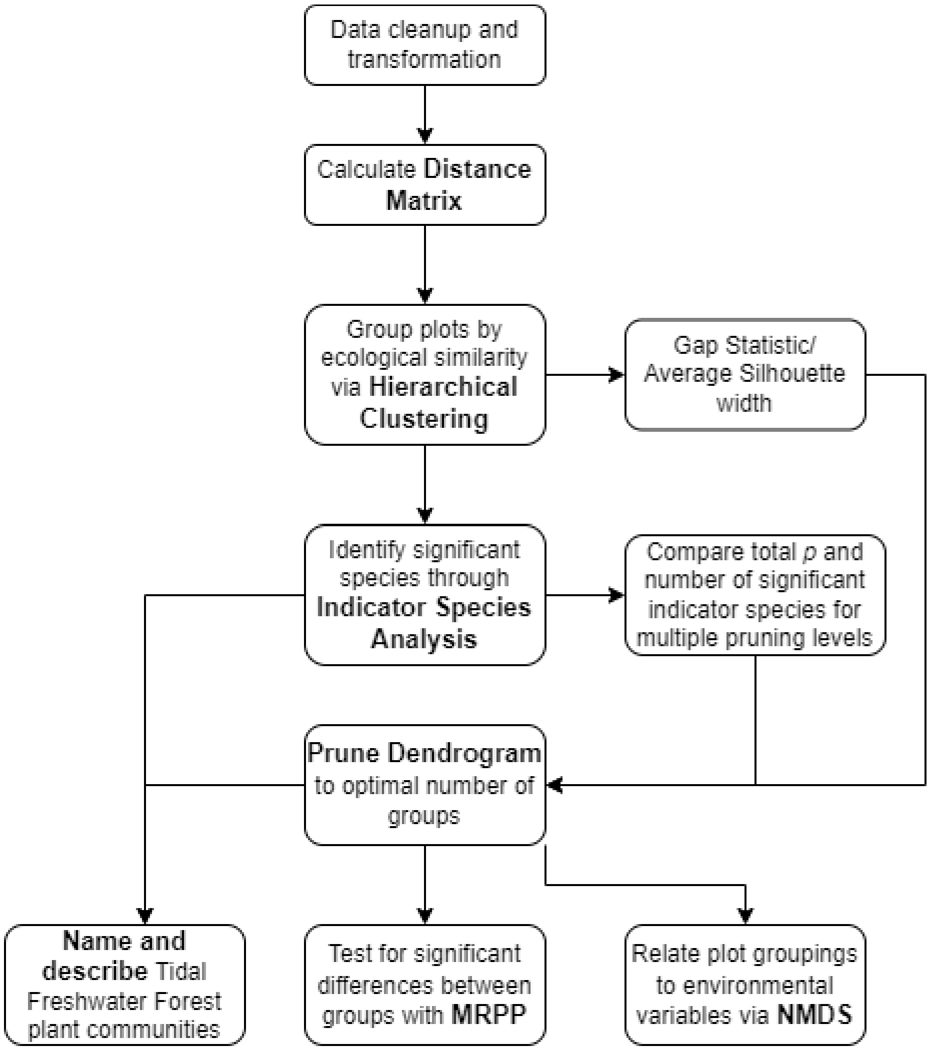

Figure 2.1 Workflow for our analyses of Altamaha River tidal fresh forest communities based on our ground reference data.

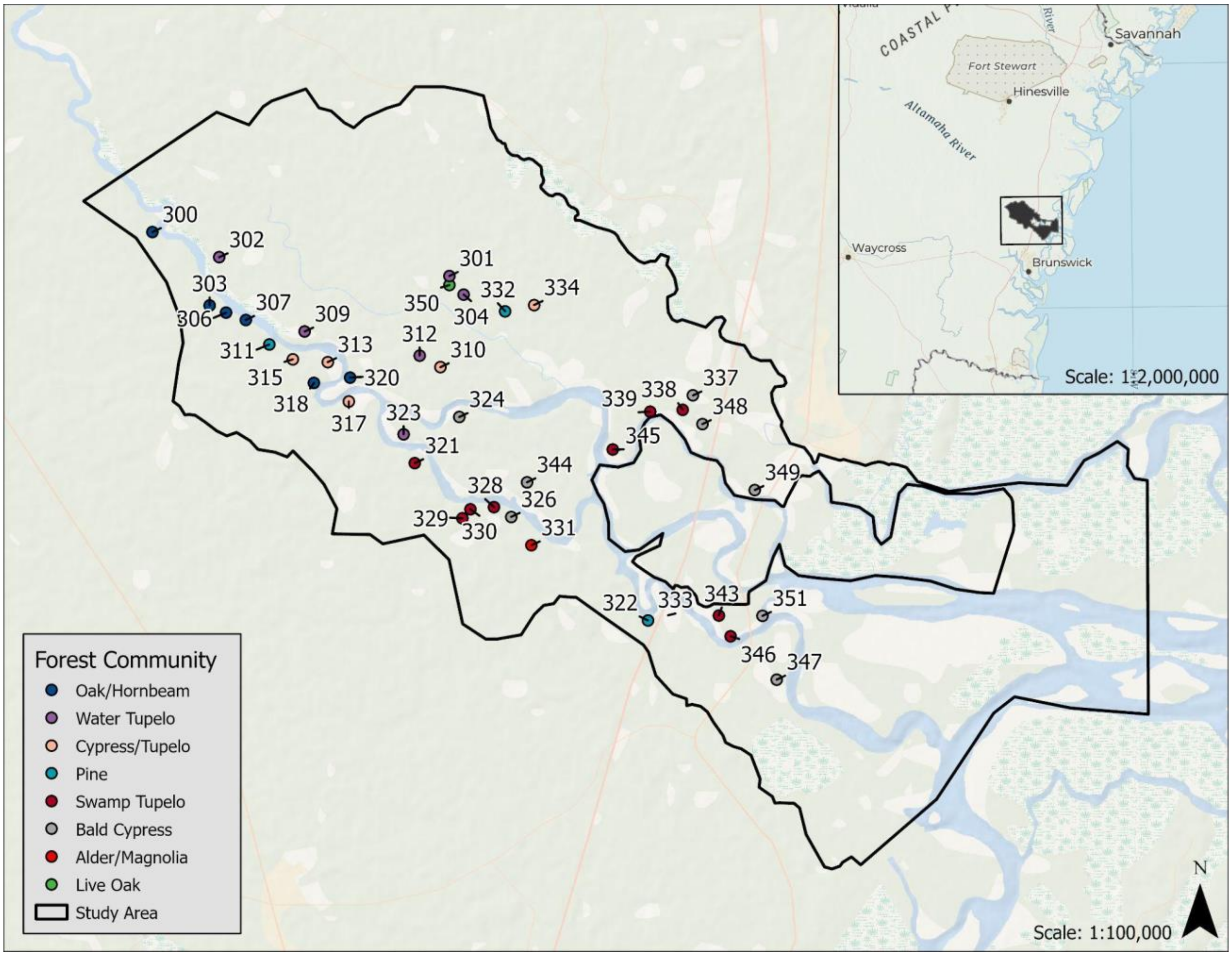

Figure 2.2 Location of our field sampling locations within our study area (black outline) on the Altamaha River, Georgia. Plots are colored based on the forest community to which they were assigned based on hierarchical clustering and indicator species analysis.

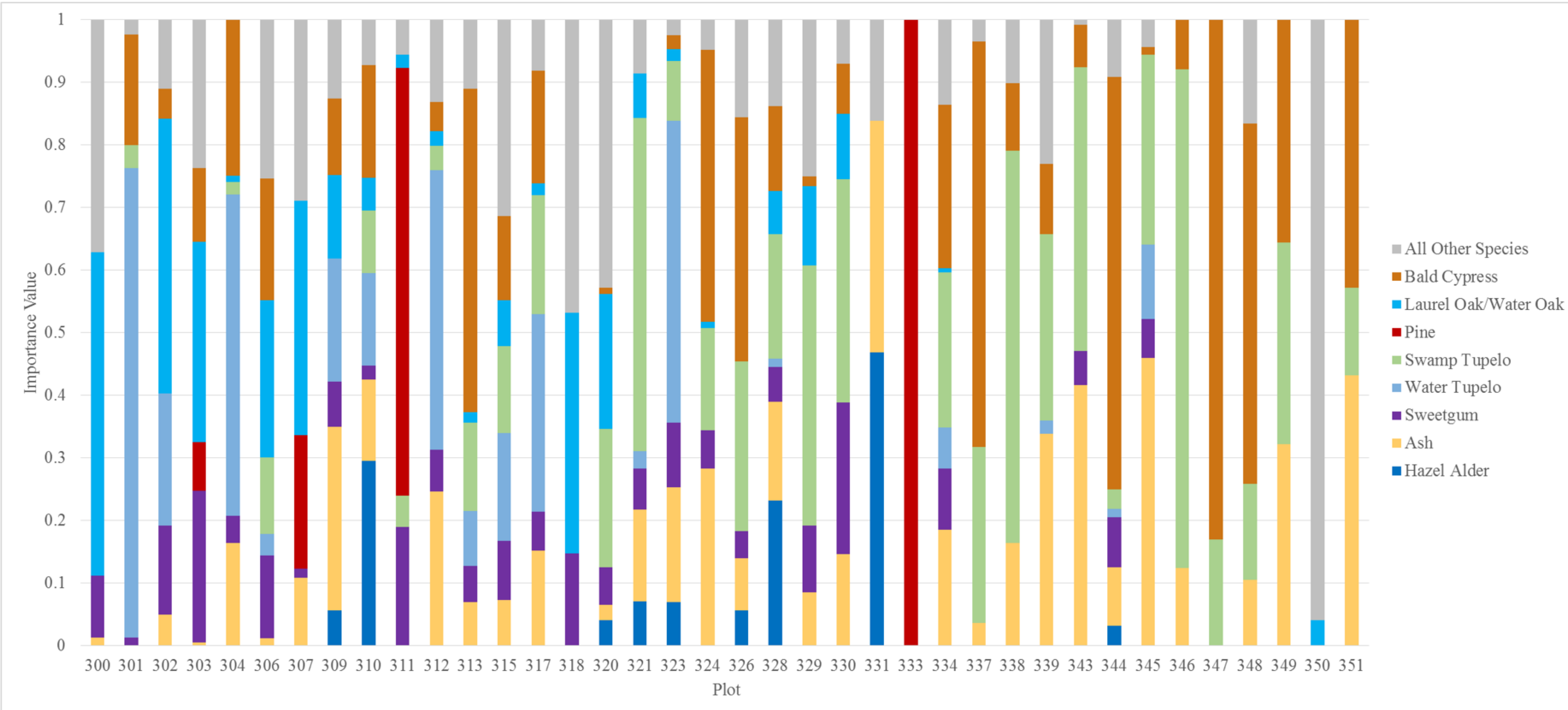

Figure 2.3 Plot-level importance values (IV) for our 38 sampling locations on the Altamaha River, GA. Bars represent the cumulative IV of all species in each plot. Only the eight species with the highest total IV across all plots are shown.

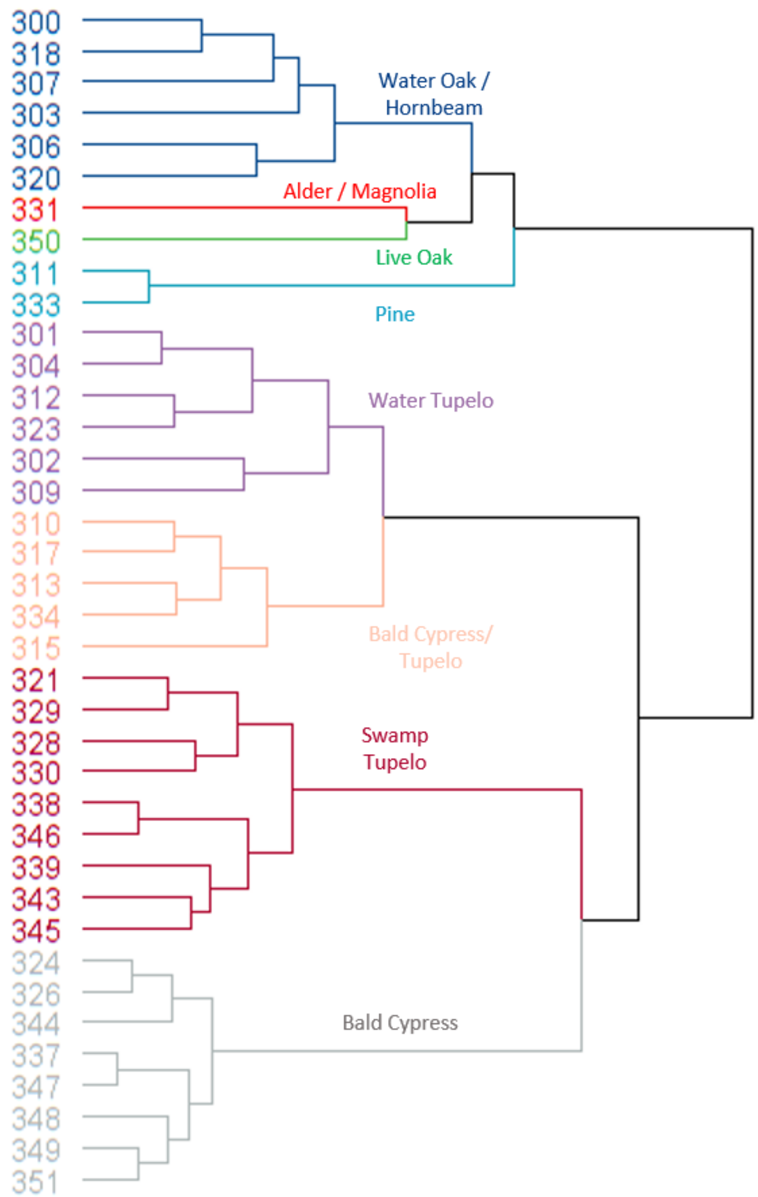

Figure 2.4 Dendrogram produced by hierarchical clustering using Hellinger distance and Ward linkage for 22 tree species from 38 plots in the Altamaha tidal fresh forest. This analysis was based on relative species abundance only. Plot names are listed on the left, and community names are given for each of the eight groups, with pruning indicated by color.

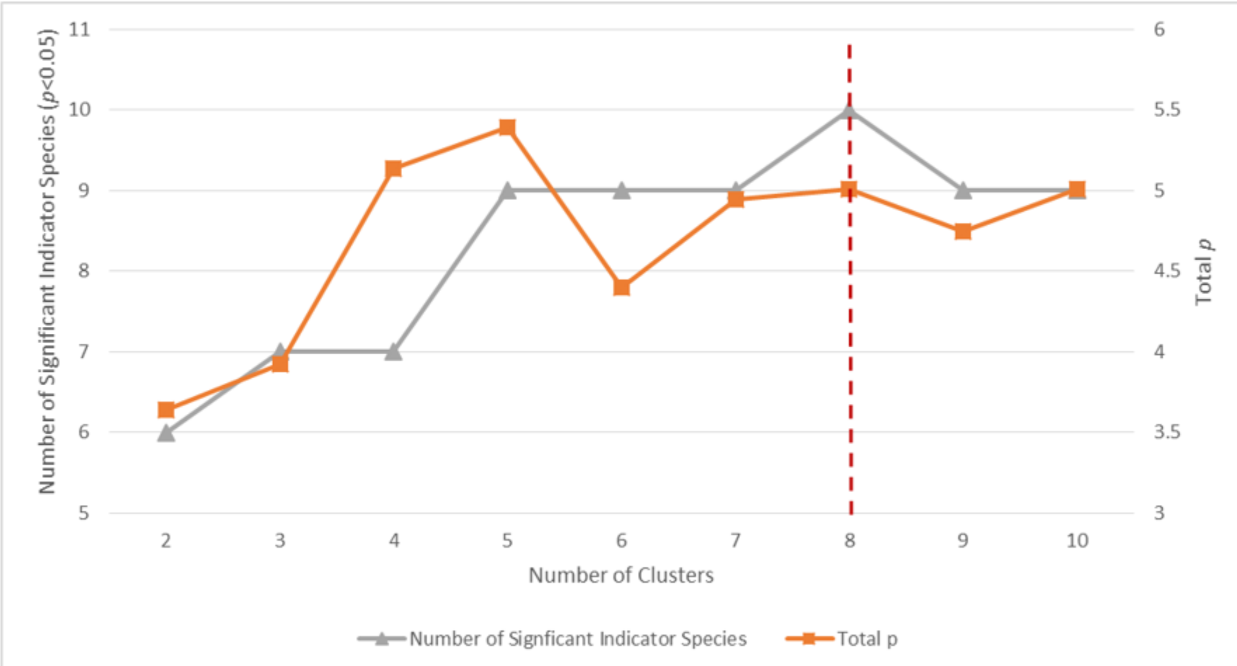

Figure 2.5 Summary of results of indicator species analyses for the Relative Abundance Only analysis. Hierarchical clustering was used to group plots (n=38) into 2-10 clusters. For each clustering level, an indicator value (IVI) was calculated for each species. *P*-values are based on 1000 Monte Carlo simulations with randomized data, then totaled for all species at each grouping level (x-axis). The vertical dashed line represents our final pruning level, selected to maximize the number of significant indicator species and minimize total *p* while giving a reasonable ecological interpretation.

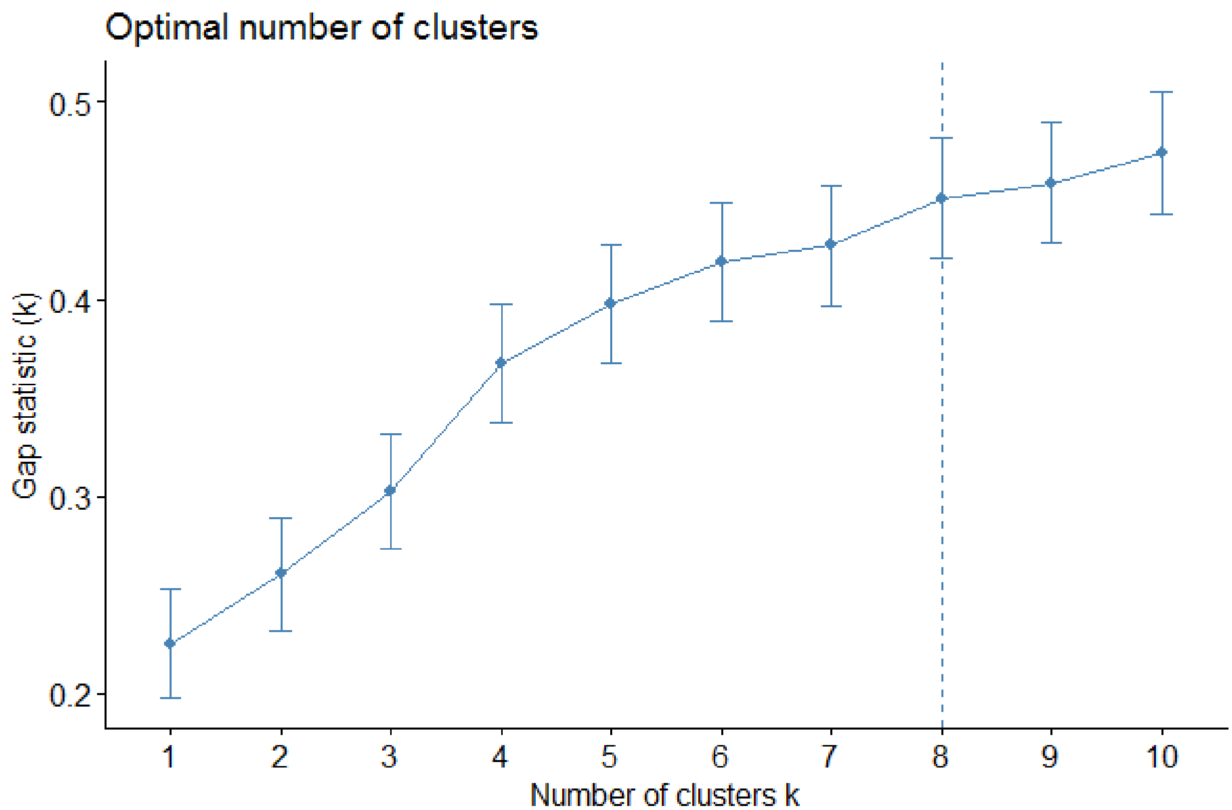

Figure 2.6 Plot of gap statistic values for the Relative Abundance Only hierarchical clustering analysis. The vertical dotted line indicates the optimal pruning level of eight clusters.

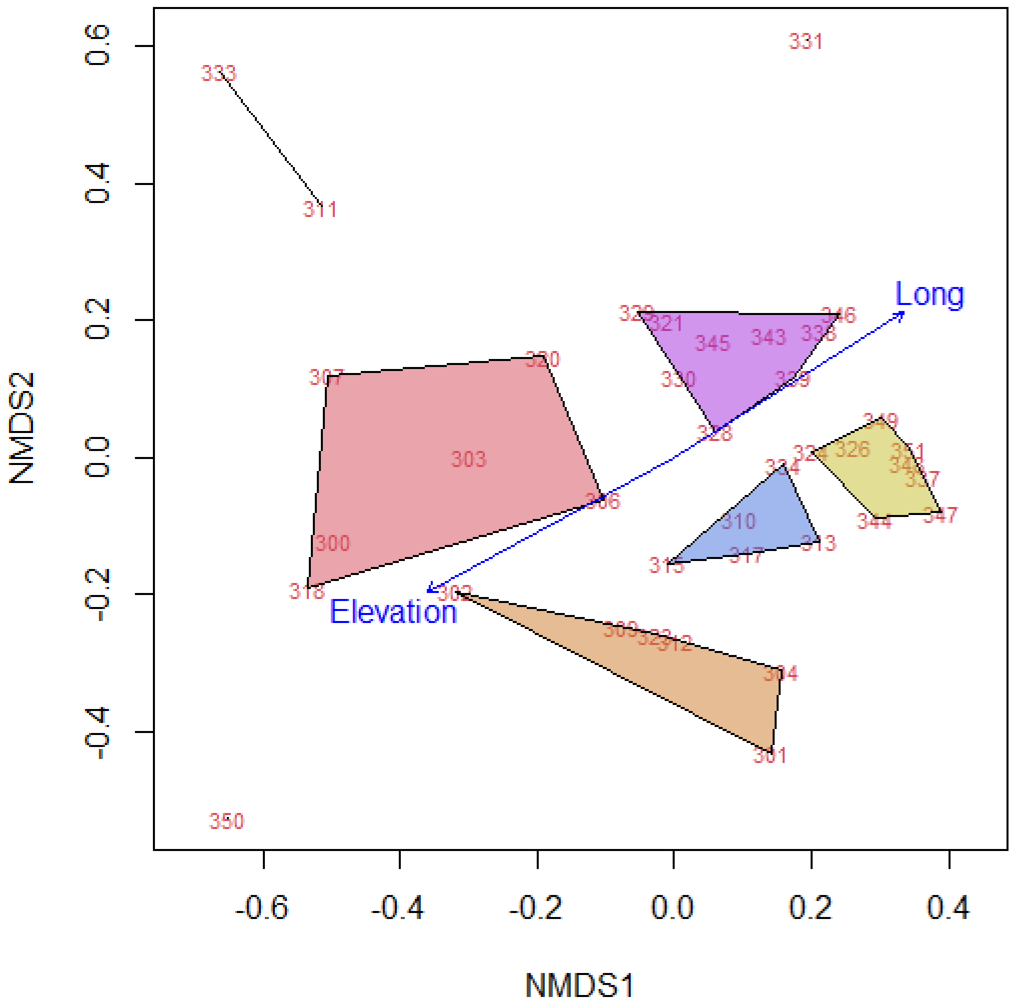

Figure 2.7 NMDS ordination of field plots in species space. Communities are based on the Relative Abundance Only analysis. They include: Oak/Hornbeam (red), Water Tupelo (orange), Swamp Tupelo (purple), Bald cypress/Tupelo (blue), Bald cypress (yellow), Pine (plots 311 and 333), Alder/Magnolia (plot 331), and Live Oak (plot 350). Biplot overlays indicate the relationship of DEM elevation (above NAVD88) and longitude ("Long", as a proxy for river distance) to plot ordination. Overlays were not statistically derived. Both elevation and longitude were significantly correlated with both axes (Table 2.2).

Table 2.1 Mean importance values for trees and shrubs in each community identified from our Relative Abundance Only analysis. Bolded numbers are dominant species that total more than 50% of the importance in each community.

Species	Common Name	Community							
		Oak/ Hornbeam	Water Tupelo	Bald Cypress/ Tupelo	Pine	Swamp Tupelo	Bald Cypress	Alder/ Magnolia	Live Oak
Acer rubrum	Red maple	0.05	0.02	0.03	0.01	0.05	0.03	0.00	0.00
Alnus serrulata	Hazel alder	0.01	0.02	0.06	0.00	0.03	0.01	**0.47**	0.00
Betula nigra	River birch	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Carya aquatica	Water hickory	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Carpinus caroliniana	American hornbeam	**0.19**	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Cephalanthus occidentalis	Buttonbush	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Fraxinus spp.	Ash	0.03	**0.16**	0.12	0.00	**0.23**	0.17	**0.37**	0.00
Standing dead trees		0.01	0.02	0.01	0.00	0.02	0.01	0.00	0.00
Ilex opaca	American holly	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00
Ilex decidua	Possumhaw	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Liquidambar styraciflua	Sweetgum	0.12	0.07	0.07	0.09	0.07	0.02	0.00	0.00
Magnolia virginiana	Sweetbay	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00
Nyssa aquatica	Water tupelo	0.01	**0.43**	**0.16**	0.00	0.02	0.00	0.00	0.00
Nyssa biflora	Swamp tupelo	0.06	0.03	**0.16**	0.02	**0.44**	0.19	0.00	0.00
Persea borbonia	Redbay	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00
Pinus spp.	Pine	0.05	0.00	0.00	**0.84**	0.00	0.00	0.00	0.00
Planera aquatica	Water elm	0.02	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Quercus laurifolia/nigra	Water oak / Laurel oak	**0.34**	0.10	0.03	0.01	0.04	0.00	0.00	0.04
Quercus lyrata	Overcup oak	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.00
Quercus virginiana	Live oak	0.01	0.00	0.00	0.00	0.00	0.00	0.00	**0.96**
Taxodium distichum	Bald cypress	0.05	0.11	**0.25**	0.00	0.07	**0.54**	0.00	0.00
Ulmus americana	American elm	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Number of Plots		6	6	5	2	9	8	1	1
Average Elevation (m above NAVD88)		1.82	1.10	1.00	2.17	1.03	1.02	0.46	6.53
Basal area ($m^2 \cdot ha^{-1}$)		41.7	73.1	71.4	33.7	47.3	37.3	12.8	10.4
Density (stems$\cdot ha^{-1}$)		1197	1117	1268	1040	1367	680	1340	1100
Mean Canopy Coverage (%)		95.88	97.13	92.85	99.75	83.00	85.50	58.50	86.25

Table 2.2 *envfit* results for the Relative Abundance Only analysis showing the correlation between NMDS axes 1 and 2 in species space with environmental variables. Elevation is the mean plot elevation above NAVD88 derived from a USGS 3DEP DEM of the study area. Longitude is the distance in meters west of 0°, and serves as a proxy for river distance.

	NMDS 1	**NMDS 2**	**r^2**	***p*-value**
Elevation	-0.88	-0.48	-0.51	< 0.001
Longitude	0.85	0.53	0.47	< 0.001

CHAPTER 3

CLASSIFICATION OF SATELLITE IMAGERY

3.1 Introduction

Tidal fresh forests are widely described as understudied (Anderson et al. 2013; Craft 2012; Doyle et al. 2007)(Doyle *et al*. 2007, Craft *et al*. 2012, Anderson *et al*. 2013, among others), despite their ecological importance and vulnerability to sea level rise. One reason for this oversight is the difficulty of conducting fieldwork in wetland ecosystems (Conner et al. 2007; Doumlele et al. 1984; Higinbotham et al. 2004; Wharton et al. 1982). Satellite imagery-based classification of vegetation is commonplace and enables mapping and monitoring of large spatial extents with less dependence on laborious fieldwork (Higinbotham et al. 2004; Ozesmi and Bauer 2002). This chapter details our efforts to classify Sentinel-2 Multispectral Imager (MSI) satellite imagery of the Altamaha River tidal fresh forest using field data and a Random Forest classifier with the goal of maximizing ecological and taxonomic detail. In particular, we wanted to accurately classify the forest-marsh transition area to facilitate subsequent temporal change analyses (see Chapter 4).

3.2 Methods

3.2.1 Sentinel-2 MSI data

This study employed 10 m spatial resolution 13- spectral band, 12-bit radiometric resolution Sentinel-2 MSI data of Altamaha River, GA tidal marsh and tidal fresh forests (Figure 1.1). These data are freely available from the European Space Agency’s (ESA) Copernicus data hub (scihub.copernicus.eu). The Sentinel-2A satellite was launched in 2015, and the Sentinel-2 constellation became fully operational with the launch of the second satellite (Sentinel-2B) in

March 2017, reducing the revisit time to five days (Persson et al. 2018). The MSI sensor has 13 spectral bands ranging from 0.443 to 2.19 µm (Table 3.1). It produces imagery with a 10 m spatial resolution in the visible (VIS) and near-infrared (NIR) spectra and a 20 m resolution for red edge and shortwave infrared (SWIR) (Immitzer *et al.* 2016). These bands can produce true color (4,3,2) and color infrared (CIR) (8,4,3) images as well as a wide variety of spectral indices which can be used to emphasize specific vegetation attributes, including chlorophyll content, water content, and biomass (Asner 1998). The horizontal geolocation error of Sentinel-2 data is less than its 10 m pixel size, and both L1C (top of atmosphere) and L2A (surface reflectance) data are pixel-registered and orthorectified (Vajsova and Åstrand 2017). Therefore, pixel values should accurately represent the spectral reflectance of ground-truth locations, and be directly comparable between multiple images (Langston et al. 2021).

The first image classified was acquired on May 28, 2021. This image was chosen because it was collected during our fieldwork (see section 2.2), facilitating visual interpretation. Additionally, the image was cloud-free and captured at a low tide. The image was delivered in the atmospherically corrected L2A format. Pre-processing was performed with the Sen2Cor280 processor in the Sentinel Application Platform (SNAP) (step.esa.int). All bands were resampled to a 10 m resolution to match the visible and NIR bands, and the image was reprojected to the NAD 1983 (2011) UTM Zone 17N (EPSG 6346) coordinate system. Using ENVI 5.6.1 (L3 Harris Geospatial, Boulder CO), images were subset to the study area. A normalized difference vegetation index (NDVI) (Table 3.2) image was produced, and pixel values below 0.1 were excluded, as very low index values indicate water (Svejkovsky et al. 2020). This mask was applied to the original image to effectively exclude water pixels. Additionally, several areas in the image were clipped out using manually delineated polygons. These areas are impoundments on Rockedundy Island, which are managed for waterfowl as part of the Altamaha Wildlife Management Area (WMA), and rice fields on Butler and Champney Islands, which are still under active cultivation (Higinbotham et al. 2004). Although the entire study area has been subject to extensive human modification, these areas are still actively managed and are not subject to the same hydrologic dynamics as the surrounding study area and therefore support atypical vegetation communities.

In addition to the Sentinel-2 data, two other sources of imagery were used to identify tidal fresh forest species: one-meter spatial resolution National Agricultural Imagery Program (NAIP) imagery from the US Department of Agriculture accessed via ArcGIS' Living Atlas (7/4/2021) and 15 cm aerial imagery collected in 2018 as part of an NSF RAPID project (Award 1803166; (Alber et al. 2019). Both datasets have four spectral bands: Red, Green, Blue, and NIR, permitting true color and CIR visualization. The higher spatial resolution of these datasets was helpful when interpreting the 10 m Sentinel-2 data and delineating training data.

3.2.2 Training Data

The Random Forest classifier requires data to train and validate the classification algorithm. Training and validation pixels were identified based on field observations and supplemented with user-defined regions of interest (ROIs). ROI polygons were manually delineated in ArcGIS Pro 2.9.2 (ESRI) using the Sentinel-2 MSI and high-resolution (0.15 m spatial resolution) aerial imagery as reference. Image interpretation and plant identification were aided by personal experience in the field and field notes and photographs taken at each plot location during field surveys (see Chapter 2.2). Class delineation was an iterative process primarily determined by spectral separability. Our initial goal was to determine if the remote sensing classification could be based on the taxonomically and ecologically distinct communities identified in Chapter 2. However, several closely related species were not spectrally separable at the spatial resolution of the Sentinel-2 MSI sensor. For instance, water tupelo and swamp tupelo are visually distinct and occupy different ecological niches but have extremely similar spectral signatures and, as a consequence, had to be combined into a single class at the genus level. Live Oak and Oak/Hornbeam forest also had similar spectral signatures. However, we were confident that including a LIDAR-derived digital elevation model (DEM) as one of the classifier predictor variables would minimize confusion, as these two classes occupy markedly different elevation ranges. After editing ROIs, the shapefiles were exported from ArcGIS Pro and imported into ENVI 5.6.1, where spectral statistics and class separability were calculated (Appendix E). This process was repeated until an acceptable compromise between ecological fidelity and spectral separability was obtained. Our final classification contained 21 classes (Table 3.2). Minor classes and those composed of mixed vegetation had low separability values based on spectral data alone but were preserved on the basis that the inclusion of a DEM and the performance of the Random Forest model would produce acceptable results. An additional class, “Pine/Sweetgum”, which was not represented in our field sites, was identified from aerial imagery.

For each image date, ROI polygons from all classes were divided randomly into training and validation groups in a 60:40 ratio (Table 3.2). These ROI polygons were converted into point features centered on the 10 m Sentinel-2 pixels.

3.2.3 Image Classification

This project used a Random Forest machine learning classifier (Breiman 2001). This technique is widely used in vegetation mapping (Immitzer et al. 2012; Persson et al. 2018; Smart et al. 2020), and others) and accepts a variety of inputs, including satellite imagery and LiDAR elevation and texture images. Random Forest classifiers work by producing a set of decision trees, each based on a different subset of training data. Classification results are calculated by averaging the outputs of a large number of independent trees. This approach helps Random Forest classify highly correlated or collinear datasets without overfitting the model to the training data (Immitzer et al. 2016). The randomized construction of decision trees also permits calculation of the relative importance of each input feature, which can be used to assess the influence of elevation and related variables on species distributions.

The volume of training data for each class varied widely, from just 48 pixels for *Panicum virgatum* to more than 3000 for *Zizaniopsis miliacea* (Table 3.1). Because of this, a Balanced Random Forest approach was used (Chen et al. 2004). Rather than drawing bootstrap samples in proportion to the total number of samples, Balanced Random Forest reduces the proportion of large classes and increases the proportion of minor classes. In our case, the number of training samples was limited to 20 times the smallest class (*P. virgatum*). Due to changes in the total number of training data for each class, unique balancing values were calculated for each year.

Supervised classification of imagery was carried out with the Random Forest classifier using the R package *randomForest* (Liaw and Wiener 2002). The classification included the following raster predictor variables: Sentinel-2 MSI spectral bands (12 separate raster bands), seven vegetation indices (MNDWI, NDMI, ARI 1, SGI, NDBI, GDVI, ARI 2), and a DEM (Table 3.1). Because of the strong influence of flooding on species distributions, elevation data is widely used in the classification of coastal vegetation (Borchert et al. 2018; Hladik et al. 2013; Ury et al. 2021). A 2-meter horizontal resolution LIDAR DEM of the study area was downloaded from NOAA's Digital Coast (coast.noaa.gov) and resampled to 10 m resolution to match the Sentinel-2 MSI data. Note that the LIDAR DEM was not corrected for potential vegetation biases (Hladik and Alber 2012). By calculating the ratio between two or more spectral bands, vegetation indices emphasize unique spectral characteristics of different species and can increase the classification accuracy of multispectral data (Gerstmann et al. 2016; Klemas 2013). The Spectral Indices tool in ENVI was used to calculate 48 vegetation indices. These VIs were used as input for a Random Forest classification. The seven vegetation indices which performed the best based on caret's *varImp* function were retained and included in the final classification (Table 3.1). The pixel values for each of the raster predictor variables were extracted for the training dataset. As part of the post-classification procedures, pixel aggregation was applied to remove the salt and pepper appearance of classified images. In this process, all groups of fewer than five raster cells were replaced by values from the surrounding cells.

3.2.4 Variable Importance and Accuracy assessment

The primary Random Forest outputs used in this analysis were class value and variable importance for each predictor variable measured as the mean decrease in accuracy. Random forest quantifies this measure by estimating how much prediction error decreases when each variable is removed from the tree (Breiman 2001). Several statistics were calculated following classification and pixel aggregation. Classification accuracy was calculated based on the out-of-bag error estimates. Additionally, classification accuracy was evaluated by constructing a confusion matrix and calculating the overall accuracy, producer's accuracy, user's accuracy, and errors of omission and commission (Congalton 1991) using the reserved validation data that were not used to train the classifier.

3.3 Results

Overall accuracy for the May 28, 2021 Sentinel-2 MSI image was 84.6%, with a Kappa coefficient of 0.81 (Table 3.3). Individual class accuracies range from 100% for Pine/Sweetgum to 27% for *Panicum virgatum* (Table 3.4). All purely forested classes performed well, with Oak/Hornbeam having the lowest accuracy at 77% and Pine/Sweetgum having the highest accuracy at 100% (Table 3.4). Salt-Stressed Tidal Forest (a composite community containing both tidal fresh forest and marsh vegetation) was overclassified at the expense of several tidal fresh marsh classes (commission error 45%) (Table 3.3). Salt-Stressed Tidal Forest was most commonly confused with bald cypress (14%), *P. virgatum (11%)*, and *Zizaniopsis miliacea (7%)* (Table 3.3). In general, forest classes had higher producer's and user's accuracies compared to marsh classes (Table 3.4). Tidal marsh class accuracies ranged from 27% for *P. virgatum* to 94% for *Juncus roemerianus*. *P. virgatum* was confused with *Spartina cynosuroides* (which occupies the same habitat) 38% of the time (Table 3.3).

The spatial distribution of classes within the image (Figure 3.2) generally corresponds well with expected species distribution patterns and observations in the field. Salt marsh vegetation such as smooth cordgrass (*S. alterniflora* Loisel.) dominate low-elevation sites near river/creek banks in the eastern part of the study area, replaced by *J. roemerianus* at slightly higher elevations in brackish marshes. Further upstream, *S. americanus* covers large expanses of Broughton Island, eventually giving way to the tidal fresh marsh species *Z. miliacea.* Salt-Stressed Tidal Forest is found along the upstream margin of the tidal fresh marsh, particularly along the banks of creeks and drainage ditches (Figure 3.2). Tupelo and bald cypress are abundant at lower elevations near river/creek banks. Tupelo is the most abundant class, covering 37.8 km^2, 25% of the study area (Table 3.5). Mixed floodplain forest occupies higher elevations that are less frequently flooded, and floodplain oak communities are found on river berms and the floodplain-upland boundary.

Upland areas are defined by human activity, with monoculture pine plantations dominating the southern bank of the Altamaha along with Pine/Sweetgum, an early successional class in clear-cuts. The exception is the live oak community found on several isolated islands in the northern part of the study area which are protected in the Altamaha WMA, and whose high elevation and sandy soils prevent colonization by flood-tolerant species.

Of the 20 predictor variables, elevation was the most important as measured by caret's *varImp* function (Mean Decrease in Accuracy of 282) (Figure 3.3). The most important spectral bands were Coastal Aerosol (B1) (Mean Decrease in Accuracy: 158), Vegetation Red Edge 1 (B5) (Mean Decrease in Accuracy: 149), SWIR 2 (B12) (Mean Decrease in Accuracy: 135), and SWIR 1 (B11) (Mean Decrease in Accuracy: 126) (Figure 3.3). The Red (B4) (Mean Decrease in Accuracy: 84) and NIR (B8) (Mean Decrease in Accuracy: 72) were among the least important. The most helpful vegetation indices were the Modified Normalized Difference Water Index (MNDWI) (Mean Decrease in Accuracy: 152) and Normalized Difference Mud Index (NDMI) (Mean Decrease in Accuracy: 137). Adopting a Balanced Random Forest approach gave a 5% improvement in overall OOB error rate over a standard Random Forest classification with all the same other parameters.

3.4 Discussion

This study represents the first detailed, remote sensing-based classification of the tidal fresh forests on the Altamaha River. We mapped 21 tidal forest and marsh vegetation classes (Figure 3.2) using moderate spatial resolution Sentinel-2 MSI satellite imagery and the Random Forest classifier and achieved an overall accuracy of 84.6% (Kappa = 0.81) (Table 3.3).

The overall classification accuracy is comparable to, or greater than, other detailed satellite remote sensing classifications of forest ecosystems. Mickelson et al. (1998)mapped 33 land cover classes in northwestern Connecticut forests using 30 m spatial resolution Landsat Thematic Mapper (TM) data, with an overall accuracy of 79%. Sheeren et al. (2016) classified 17 tree species using 8-meter, 4-band Formosat data. Despite this low spectral resolution, their Random Forest classification achieved an overall kappa of 0.9 and overall accuracy of 93%. Clark (2020) mapped forest types in California at a forest alliance level based on the U.S. National Vegetation Classification, achieving an overall accuracy of 74.3% for 16 classes using Sentinel-2 data and a Support Vector Machine (SVM) classifier. (See Appendix B for an explanation of the USNVC classification system).

In all of these studies, misclassification was generally the result of confusion between classes with closely related species or mixed classes with similar species compositions (Clark 2020; Mickelson et al. 1998; Sheeren et al. 2016). For example, in his classification of Sentinel-2 imagery, Clark (2020) had a producer's accuracy of just 12.8% for Black Oak (*Quercus kelloggii*), which was mainly confused with Oregon white oak (*Quercus garryana*), a more abundant species in the same genus. Mixed classes (those containing two or more species) present a similar challenge, as their spectral characteristics are a hybrid of their constituent species (Mickelson et al. 1998). Mickelson et al. (1998) had several mixed classes with the same dominant species, distinguished only by differences in codominant or understory species. For example, among their ten oak-dominated classes, 74% of total commission errors were the result of confusion with other oak-dominated classes (Mickelson et al. 1998). Errors in our classification followed similar patterns. For instance, *S. americanus* was misclassified as its congener *S. tabernaemontani* 15% of the time, and Oak/hornbeam was confused with Live Oak 11% of the time. (Table 3.3). These types of errors are to be expected, given the similar spectral characteristics of these classes.

As in this study, all of these classifications attempted to identify trees at the genus or species level (Clark 2020; Mickelson et al. 1998; Sheeren et al. 2016). As described above, this introduces issues with spectral separability, which these studies resolved by using multi-season or time series imagery to exploit differences in phenology between closely related species (Clark 2020; Mickelson et al. 1998; Sheeren et al. 2016). The high classification accuracy we achieved for 21 classes with a single image date demonstrates the capabilities of the Sentinel-2 MSI sensor. Using multi-date imagery could improve accuracy or permit an even more detailed classification. For instance, we might be able to resolve water tupelo and swamp tupelo, which we were forced to merge due to a lack of spectral separability.

In a study closely related to this analysis, Smart et al. (2020) achieved an overall accuracy of 85% using Random Forest to classify Landsat imagery of ghost forests in North Carolina. Another similar study by Ury et al. (2021)used Landsat data to monitor forest-marsh transition. Unlike Smart and Ury, we did not identify a specific “ghost forest” class. Some relict dead cypress trees are present in what is now brackish marsh, but they were not numerous or dense enough to be spectrally separable from the surrounding marsh vegetation (Appendix E). Our nearest comparable class was “Salt-Stressed Tidal Forest”, a transitional forest state which contains both living and dead trees, as well as marsh vegetation.

The detailed classification results in this study represent a substantial improvement over existing classifications of coastal ecosystems, particularly those which focus on the wetland-upland boundary. These studies typically use broad land cover classes such as open water, tidal marsh, transitional forest, and upland (Raabe and Stumpf 2015); marsh, ghost forest, and forest (Smart et al. 2020); and sometimes low spatial resolution MODIS data (White and Kaplan 2021). While such classification schemes have their uses, a classification with more detailed classes and higher spatial resolution has several advantages. Because species have different tolerances for salinity, a single “forest” or “marsh” class may not accurately identify the areas at risk of salinization. For instance, the Georgia coast has extensive tidal freshwater marshes, which have very low tolerance to salinity (Solohin et al. 2020). Tidal fresh marshes are more productive and ecologically diverse than the more saline downstream brackish and salt marshes (Solohin et al. 2020), but any transition from tidal freshwater marsh to brackish or salt marsh would not be captured by a single “marsh” class.

Similarly, tidal fresh forest species have varying salinity tolerances. Of all tidal fresh forest vegetation native to Georgia, bald cypress has the highest salinity tolerance, capable of surviving chronic exposure of 3-4 psu (Duberstein et al. 2020). Therefore, as rising salinity causes mortality in other tidal fresh forest species, bald cypress could increase in dominance in areas affected by saltwater intrusion (Krauss et al. 2009). Our ability to accurately classify bald cypress (producer’s accuracy of 80%) demonstrates the viability of monitoring this trend via satellite remote sensing.

The vegetation distributions in our classified image (Figure 3.2) are consistent with existing research on the Altamaha and other similar systems and reflect the physiological constraints imposed by salinity and flooding (Wharton et al. 1982). The distribution of marsh vegetation is broadly consistent with prior studies of the Altamaha estuary, with three major zones visible: tidal fresh, brackish, and salt (Wiegert and Freeman 1990). *S. alterniflora* is most abundant downstream in salt marshes, where salinities are highest (White and Alber 2009). *S. cynosuroides* increases in dominance further upstream in brackish areas (<15 psu) (White and Alber 2009). *Juncus roemerianus* is the dominant brackish marsh plant, particularly in higher elevation, less frequently flooded areas of Broughton Island and Rockedundy Island

(Higinbotham et al. 2004). Tidal fresh marshes extend from the western edge of Broughton Island upstream to the margin of the tidal fresh forest and are dominated by *Z. miliacea* and *S. tabernaemontani* (Higinbotham et al. 2004).

The dominance of our Tupelo class (38 km^2, 25% of the total study area) supports the findings of Duberstein et al. (2014), who documented the dominance of both water tupelo and swamp tupelo in the Altamaha tidal fresh forest (Duberstein et al. 2014). The effects of drainage ditches and natural creeks on vegetation distributions are clearly visible (Figure 3.2). These features can accelerate forest-marsh transition by facilitating saltwater intrusion and subsequent elevation loss due to erosion and subsidence (Bhattachan et al. 2018; Poulter et al. 2008). In our classified image, they appear to be associated with the presence of Salt-Stressed Tidal Forest (Figure 3.2) (Doyle et al. 2021). Unlike other classifications of the tidal forest/tidal marsh boundary (Smart et al. 2020; Ury et al. 2021), we found little to no shrub/scrub vegetation. In these studies, shrubs represented a transitional state between forest and marsh (Smart et al. 2020; Ury et al. 2021), but in our classified image (Figure 3.2), the transition from tidal fresh marsh to tidal fresh forest is quite abrupt, and shrub/scrub vegetation is limited to creek banks.

Of the 20 predictor variables, elevation was most important as measured by caret's *varImp* function (Mean Decrease in Accuracy: 282) (Figure 3.3). This result reinforces the findings of prior studies (Alexander and Hladik 2015; Hladik et al. 2013; Huylenbroeck et al. 2020) and emphasizes the importance of maintaining accurate, up-to-date elevation data of coastal regions. Similar to other studies, our results show the importance of the blue and SWIR bands for vegetation mapping and the relative unimportance of the red and NIR (Grybas and Congalton 2021; Immitzer et al. 2016; Persson et al. 2018). Blue wavelengths are sensitive to chlorophyll content, which may explain the importance of Band 1 (Grybas and Congalton 2021).

The reflectance of senescing vegetation peaks in the SWIR wavelengths and well-timed autumnal images can maximize spectral separability by capturing plant species at different stages of senescence (Mickelson et al. 1998; Persson et al. 2018), and others). The high importance values of the SWIR bands in our classification are likely elevated because of our choice of autumn image dates.

Interestingly, across previous studies, differences in spatial resolution do not seem to have a large impact on forest classification accuracy (Clark 2020; Sheeren et al. 2016), and others). Spatial resolution is always a tradeoff between spectral and radiometric resolution, data size, expense, and areal coverage. Our results and others (Immitzer et al. 2016; Persson et al. 2018; Sunde et al. 2020; Svejkovsky et al. 2020), and others) suggest that many forest canopies are homogeneous enough at 10 m resolution that smaller pixels may increase within class variability and lead to greater classifier error. As tidal marsh classes were more mixed and generally had lower classification accuracies in our study, they may have more accurate results using a smaller pixel size. A higher resolution DEM would be particularly valuable, as the elevation differences between marsh species at a 10 m spatial resolution are not great enough to overcome the spectral ambiguity of mixed pixels. Alternatively, species-level classes could be combined into more general species associations when using coarser spatial resolution imagery.

The potential future applications of a detailed habitat classification are manifold. Remote sensing studies are widely used for temporal change studies in coastal ecosystems where the areal extent or rate of change makes on-the-ground sampling impractical (Ozesmi and Bauer 2002; Svejkovsky et al. 2020; Ury et al. 2021) (See Chapter 4). In conjunction with appropriate ground reference data, reflectance data can be linked to various biophysical variables such as leaf area, water content, and nutrient deficiency (Asner 1998)(Asner 1998). With LiDAR data, which provides more information on forest structure, detailed estimates of biomass and carbon dynamics are possible (Schumacher et al. 2019; Smart et al. 2020). Finally, our vegetation map, in combination with a DEM, river discharge data, and data on tidal fresh forest species salinity tolerance, could be used to create a model of tidal fresh forest response to sea level rise analogous to the Sea Level Affects Marshes Model (SLAMM) (Craft et al. 2009).

3.5 Conclusions

The results of this study demonstrate that detailed, accurate classification of tidal fresh forests is possible using freely available, moderately high-resolution Sentinel-2 MSI satellite imagery. We mapped 21 classes of tidal marsh and forest vegetation with an overall accuracy of 84.6%. This represents a substantial improvement in ecological detail over existing remote sensing classifications of similar ecosystems, with little to no reduction in overall accuracy. Importantly, we were able to effectively discriminate between forests undergoing forest-marsh transition and both marsh and healthy forest vegetation. These results show potential for ongoing monitoring of tidal fresh forests and modeling of potential tidal forest loss.

3.6 References

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3.7 Figures and Tables

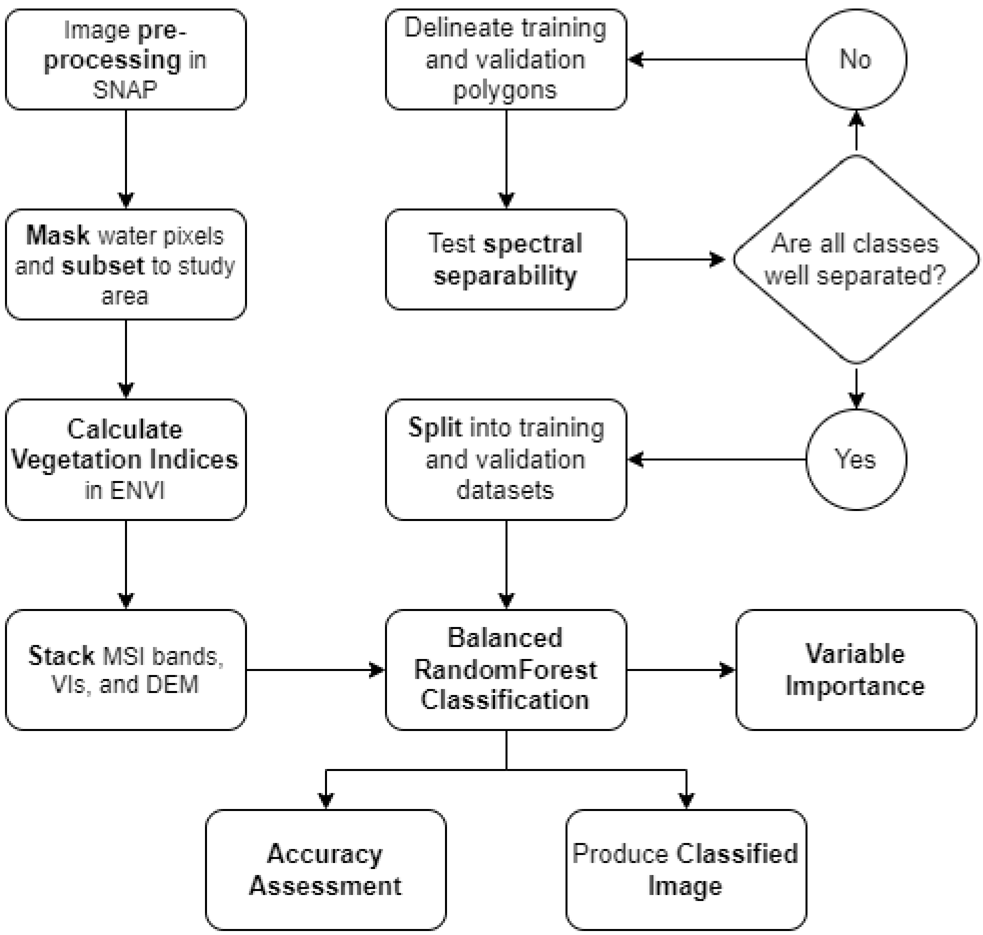

Figure 3.1 Workflow for our Balanced Random Forest classification of Sentinel-2 MSI data.

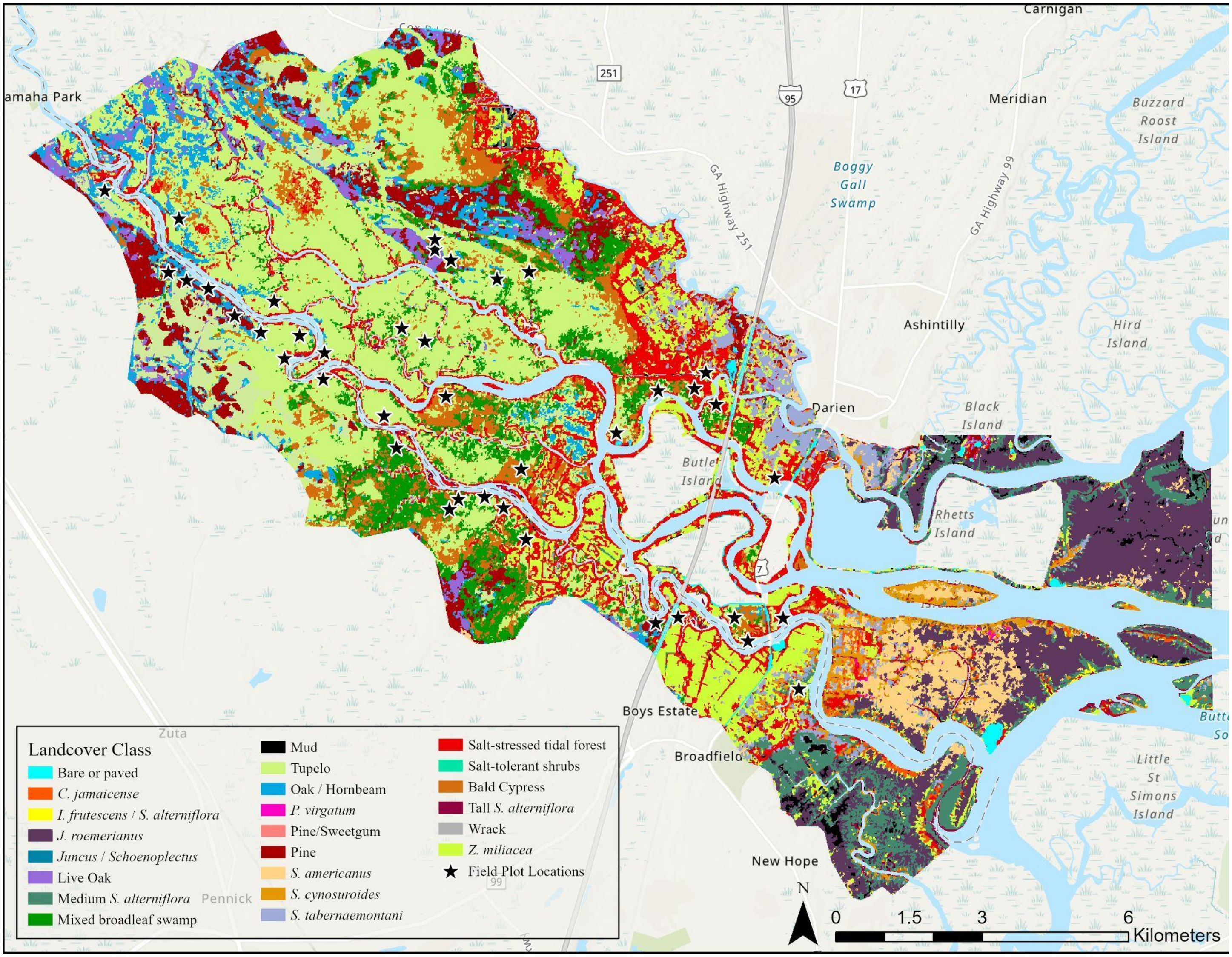

Figure 3.2. Final Balanced Random Forest classified image for the 05/28/2021 image date with 21 land cover classes. Overall classification accuracy was 84.6%. The classified image was smoothed with a 5-pixel minimum aggregation applied prior to accuracy assessment.

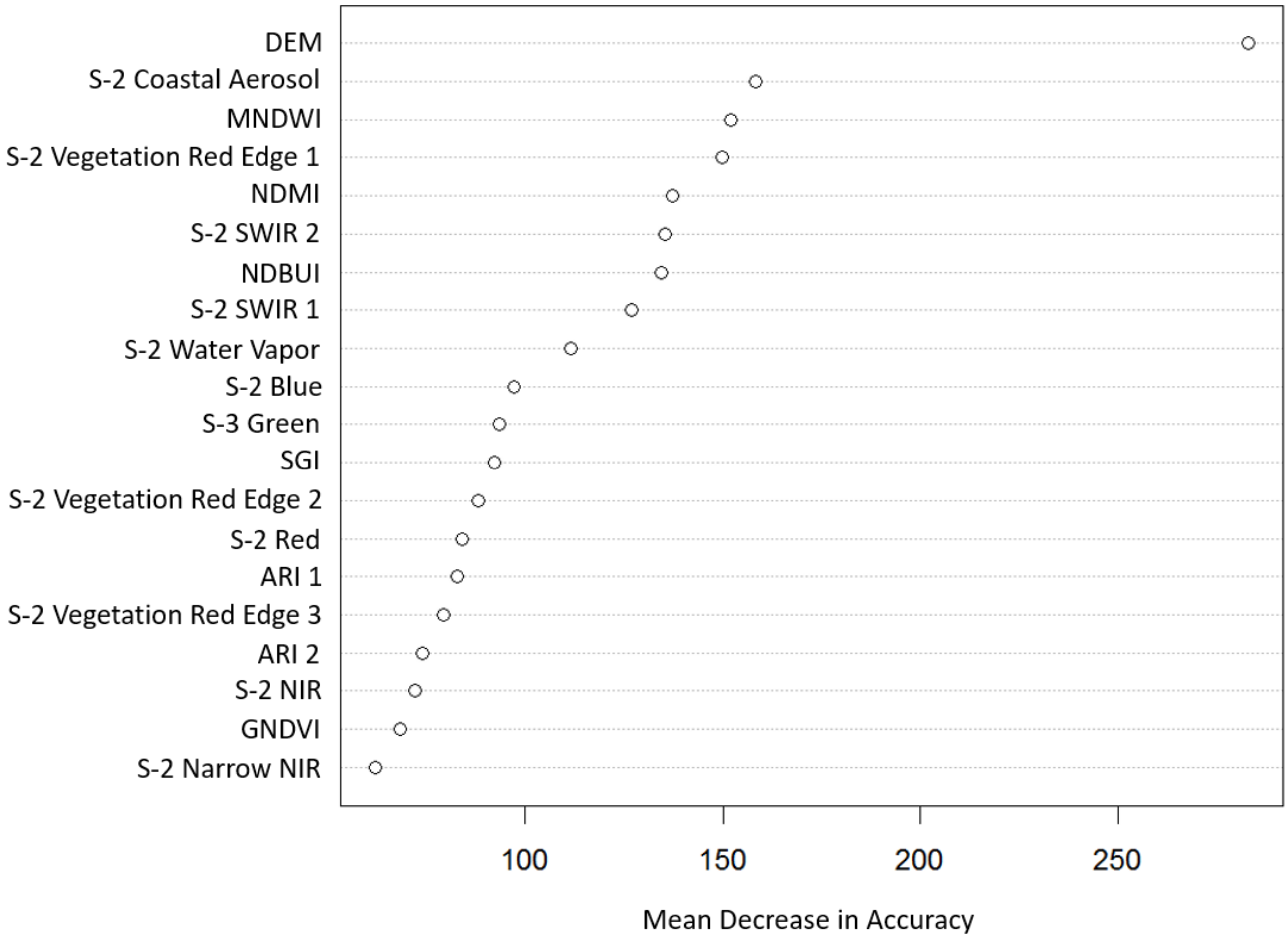

Figure 3.3 Variable importance values for predictor variables in our Balanced Random Forest classification of the 05/28/2021 image. The Y-axis shows predictor variable input bands: a digital elevation model (DEM), twelve Sentinel-2 MSI spectral bands, and seven vegetation indices derived from the MSI data (See Table 3.2). The X-axis shows the mean decrease in accuracy; that is, how much the average error rate increases when a variable is excluded.

Table 3.1 Land cover reference data for training and validation for the 05/28/2021 Random Forest image classification generated based on ground reference data and visual interpretation of orthoimagery. Cover class is the classified habitat grouping. The description column details vegetation in each class. Habitat indicates the salinity range: BM is brackish marsh, TFF is tidal fresh forest, and TFM is tidal fresh marsh. Plots are the number of ground reference sites surveyed for each cover class. Training and validation pixels are the numbers of pixels used to train and validate the classification.

Cover Class	Description	Habitat	Plots	Training pixels	Validation pixels
Bare or paved	Urban areas, roads, and unvegetated bare earth, such as dredge spoils.	Upland	0	378	259
C. jamaicense	Sawgrass	TFM	0	189	104
Iva frutescens / S. alterniflora	Marsh-elder codominant with medium *S. alterniflora,* restricted to a small area on Broughton Island.	BM	0	106	72
J. roemerianus	Black needlerush	SM/BM	0	3392	1813
Mixed broadleaf swamp	Seasonally flooded hardwood forest of sweetgum, ash, tupelo, and oak.	TFF		611	321
Mud	Bare mud on creekbanks and marsh dieback areas.	All habitats	0	304	396
Tupelo	Tupelo dominated swamps, both *N. biflora* (Swamp tupelo) and *N. aquatica* (Water tupelo).	TFF	15	949	452
P. virgatum	Switchgrass	BM	0	48	37
Pine	Pine trees, primarily in managed plantation forests.	Upland	3	1559	1588
Pine/Sweetgum	An early successional forest of young pine trees and sweetgum in recently logged upland areas.	Upland	0	939	672
Oak/Hornbeam	Canopy dominated by flood tolerant oak species, including *Q. nigra* (Water Oak), *Q. laurifolia* (Laurel Swamp Oak), *Q. michauxii* (Swamp Chesnut Oak), *Q. lyrata* (Overcup Oak).	TFF	6	596	413
Live oak	*Q. virginianus,* in our study area confined to sandhills on the north bank of the Altamaha.	Upland	1	550	259
S. americanus	Threesquare Bullrush	BM	0	2211	2488
S. tabernaemontani	Softstem Bullrush	BM/TFM	0	524	360
Salt-tolerant shrubs	*Baccharis halimfolia, Myrica cerifera*, and other shrubs. Primarily on high ground at the margins of the marsh.	BM/TFM	0	175	126
Medium *S. alterniflora*	Medium form *Spartina*, .5 - 1.0 m	SM	0	1661	775
S. cynosuroides	Big cordgrass	BM/TFM	0	430	306
Tall *S. alterniflora*	Tall form *Spartina*, >1.0 m in height	SM	0	156	270
Salt-stressed tidal forest	Forested sites which have been affected by saltwater intrusion and are transitioning to marsh.	TFF, TFM	9	575	258
Bald Cypress	Bald Cypress dominated swamps	TFF	5	495	503
Z. miliacea	Giant cutgrass	TFM	0	2679	840

Table 3.2 Names and descriptions of the predictor rasters used for Balanced Random Forest classifications. All predictor bands were resampled to a 10 m resolution to match the visible and NIR bands, and the image was reprojected to the NAD 1983 (2011) UTM Zone 17N (EPSG 6346) coordinate system.

Predictor Rasters	Description	Bandwidth (nm)	Native resolution (m)	Purpose	References	Data Source
DEM	Elevation in meters relative to NAVD88 vertical datum.	-	4.57	Elevation is strongly correlated with vegetation distributions.	Flitcroft *et al*. 2018	NOAA
S-2 MSI Band 1	Coastal Aerosol (443 nm)		60	Coastal and aerosol studies	Persson *et al.*	ESA
S-2 MSI Band 2	Blue (490 nm)	98	10	Distinguish between soil and vegetation, and deciduous or coniferous trees.	Persson *et al.* 2018	ESA
S-2 MSI Band 3	Green (560 nm)	45	10	Assessment of plant vigor	Persson *et al.*	ESA
S-2 MSI Band 4	Red (665 nm)	38	10	Detects chlorophyll absorption for vegetation discrimination	Persson *et al.* 2018	ESA
S-2 MSI Band 5	Vegetation Red Edge (705 nm)	19	20	Vegetation classification	Persson *et al.* 2018	ESA
S-2 MSI Band 6	Vegetation Red Edge (740 nm)	18	20	Vegetation classification	Persson *et al.* 2018	ESA
S-2 MSI Band 7	Vegetation Red Edge (783 nm)	28	20	Vegetation classification	Persson *et al.*	ESA
S-2 MSI Band 8	NIR (842 nm)	145	10	Plant biomass detection	Persson *et al.*	ESA
S-2 MSI Band 8a	Narrow NIR (865 nm)	33	20	Plant biomass detection	Persson *et al.*	ESA
S-2 MSI Band 9	Water Vapor (945 nm)		60	Water vapor detection	Persson *et al.*	ESA
S-2 MSI Band 11	SWIR (1610 nm)	143	20	Detects moisture content of soil and vegetation	Persson *et al.* 2018	ESA
S-2 MSI Band 12	SWIR (2190 nm)	242	20	Detects moisture content of soil and vegetation	Persson *et al.*	ESA
Normalized Difference Mud Index	$\mathrm{MNDWI} = \frac{(\mathrm{B7} - \mathrm{B9})}{(\mathrm{B7} + \mathrm{B9})}$	-	10	Highlights mud and shallow water.	Bernstein *et al.* 2012	Derived from S-2 MSI
Modified Normalized Difference Water Index	$\mathrm{MNDWI} = \frac{(\mathrm{B2} - \mathrm{B11})}{(\mathrm{B2} + \mathrm{B11})}$	-	10	Enhances features with high water content.	McFeeters *et al.* 1998	Derived from S-2 MSI
Sum Green Index	$SGI = \frac{B3}{12}$	-	10	Emphasize small differences in vegetation greenness.	Lobell and Asner 2003	Derived from S-2 MSI
Normalized Difference Built Up Index	$\mathrm{NDBUI} = \frac{(\mathrm{B11} - \mathrm{B8})}{(\mathrm{B11} + \mathrm{B8})}$	-	10	Emphasize urban areas where manmade surfaces reflect a greater proportion of SWIR	Zha *et al.* 2003	Derived from S-2 MSI
Green Normalized Difference Vegetation	$\mathrm{GNDVI} = \frac{(\mathrm{B8} - \mathrm{B3})}{(\mathrm{B8} + \mathrm{B3})}$	-	10	Emphasizes green, healthy vegetation.	Gitelson and Merzlyak 1998	Derived from S-2 MSI
Anthocyanin Reflectance Index 1	$\mathrm{ARI1} = \frac{1}{\mathrm{B3}} - \frac{1}{\mathrm{B5}}$	-	10	Highlights stressed and senescing vegetation.	Gitelson *et al.* 2001	Derived from S-2 MSI
Anthocyanin Reflectance Index 2	$\mathrm{ARI2} = \mathrm{B7}(\frac{1}{\mathrm{B3}} - \frac{1}{\mathrm{B5}})$	-	10	Highlights stressed and senescing vegetation.	Gitelson *et al.* 2001	Derived from S-2 MSI

Table 3.3 Balanced Random Forest confusion matrix for tidal forest and tidal marsh cover classes for the Sentinel-2 MSI image collected 05/28/2021. Columns represent reference data (what the pixel actually was based on validation data), and rows represent image data (what the pixel was classified as). Shaded cells are those where the classification was accurate. Percentages are rounded to the nearest decimal place and may not sum to 100% for each cover class. Overall classification accuracy was 84.6%.

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium*S. alterniflora*	*S. cynosuroides*	Tall*S. alterniflora*	Salt-stressed tidal forest	Bald cypress	*Z. miliacea*
Bare or paved	1.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.00	0.45	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.03	0.01	0.00	0.00
Iva frutescens / S. alterniflora	0.00	0.08	0.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.09	0.00	0.00	0.00
J. roemerianus	0.00	0.00	0.00	0.94	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.02	0.01	0.02	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.97	0.00	0.11	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Mud	0.00	0.00	0.00	0.00	0.00	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Tupelo	0.00	0.00	0.00	0.00	0.03	0.00	0.82	0.00	0.01	0.00	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Pine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.04	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	1.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.77	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.83	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.93	0.15	0.00	0.02	0.00	0.00	0.00	0.00	0.00
S. tabernaemontani	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.42	0.02	0.04	0.10	0.00	0.02	0.00	0.05
Salt-tolerant shrubs	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.02	0.04	0.46	0.02	0.07	0.02	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.15	0.14	0.05	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.03	0.75	0.05	0.13	0.03	0.00	0.07
S. cynosuroides	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.25	0.21	0.06	0.62	0.05	0.00	0.00	0.00
Tall *S. alterniflora*	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.63	0.02	0.00	0.01
Salt-stressed tidal forest	0.00	0.06	0.07	0.00	0.00	0.05	0.04	0.11	0.00	0.00	0.00	0.00	0.01	0.02	0.05	0.01	0.05	0.00	0.82	0.14	0.07
Bald cypress	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.82	0.01
Z. miliacea	0.00	0.06	0.03	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.03	0.05	0.00	0.02	0.10	0.00	0.73

Table 3.4 Balanced Random Forest classification errors of commission, errors of omission, producer's accuracies, and user's accuracies for each cover class for the 05/28/2021 image. Percentages are rounded to the nearest decimal place and may not sum to 100% for each cover class.

Cover class	Errors of commission	Errors of omission	Producer's accuracy	User's accuracy
Bare or paved	11.64	0.31	99.69	88.36
C. jamaicense	48.91	19.24	80.76	51.09
Iva frutescens / S. alterniflora	39.56	2.53	97.47	60.44
J. roemerianus	6.29	14.10	85.90	93.71
Mixed deciduous forest	15.23	2.80	97.20	84.77
Mud	4.49	36.83	63.17	95.51
Nyssa spp. swamp	15.65	17.23	82.77	84.35
P. virgatum	16.67	12.95	87.05	83.33
Pinus spp.	4.52	16.04	83.96	95.48
Pinus / L. styraciflua	5.36	0.27	99.73	94.64
Oak/Hornbeam forest	13.28	17.48	82.52	86.72
Live Oak upland forest	6.55	9.15	90.85	93.45
S. americanus	4.37	46.59	53.41	95.63
S. tabernaemontani	53.85	41.32	58.68	46.15
Salt-tolerant shrubs	61.59	19.87	80.13	38.41
Medium *S. alterniflora*	33.41	61.50	38.50	66.59
S. cynosuroides	51.52	62.92	37.08	48.48
Tall *S. alterniflora*	36.19	46.73	53.27	63.81
Salt-stressed tidal forest	53.10	10.50	89.50	46.90
T. distichum swamp	4.63	20.02	79.98	95.37
Z. miliacea	15.68	44.13	55.87	84.32

Table 3.5 Land cover composition of the Altamaha tidal fresh forest study site from the 05/28/2021 image. Class area is in square kilometers. Percentages have been rounded to the nearest decimal place and may not sum to 100.

Cover class	Class Area	Percent of total
Bare or paved	1.18	0.79%
C. jamaicense	1.12	0.75%
Iva frutescens / S. alterniflora	0.19	0.12%
J. roemerianus	14.20	9.52%
Mixed deciduous forest	10.30	6.90%
Mud	1.38	0.92%
Nyssa spp. swamp	37.83	25.34%
P. virgatum	0.11	0.08%
Pinus spp.	8.07	5.41%
Pinus / L. styraciflua	5.53	3.70%
Oak/Hornbeam forest	7.00	4.69%
Live Oak upland forest	3.61	2.42%
S. americanus	5.55	3.72%
S. tabernaemontani	4.69	3.14%
Salt-tolerant shrubs	0.64	0.43%
Medium *S. alterniflora*	8.03	5.38%
S. cynosuroides	2.45	1.64%
Tall *S. alterniflora*	1.47	0.98%
Salt-stressed tidal forest	14.99	10.04%
T. distichum swamp	9.54	6.39%
Z. miliacea	11.40	7.63%

CHAPTER 4

TEMPORAL CHANGE

4.1 Introduction

Hurricanes are a major source of ecological disturbance in coastal regions (Ross et al. 2020) and have been implicated in tidal fresh forest dieback and marsh transgression (Ury et al. 2021). In 2016 and 2017, the Georgia coast was impacted by two major tropical storms: Matthew and Irma (Cangialosi et al. 2018; Stewart 2017). Hurricane Irma (2017) was one of the most powerful storms recorded on the Georgia coast in the last century (Alber et al. 2019). The damage from hurricane-force winds and storm surges has immediate impacts on tidal fresh forest health, and long term can precipitate shifts in vegetation distributions (Middleton 2016). One of the major advantages of satellite remote sensing is the ability to monitor change over time without the need to make repeated visits to the field (Ozesmi and Bauer 2002). This is particularly advantageous for studying ecosystem response to hurricanes, as a single satellite image instantaneously captures a spatially explicit measure of the storm's impact, and the regular re-imaging of the site simplifies tracking the long-term effects (Svejkovsky et al. 2020).

The overall objective of this chapter was to classify six Sentinel-2 Multispectral Imager (MSI) images taken annually from 2016 to 2021 and use these classified images to track changes in vegetation distributions. These images capture the effects of hurricanes Irma (2017) and Matthew (2016) on the tidal fresh marshes of the Altamaha River. The Random Forest classifier was used to identify between 21 and 23 vegetation classes on each date, and change detection analysis was used to quantify changes. Of particular interest were any land cover shifts near the marsh-tidal forest boundary.

4.2 Methods

4.2.1 Sentinel-2 Multispectral Imager Data

Images from the Sentinel-2 MSI were acquired from the Copernicus Open Access Hub provided by the European Space Agency (ESA) (scihub.copernicus.eu). Six anniversary images, taken each fall from 2016-2021, were used to assess change over time (Table 4.1). Fall image dates were chosen to capture any damage from hurricanes and to maximize spectral separability by exploiting variation in seasonal senescence between species (Mickelson et al. 1998; Persson et al. 2018). The 2016 image was delivered in the non-atmospherically corrected L1C format and was atmospherically corrected using the Sen2Cor 280 processor in the Sentinel Applications Platform (SNAP) (step.esa.int). Images captured since 2016 were provided in the L2A format with atmospheric correction pre-applied (Table 4.1, Figure 4.1).

4.2.2 Training and Validation Data

The Random Forest classifier requires data to train and validate the classification algorithm. Training and validation pixels were identified based on field observations and supplemented with user-defined regions of interest (ROIs). ROI polygons were manually delineated in ArcGIS Pro 2.9.2 (ESRI) using the Sentinel-2 MSI and high resolution (0.15 m spatial resolution) aerial imagery (acquired as part of an NSF RAPID grant (Alber et al. 2019)) as reference. Image interpretation and plant identification were aided by personal experience in the field and field notes and photographs taken at each plot location during field surveys (see Chapter 2.2). The classes used in our classification of the May 28, 2021, image were used for all other image dates, with the addition of another marsh class (*Juncus/Schoenoplectus*) that was not present in 2021.

Based on visual interpretation of the high-resolution aerial imagery, most classes exhibited relatively limited change throughout the study period, so by positioning ROIs away from the transitional areas between vegetation types, we could the same training and validation ROIs for all image dates. The exceptions were Wrack, Mud, and the *Juncus/Schoenoplectus* class. Wrack was abundant in the 2017-2018 images but decreased in abundance throughout our sampling period and was absent entirely in 2020 and 2021 (Table 4.2). In places where wrack has lain for extended periods, the marsh vegetation will die, and a mudflat will form (Wiegert and Freeman 1990). To accurately classify these classes, we drew unique training and validation polygons for Wrack and Mud for each year. The *Juncus/Schoenoplectus* class was primarily confined to Rockedundy Island but exhibited a dramatic shift in range and robustness throughout the study period. In 2016 it appeared healthy and had a north-south distribution, but by 2020 it was concentrated on the southern bank of the island and by 2021 had disappeared entirely and been replaced by *Juncus roemerianus* and medium *Spartina alterniflora*. As with Mud and Wrack, we adjusted the training and validation polygons to accommodate these shifts. Because of this, the number of classes and training and validation pixels varied with each image date (Table 4.2). From 2016 to 2019, we had 23 classes (Table 4.2). In 2020 there were 22 classes due to the absence of Wrack, and in 2021, 21 classes due to the absence of both Wrack and *Juncus/Schoenoplectus* (Table 4.2).

4.2.3 Image Classification

Classification of all images proceeded using the same methodology as the initial classification in Chapter 3. Classification was performed in R version 4.1.0 (R Core Team 2021) using the *randomForest* package (Liaw and Wiener 2002). Because of the large differences in class sizes in our training and validation datasets, we used a Balanced Random Forest approach, which reduces the proportion of large classes and increases the proportion of minor classes. In our case, the number of training samples was limited to 20 times the smallest class (*Panicum virgatum*). Raster predictor bands included all twelve Sentinel-2 MSI spectral bands, a digital elevation model (DEM), and seven vegetation indices derived from the MSI data (Table 3.1). Following classification and post-classification smoothing, classification accuracy was evaluated by constructing a confusion matrix and calculating the overall accuracy, producer's accuracy, user's accuracy, and errors of omission and commission (Congalton 1991) using the reserved validation data that were not used to train the classifier.

4.2.4 Change Detection Analysis

Temporal change between classified images was calculated in ENVI 5.6.1 (L3 Harris Geospatial, Boulder, CO) using the Thematic Change Workflow tool. Change was calculated between each subsequent year (2016-2017, 2017-2018, 2018-2019, 2019-2020, and 2020-2021) and over the entire study period (2016-2021). Outputs included areal change statistics and to-from pixel statistics, which were arranged in a change matrix and used to calculate percent change. To examine larger-scale trends that might be obscured by classification error, we merged our detailed marsh classes into three: salt marsh, mesohaline marsh, and tidal fresh marsh, and performed a final temporal change analysis for the 2016-2020 period.

4.3 Results

4.3.1 Image Classification

Sentinel-2 MSI imagery was classified using the Random Forest classifier, and standard confusion matrices were generated to assess image and class accuracies. Overall classification accuracies ranged from 82% in 2016 to 86 % in 2021, with reasonably consistent class accuracies for major classes (Table C1, Figure D1). Pine/Sweetgum and *S. americanus* were the most accurately classified across image dates, with producer's accuracies ranging from 97% to 100% and 93% to 99%, respectively (Table C2). Salt-Tolerant Shrubs and *P. virgatum* were consistently least accurate, with producer's accuracies ranging from 36% to 51% and 27% to 70%, respectively. (Table C2). Salt-Tolerant Shrubs were most commonly confused with *J. roemerianus*, *Zizaniopsis miliacea*, and *Spartina cynosuroides* (Table C1a-C1f). *P. virgatum* was most commonly confused with *S. cynosuroides* and *J. roemerianus* (Table C1a-C1f). Among forest classes, Salt-Stressed Tidal Forest and Oak/Hornbeam were the least accurately classified across our six image dates (Table C2). Producer's accuracy for Salt-Stressed Tidal Forest was highly variable, ranging from 20% in 2018 to 76% in 2016. Salt-Stressed Tidal Forest was mainly confused with *Z. miliacea* and Tupelo classes (Table C1a-C1f). Oak/Hornbeam was somewhat more consistent, with producer's accuracies between 40% (2019) and 70% (2018) (Table C2). Confusion was mainly between Pine and Live Oak classes (Table C1a-C1f). Besides *P*. *virgatum*, Tall *S. alterniflora* and *Cladium jamaicense* were the least accurately classified marsh classes. Tall *S. alterniflora* producer's accuracies ranged from 41% to 70% (Table C2), and it was commonly confused with Medium *S. alterniflora* and *S. cynosuroides* (Table C1a-C1f). Producer's accuracies for *C. jamaicense* ranged from 36% to 65% (Table C2), and it was commonly confused with *Schoenoplectus tabernaemontani* (Table C1a-C1f).

Elevation was consistently the most important predictor variable as assessed by *caret*'s varImp function (Kuhn 2008). The digital elevation model (DEM) was ranked as the most important variable in all classifications except Sept. 25, 2021, when it ranked second (Table C3). Of the Sentinel-2 spectral bands, the Coastal Aerosol band (B1, 443 nm) was consistently the most important (Table C3). The Vegetation Red Edge (B5, 705 nm) and Water Vapor (B9, 945 nm) bands were also among the most important predictors (Table C3). As in the May 28, 2021 classification, NDMI and MNDWI were the most important vegetation indices for all other image dates (Table C3).

4.3.2 Overall Temporal Change

We did not observe substantial changes from any forest class to any marsh class for our study period from 2016 to 2021 (Table D1f, Figure D1a, and Figure D1f). Most land cover classes were consistently distributed, with only moderate changes at the edges of zones (Figures D1a and D1f). The classes with the greatest reductions in area were wrack, *Juncus/Schoenoplectus*, and *C. jamaicense*. Both wrack and *Juncus/Schoenoplectus* lost 100% of their area between 2016 and 2021. *C. jamaicense* lost 0.26 km2, 38% of its initial area (Table D1f). The class with the greatest increase in area was Tupelo, which gained 9 km^2. The most stable classes were *Iva frutescens/S. alterniflora*, which decreased in area by just 0.02 km^2, and Pine, which increased by 0.4 km^2. Between 2016 to 2021, Salt-Stressed Tidal Forest showed a slight increase in total area from 9.17 to 9.83 km^2, but only 47% of initial state Salt-Stressed Tidal Forest pixels remained in the same class in 2021 (Table D1f). Of the initial state pixels, 18% changed to *Z. miliacea* in 2021, and 13% changed to Tupelo (Table 4.3).

4.3.3 Temporal Change from Year-to-Year

There were substantial year-to-year fluctuations in the total area of land cover classes, making it difficult to discern a trend in land cover change from classification error (Table 4.2). For example, from 2020 to 2021, Tupelo increased in total area from 21 to 36 km^2 (Table 4.2). In the same interval, the mixed deciduous floodplain class decreased from 17 to 11 km^2 (Table 4.2). Tidal marsh classes were equally variable, with some classes (e.g., *Z. miliacea*) nearly doubling in area in a single year (Table 4.2). Salt-Stressed Tidal Forest increased from 6.81 to 12.69 km^2

between 2017 and 2018 before declining to 8.06 km^2 the following year (Table 4.2). The majority of these changes occurred between marsh classes and other marsh classes or forest classes with other forest classes, which gives us confidence in monitoring forest-marsh transition. The exception was Salt-Stressed Tidal Forest, which frequently gained and lost pixels to *Z. miliacea*, *S. tabernaemontani*, and other tidal freshwater marsh classes. For example, 39% (3.6 km^2) of Salt-Stressed Tidal Forest in 2016 became *Z. miliacea* in 2017, but the following year (2017-2018), 10% of *Z. miliacea* (1.7 km^2) became Salt-Stressed Tidal Forest (Table D1a-D1f).

4.3.4 Temporal Change with Merged Marsh Classes

When tidal marsh classes were merged into salt marsh, mesohaline marsh, and tidal fresh marsh classes, change from 2016-2021 between marsh classes and between forest and marsh was reduced (Table D1g). From the total 84 km^2 area of all forest classes, only 0.02 km^2 (0.024%) was converted to any marsh class. 2.0 km^2 (2.4%) of all forest classes became Salt-Stressed Tidal Forest, but 1.98 km^2 (21%) of Salt-Stressed Tidal Forest reverted to other forested classes, resulting in a net loss of only 0.02 km^2 of healthy forest. 18% (1.7 km^2) of Salt-Stressed Tidal forest became tidal fresh marsh, while 4% (~0.3 km^2) became mesohaline marsh and salt marsh (Table D1g). A similar amount of Salt-Stressed Tidal Forest (1.1 km^2, 11.9%) changed to Tupelo. There was a decrease in the total area of tidal fresh marsh (21 km^2 to 11 km^2), most of which was converted to mesohaline marsh (2.5 km^2, 10.5%) or salt marsh (1 km^2, 4.6%). Because of this, these more salt-tolerant classes increased in area, with mesohaline marsh growing by 34% to 10 km^2 and salt marsh growing by 26% to 7.6 km^2.

4.4 Discussion

This study classified satellite imagery for a six-year period (2016-2021) to monitor changes in the abundance and distribution of tidal fresh forest and tidal marsh vegetation, the first study of its kind for the Altamaha tidal fresh forest. We found that while there were no major changes from forest classes to marsh classes indicative of large-scale habitat shifts, there were substantial year-to-year changes between classes within these two broad categories.

Overall accuracies for each of our six images ranged from 80-86% (Table C1a-C1f). In general, class accuracy had a positive association with the amount of training data available, even with the use of the Balanced Random Forest classification technique. For example, *J. roemerianus*, the class best represented in the training data (~3000 pixels), had consistently high producer's accuracies (84% to 94%) (Table C2). Salt-tolerant Shrubs, however, with just 175 training pixels, was one of the most error-prone classes, and its producer's accuracy never exceeded 51% (Table C2). The relationship between the amount of training data and classification accuracy is well established (Lu and Weng 2007). In our case, merging the smaller marsh classes with the most ecologically or spectrally similar class could reduce overall and class errors without unduly compromising our objective of monitoring tidal fresh forests.

While classification accuracies for our forest classes were generally good (Tables C1a-C1f), classifier error most likely resulted in the observed change in class areas and distributions on a year-to-year basis. For example, from 2020 to 2021, Tupelo increased in total area from 21 to 36 km^2, an increase of 171% (Table 4.2). We doubt that this represents an actual change in land cover, based on published rates of forest succession for tupelo swamps (Song et al. 2012). Examination of the classified images (Figures C1a-C1f) and change matrices (Table C1a-C1f) show that this increase came at the expense of the Mixed Deciduous Forest and Bald Cypress classes. These classes are frequent neighbors, occupy similar elevation ranges, and Mixed Deciduous Forest contains some tupelo trees, all factors which contribute to classifier error. Subtle differences in phenology from year to year could change land cover class spectral signatures and cause the classifier to erroneously assign the same pixel to different classes in subsequent years, even if the land cover did not actually change (Ozesmi and Bauer 2002; Plakman et al. 2020). Because our training and validation datasets covered only a small proportion of our study area (~3.4km^2 out of a total study area of ~150 km2), such erroneous changes were unlikely to be captured by the accuracy assessment process. To avoid these types of errors, others have recommended that a 75% Producer's accuracy be the cutoff for inclusion in temporal change analyses (D. Mishra, pers. comm.).

An additional source of classification error was mixed pixels. At the 10 m spatial resolution of the Sentinel-2 MSI sensor, many pixels, particularly in transitional zones between more homogeneous areas, contain more than one type of vegetation, particularly in tidal marsh areas. This complicates classification, as these pixels will have a spectral signature that is a hybrid of their component species (Lu and Weng 2007). Variable phenology (discussed above) complicates classification of mixed pixels further. We suspect that this may cause the pattern of the alternately increasing and decreasing area of Salt-Stressed Tidal Forest. Salt-Stressed Tidal Forest is a composite of tidal fresh forest vegetation (primarily bald cypress) and TFM vegetation (*Z. miliacea*, *S. tabernaemontani*, among others). These marsh vegetation persist through the winter when bald cypress is leafless (White and Kaplan 2021). Thus, the extent of leaf loss at the time of imaging will change the relative influence of marsh and forest vegetation on the class's spectral signature (White and Kaplan 2021).

Despite these potential sources of misclassification, there were several important results from our temporal change analyses. At a fine spatial scale (10 m), there were changes over our six-year study period, but there was no sign of large-scale ecotone shifts. Most importantly, there was no apparent trend for tidal fresh forest to transition to stressed forest or for stressed forest to transition to marsh. Salt-Stressed Tidal Forest increased in area by 0.66 km^2, but these increases came primarily from mud and tidal fresh marsh classes rather than forest (Tables D1a-D1g). We were unable to identify any year-to-year trends in forest cover in the aftermath of Hurricanes Matthew and Irma (pulse disturbances) or over the study period from 2016 to 2021 (press disturbance). However, we did observe an increase in the area of salt marsh and brackish marsh in our Merged Marsh Classes analysis. These results are consistent with the findings of Alber *et al.* (2019) that tree mortality was limited, but that there was an expansion of salt-tolerant marsh vegetation and a loss of tidal fresh marsh (Alber et al. 2019).

The lack of a clear trend in forest cover could be due to several factors. First, a six-year time frame may not be long enough for the effects of sea level rise or saltwater intrusion to manifest (Taillie et al. 2019). Sentinel-2 began collecting data in the fall of 2015, limiting us to a six-year study period (Immitzer et al. 2016). Prior studies of sea level rise and forest-marsh transition examined change over ten years or more using Landsat or MODIS imagery, which have decades-long data catalogs (Raabe and Stumpf 2015; Smart et al. 2020; Ury et al. 2021; White and Kaplan 2021). Repeating this study with Landsat data (30 m spatial resolution) might provide a better understanding of trends over multidecadal timescales, at the expense of the finer spatial resolution of Sentinel-2 MSI (10 m). Visual interpretation of panchromatic high-resolution NAIP orthoimagery shows a gradual decline in tidal fresh forest extent and canopy cover since the 1980s, but only at the downstream limits of forested area.

Our study site may be less vulnerable than other tidal fresh forests on the Gulf and eastern US coasts. Most research on tidal fresh forests and forest-marsh transition in the US has been performed at the Alligator River NWR, NC (Doyle et al. 2021; Smart et al. 2020; Taillie et al. 2019; Ury et al. 2021), Delmarva Peninsula (Brinson et al. 1995; Jin et al. 2017; Kearney et al. 2019; Middleton 2016; Nordio and Fagherazzi 2022), and the Gulf coast from Florida to Louisiana (Bianchette et al. 2009; Desantis et al. 2007; Doyle et al. 2010; Langston et al. 2017; McCarthy et al. 2021; Raabe and Stumpf 2015). The majority of these studies have documented substantial loss of tidal fresh forest, some in as little as five years (Ury et al. 2021). A combination of factors could be responsible for the relative stasis at our Altamaha River study site.

Direct landfall of hurricanes in Georgia is relatively rare, totaling just 14 instances since 1851 and none since 1979 (Bossak et al. 2014). Instead, prevailing atmospheric conditions tend to divert storms north to the Carolinas or out into the Atlantic (Bossak et al. 2014). While storms which do not make landfall can still have adverse impacts on coastal areas (Jackson 2010), the lower Georgia coast has historically been less-frequently affected by hurricane-force winds than either Florida or the Carolinas (Bossak et al. 2014). Lower wind speeds reduce damage from windthrow, one of the primary sources of acute tree mortality from storms (Sharma et al. 2021; Song et al. 2012). Additionally, the relatively unbroken canopy in the majority of the Altamaha River's tidal fresh forest reduces the risk of windthrow (Shaffer et al. 2009). The main effect of hurricanes on the Altamaha River's tidal fresh forest is defoliation, and this damage is quickly reversed during the next growing season (C. Craft, pers. comm.).

In the weeks to months following a hurricane, salty water delivered by the storm surge stresses trees by impairing their uptake of water and nutrients (Doyle et al. 2021). In comparison to the tidal fresh forests in the Gulf or north Atlantic coast, the extensive marshes of the Altamaha River delta absorb much of the energy of storm surges, limiting the extent of saltwater intrusion within the tidal fresh forest. The large drainage of the Altamaha delivers higher volumes of freshwater than the rivers at the majority of other study sites in the literature, which can help to flush salinity from the system (Shaffer et al. 2009). Data from a GCE LTER data logger located in the Altamaha River near Lewis Island (81° 29’ 34.1” W, 31° 22’ 45.8” N) showed a dramatic spike in salinity up to 10.2 PSU for Hurricane Matthew and 21.9 PSU for Hurricane Irma, but salinity returned to normal within twelve hours (Di Iorio 2018). Following both storms, salinity levels were suppressed below normal and showed no signs of tidal influence, likely due to increased freshwater discharge as a result of inland precipitation from the storms (Figure 1.3).

Along with this freshwater input, the Altamaha River delivers substantial amounts of sediment to the tidal fresh forest (1.3-2.2mm yr^{-1}) (Craft 2012). While not enough to keep up with the 3 mm yr^{-1} rate of local sea level rise (Craft 2012), the dynamic is more favorable than for tidal fresh forests at other sites (Anderson and Lockaby 2007). Altogether, the tidal fresh forests of the Altamaha River may be less acutely threatened than tidal fresh forests in other areas, but the long-term prognosis is not good, with one model predicting that under current sea level rise scenarios, 24% of Georgia’s tidal fresh forests could be converted to marsh by 2100 (Craft et al. 2009).

4.5 Conclusions

Tidal fresh forests are among the ecosystems most acutely threatened by sea level rise and saltwater intrusion. Given their role in carbon sequestration and other critical ecosystem services, monitoring tidal fresh forest health is vitally important. In this chapter, we classified six Sentinel-2 MSI images from 2016 to 2021 and calculated changes in land cover. We did not observe any long-term (2016-2021) changes in forest cover in response to hurricanes Matthew and Irma, a result consistent with other research conducted on the Altamaha River in the same time frame (Alber et al. 2019). We were unable to discern any short-term trends in tidal fresh forest class distributions due to the instability of our classification results from year to year. In future studies, we will refine our classification and temporal change methodologies to reduce these errors and better elucidate trends in vegetation distributions.

4.6 References

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4.7 Tables and Figures

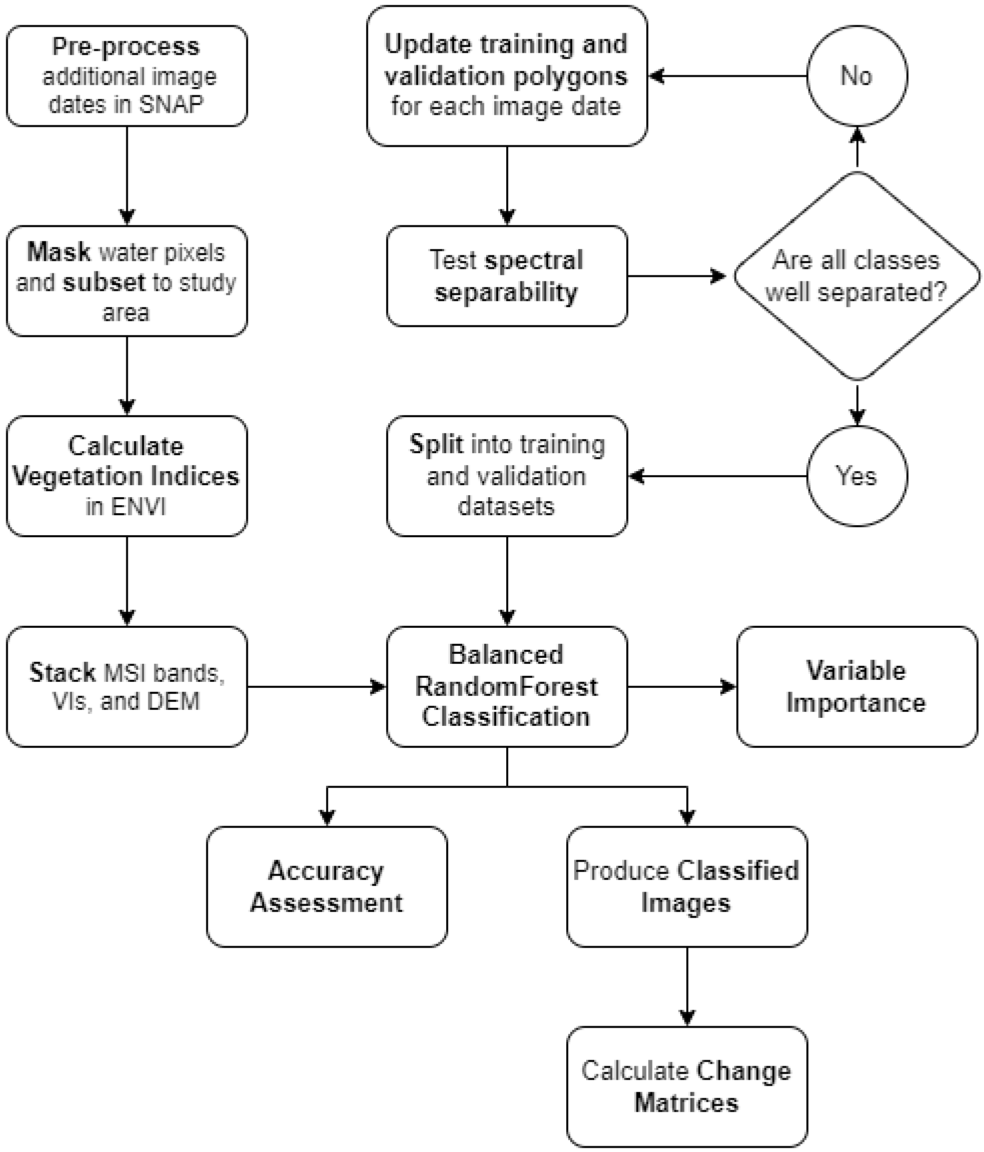

Figure 4.1 Workflow for our temporal change analysis of classified Sentinel-2 MSI imagery.

Table 4.1 Sentinel-2 MSI images chosen for classification and temporal change analysis. Cloud-free images as close to one year apart as possible were selected. All but the 2016 image were delivered with atmospheric correction applied. The 2016 image was corrected using Sen2Cor in SNAP (see section 4.2.1).

Image Name	Collection Date	Processing Level
S2A_MSIL1C_20161001T160052_N0204_R097_T17RMQ	10/01/2016	L1C (Top of atmosphere)
S2B_MSIL2A_20170901T155859_N9999_R097_T17RMQ	09/01/2017	L2A (Surface reflectance)
S2A_MSIL2A_20181021T160311_N9999_R097_T17RMQ	10/21/2018	L2A (Surface reflectance)
S2A_MSIL2A_20190926T160021_N0213_R097_T17RMQ	09/26/2019	L2A (Surface reflectance)
S2A_MSIL2A_20201030T160411_N0214_R097_T17RMQ	10/30/2020	L2A (Surface reflectance)
S2A_MSIL2A_20210528T155901_N0300_R097_T17RMQ	05/28/2021	L2A (Surface reflectance)
S2A_MSIL2A_20210925T160021_N0301_R097_T17RMQ	09/25/2021	L2A (Surface reflectance)

Table 4.2 Number of training pixels (A) and validation pixels (B) for each classified image. The "-" symbol indicates that the class was not present that year.

A	Number of Training Pixels					
Cover Class	2016	2017	2018	2019	2020	2021
Bare or paved	378	378	378	378	378	378
C. jamaicense	189	189	189	189	189	189
Iva frutescens / S. alterniflora	106	106	106	106	106	106
J. roemerianus	3392	3392	3392	3392	3392	3392
Juncus/Schoenoplectus	456	543	543	543	456	-
Mixed broadleaf swamp	304	304	304	304	304	304
Mud	119	119	164	607	454	611
Tupelo	949	949	949	949	949	949
P. virgatum	48	48	48	48	48	48
Pine	1559	1559	1559	1559	1559	1559
Pine/Sweetgum	939	939	939	939	939	939
Oak/Hornbeam	596	596	596	596	596	596
Live oak	550	550	550	550	550	550
S. americanus	2211	2211	2211	2211	2211	2211
S. tabernaemontani	524	524	524	524	524	524
Salt-tolerant shrubs	175	175	175	175	175	175
Medium *S. alterniflora*	1661	1661	1661	1661	1661	1661
S. cynosuroides	430	430	430	430	430	430
Tall *S. alterniflora*	156	156	156	156	156	156
Salt-stressed tidal forest	575	575	575	575	575	575
Bald Cypress	495	495	495	495	495	495
Wrack	46	644	1176	514	-	-
Z. miliacea	2679	2679	2679	2679	2679	2679

B	Number of Validation Pixels					
Cover Class	2016	2017	2018	2019	2020	2021
Bare or paved	259	259	259	259	259	259
C. jamaicense	104	104	104	104	104	104
Iva frutescens / S. alterniflora	72	72	72	72	72	72
J. roemerianus	1813	1813	1813	1813	1813	1813
Juncus/Schoenoplectus	151	256	256	256	151	-
Mixed broadleaf swamp	396	396	396	396	396	396
Mud	126	126	126	231	491	321
Tupelo	452	452	452	452	452	452
P. virgatum	37	37	37	37	37	37
Pine	1588	1588	1588	1588	1588	1588
Pine/Sweetgum	672	672	672	672	672	672
Oak/Hornbeam	413	413	413	413	413	413
Live oak	259	259	259	259	259	259
S. americanus	2448	2448	2448	2448	2448	2448
S. tabernaemontani	360	360	360	360	360	360
Salt-tolerant shrubs	126	126	126	126	126	126
Medium *S. alterniflora*	775	775	775	775	775	775
S. cynosuroides	306	306	306	306	306	306
Tall *S. alterniflora*	270	270	270	270	270	270
Salt-stressed tidal forest	258	258	258	258	258	258
Bald Cypress	503	503	503	503	503	503
Wrack	63	486	806	345	-	-
Z. miliacea	840	840	840	840	840	840

Table 4.3 Summary of total area for each class from 2016 to 2021 in square kilometers. Net change indicates the difference between the total class area in 2021 and the total class area in 2016.

Landcover Class	Classified Area						Net change,
	2016	2017	2018	2019	2020	2021	2016-2021
Bare or paved	0.57	1.09	0.63	0.60	0.54	0.75	+0.18
C. jamaicense	0.94	2.22	1.25	1.76	0.77	0.68	-0.26
Iva frutescens / S. alterniflora	0.23	0.22	0.16	0.24	0.20	0.21	-0.02
J. roemerianus	16.52	15.48	13.38	15.98	16.15	14.16	-2.36
Juncus/Schoenoplectus	1.74	1.97	0.79	1.57	1.01	0.00	-1.74
Mixed deciduous floodplain	15.97	11.86	14.55	15.13	17.17	11.94	-4.03
Mud	1.89	0.46	0.71	3.28	2.92	4.36	+2.46
Nyssa spp.	26.86	36.23	26.39	32.59	20.65	35.91	+9.05
P. virgatum	0.11	0.26	0.20	0.15	0.11	0.31	+0.2
Pinus spp.	8.92	7.36	8.94	9.66	9.81	9.32	+0.4
Pinus / L. styraciflua	4.82	6.86	5.69	5.47	4.68	5.37	+0.55
Floodplain *Quercus* spp.	6.03	6.88	5.93	4.30	5.62	7.58	+1.55
Upland *Quercus* spp.	6.48	4.32	5.45	5.77	5.01	3.56	-2.91
S. americanus	4.79	5.29	3.74	4.49	4.85	7.03	+2.23
S. tabernaemontani	8.16	4.74	6.14	6.03	5.45	4.79	-3.37
Salt-tolerant shrubs	0.43	0.36	0.38	0.34	0.58	0.56	+0.13
Medium *S. alterniflora*	4.95	7.29	10.36	5.77	6.82	6.75	+1.8
S. cynosuroides	1.81	1.97	2.70	1.80	2.11	2.11	+0.31
Tall *S. alterniflora*	0.89	0.77	0.87	0.96	0.61	0.68	-0.21
Salt-stressed tidal forest	9.17	6.81	12.69	8.06	13.05	9.83	+0.66
T. distichum	14.48	9.07	9.33	12.71	10.23	11.00	-3.48
Wrack	0.23	1.06	1.74	0.91	0.00	0.00	-0.23
Z. miliacea	13.16	16.94	17.40	11.72	20.88	12.32	-0.84

CHAPTER 5

CONCLUSION

The goal of this study was to observe the large-scale impacts of hurricanes on the tidal fresh forest of the Altamaha River, GA, through the following objectives.

1. Characterize TFF vegetation communities
2. Map these communities using satellite-based multispectral imagery
3. Conduct a temporal change analysis to monitor changes in vegetation distributions.

We identified eight tidal fresh forest communities using hierarchical clustering and additional multivariate statistical analyses. These communities correspond well with prior characterizations of tidal fresh forests throughout the Southeastern U.S. Overall species distributions and the influence of environmental variables (elevation and river distance) were also consistent with existing studies. Compared to prior studies, our more widely distributed sample plots better represented the diversity of the Altamaha River tidal fresh forest and adjacent upland areas. These results contribute to our understanding of the community and structure of the Altamaha River tidal fresh forests, a relatively understudied ecosystem, and represent an important first step in anticipating and managing future threats from tropical storms and sea level rise.

We mapped 21 classes of tidal marsh and forest vegetation with an overall accuracy of 84.6%, demonstrating that detailed, accurate classification of tidal fresh forests is possible using freely available, moderately high-resolution Sentinel-2 MSI satellite imagery. This represents a substantial improvement in ecological detail over existing remote sensing classifications of similar ecosystems, with little to no reduction in overall accuracy. Importantly, we were able to effectively discriminate between forests undergoing forest-marsh transition and both marsh and healthy forest vegetation.

Finally, we classified six Sentinel-2 MSI images from 2016 to 2021 and calculated changes in land cover. We did not observe any long-term (2016-2021) changes in land cover in response to hurricanes Matthew and Irma, a result consistent with other research conducted on the Altamaha River in the same time frame (Alber et al. 2019). We were unable to discern any short-term trends in vegetation distributions due to the instability of our classification results from year to year.

Tidal fresh forests are among the ecosystems most acutely threatened by sea level rise and saltwater intrusion. Given their role in carbon sequestration and other critical ecosystem services, monitoring tidal fresh forest health is vitally important. In future studies, we will refine our classification and temporal change methodologies to reduce these errors and better elucidate trends in vegetation distributions.

APPENDIX A

COMMUNITY ANALYSIS WITH RELATIVE ABUNDANCE AND SALT-STRESS

Methods

The methodology for this analysis was the same as for the Relative Abundance Only analysis (Chapter 2), but with the inclusion of a binomial variable to distinguish sites suffering from saltwater intrusion, as assessed in the field based on tree morphology and herbaceous vegetation cover. The variable was added to the table of relative abundance values prior to Hellinger transformation or distance matrix calculation. All subsequent steps (hierarchical clustering, indicator species analysis, MRPP, and NMDS) used the same parameters as the Relative Abundance Only analysis.

Results: Salt-Stressed Analysis

Hierarchical clustering including the salt stress variable produced a dendrogram with an agglomerative coefficient of 0.88 (scale of 0 - 1), indicating fairly strong clustering (Figure A1). Following Duberstein et al. (2014), based on indicator species analysis, we plotted the number of significant indicator species and the total *p* value for all species at each clustering level (Figure A2). Clustering levels with low total *p* values and a high number of indicator species represent optimal pruning levels (McCune and Grace 2002). Based on these criteria, three, four or nine clusters are possible. We chose to prune at nine clusters, as this gave the most reasonable ecological interpretation and agreed with the gap statistic (see Figure A3). Subsequent MRPP and NMDS analyses provided additional support for this decision (see Figure A4). Cophenetic distance measures how closely the dendrogram preserves pairwise distances compared to the original distance matrix. Our value is 0.79 (on a scale of 0 - 1), which indicates high fidelity to the original distances.

Inspection of the dendrogram reveals clear ecological stratification based on species composition and environmental conditions (Figure A1). The two highest level clusters separate stressed from non-stressed plots. Pruning at three clusters would produce a clear division within non-stressed plots between those plots which are continuously or frequently flooded and seasonally flooded or upland plots. The former are occupied by flood tolerant species such as tupelo and bald cypress, while the latter have varying compositions of oak (*Quercus* spp.) and pine (*Pinus* spp.). Within these two broad categories, many species are widely distributed (Table A1), so subsequent groupings are dependent on relative abundance rather than presence-absence.

MRPP results indicated that these nine communities have significantly different species compositions, A=0.516, p=0.001, meaning that more than half of the variation in species composition could be explained by cluster identity. Mean within group distance was 0.351 and mean between group distance was 0.677.

NMDS ordination showed clear separation between groups of plots and strong environmental gradients (Figure A4). A two dimensional solution was chosen as it provided an acceptably low stress score of 0.13 and optimal ecological interpretation (Clarke 1993). Both longitude and elevation were strongly correlated with both axes (p=0.001) (Table A2). Alder/Magnolia, Stressed Cypress, and Stressed Tupelo communities, which contained all plots identified in the field as salt-stressed, were well separated from non-stressed communities (Figure A4). NMDS reinforces the spatial pattern visible in the map (Figure A5), that stressed sites are significantly associated with elevation and longitudinal position on the river (Table A2).

Prior plant community characterizations of the Altamaha tidal fresh forest were based on less widely distributed field sites which did not fully capture the diversity of floral communities present (Duberstein et al. 2014; U.S. Fish and Wildlife Service 2014). Using our more extensive ground-reference dataset, we produced a more detailed community analysis supported by hierarchical clustering (Figure A1, Table A2), MRPP, and NMDS results (Figure A4, Table A2).

Clustered forest communities for the Salt-Stressed analysis

Communities with the same name as those in the Relative Abundance Only analysis are the same community, but importance values (IV), mean basal area, and stem density may have changed due to the reassignment of some plots.

1. Oak/Hornbeam

   Unchanged from the Relative Abundance Only analysis

2. Water Tupelo

   This community covered substantial areas of the backswamp further from the river. When we visited in May of 2021, they were flooded to depths of 2 - 10 cm. The canopy was dominated by water tupelo (36% of IV), with some bald cypress (13% of IV). Individuals of both species were generally mature and large in stature, with heights of up to 35 m. Canopy coverage was complete (96%) (Table A1). The understory was sparse, but mainly ash (14% of IV) and sweetgum (7% of IV). Herbaceous ground cover was variable. In less deeply flooded areas, lizard’s tail was abundant.

3. Pine

   Unchanged from the Relative Abundance Only analysis.

4. Bald Cypress

These plots represent almost homogeneous stands of bald cypress (45% of IV). Swamp tupelo was sparsely present in the understory or canopy (17% of IV). The uniformly tall canopy and nearly complete canopy closure (89%) largely excluded understory and underbrush species, but sweetgum and red maple were sometimes present. Ground cover was mainly lizard's tail, dwarf palmetto (*Sabal minor* [Jacq.] Pers.), and pickerelweed (*Pontederia cordata* L.).

5. Swamp Tupelo

   This was the most abundant community in our study area, typically occupying areas adjacent to the main channel of the river. The canopy is dominated by swamp tupelo (38% of IV), with sweetgum (10% of IV) and ash (23% of IV) occasionally emerging from the understory. The abundance of these trees in the understory contributes to this community having the highest average density, at 1500 stems·ha^{-1}. A dense network of surface roots created low hummocks which supported less flood tolerant vegetation such as dwarf palmettos or oaks. Ground cover was abundant, typically a mixture of lizard's tail and pickerelweed.

6. Alder/Magnolia

   Unchanged from the Relative Abundance Only analysis.

7. Stressed Bald Cypress

   This community represents various stages in the transition from the Bald Cypress Community to tidal freshwater marsh or brackish marsh. Living trees were mature bald cypress (57% of IV), swamp tupelo (21% of IV), and ash (18% of IV). The leaf area of living trees was reduced, and many had dead branches in their crown, both indicators of osmotic stress due to saltwater intrusion. Standing dead trees (ghost forest), likely bald cypress, were common. Saplings and seedlings were few to none. Salt tolerant shrubs such as Southern wax myrtle or groundsel tree (*Baccharis halimifolia* L.) were present on hummocks. At lower elevations, the more open canopy (83.5% coverage) permitted herbaceous marsh vegetation to become established. The composition of this transitional marsh varied, but included softstem bulrush (*Schoenoplectus tabernaemontani* [C.C.Gmel] Palla), hop sedge (*Carex lupulina* Muhl. ex Willd.), big cordgrass, Southern Cattail (*Typha domingensis* Pers.), and pickerelweed, among others. The basal area (27.4 $m^2 \cdot ha^{-1}$) and stem density (404 $stems \cdot ha^{-1}$) of this community were the lowest of all communities. The dominance of bald cypress and low stem density in this community is consistent with patterns reported by Krauss *et al*. (2007) and Krauss *et al.* (2009).

8. Stressed Tupelo

This community was represented by three plots. Swamp tupelo is the most abundant canopy tree (57% of IV), along with scattered ash trees (21% of IV). All trees showed signs of salt stress: small stature, reduced leaf area, and dead branches. Seedlings and saplings were nonexistent. Canopy coverage was the lowest of all communities at 74%, which permitted dense herbaceous ground cover, primarily softstem bulrush, southern cattail, lizard’s tail, and pickerelweed.

9. Live Oak

Unchanged from the Relative Abundance Only analysis.

References

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Duberstein, J.A., Conner, W.H., & Krauss, K.W. (2014). Woody vegetation communities of tidal freshwater swamps in South Carolina, Georgia and Florida (US) with comparisons to similar systems in the US and South America. Journal of vegetation science, 25, 848-862

McCune, B., & Grace, J.B. (2002). Analysis of Ecological Communities. Gleneden Beach, OR: MjM Software Design

U.S. Fish and Wildlife Service. (2014). National Wetlands Inventory. Washington, D.C.: U.S. Department of the Interior, Fish and Wildlife Service

Tables and Figures

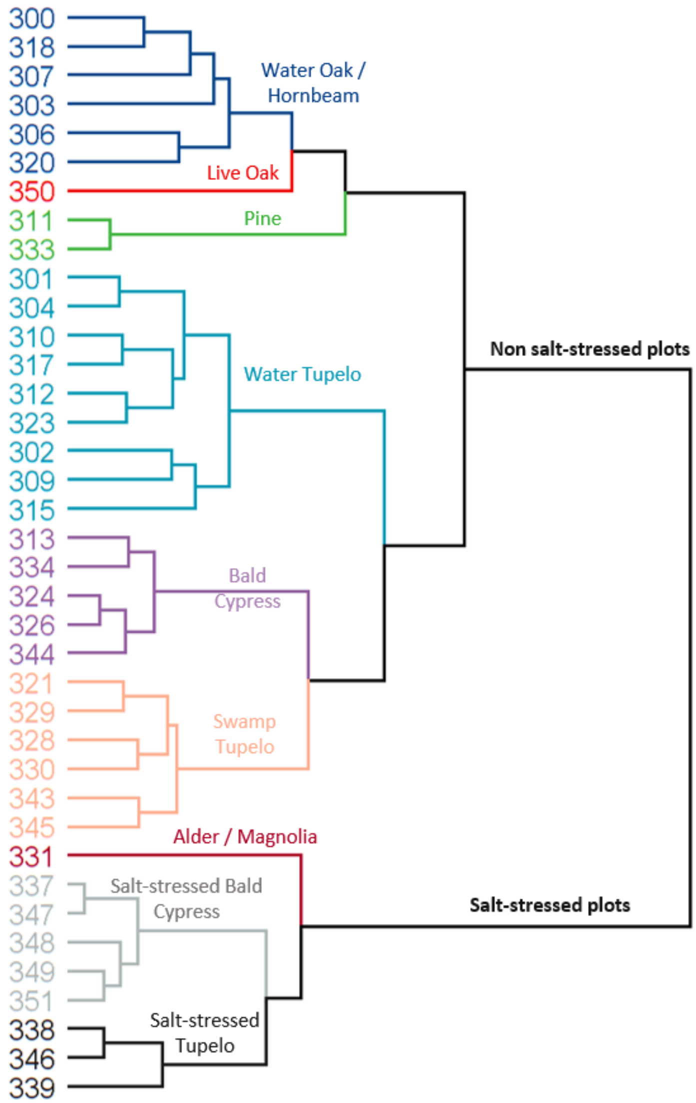

Figure A1 Dendrogram produced by hierarchical clustering using Hellinger distance and Ward linkage for 22 tree species from 38 plots in the Altamaha tidal fresh forest. This analysis was based on relative species abundance and a binomial variable assessing whether or not the site appeared to be suffering from saltwater intrusion. Plot names are listed on the left, and community names are given for each of the 9 groups, with pruning indicated by color. The strong influence of the salt stress variable is clearly visible.

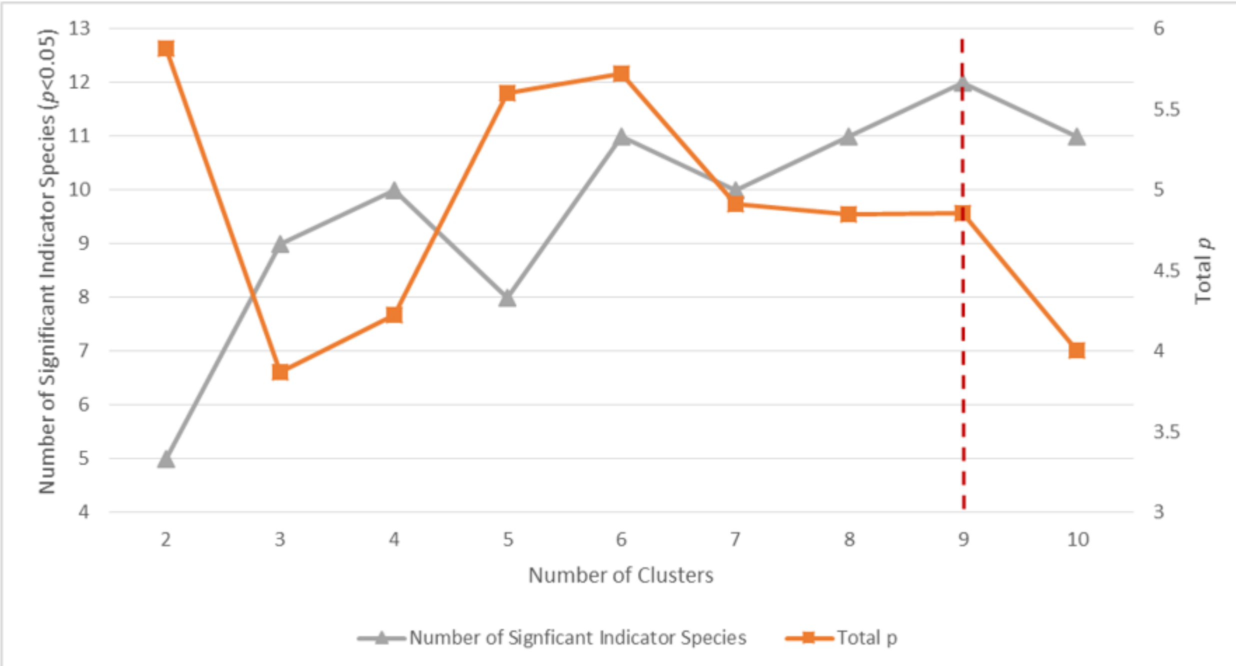

Figure A2 Summary of results of indicator species analyses for the Salt-Stressed analysis. Hierarchical clustering was used to group plots (n=38) into 2-10 clusters. For each clustering level, an indicator value (IVI) was calculated for each species. P-values are based on 1000 Monte Carlo simulations with randomized data, then totaled for all species at each grouping level (x axis). The dashed line represents our final pruning level, selected to maximize the number of significant indicator species and minimize total p while giving a reasonable ecological interpretation.

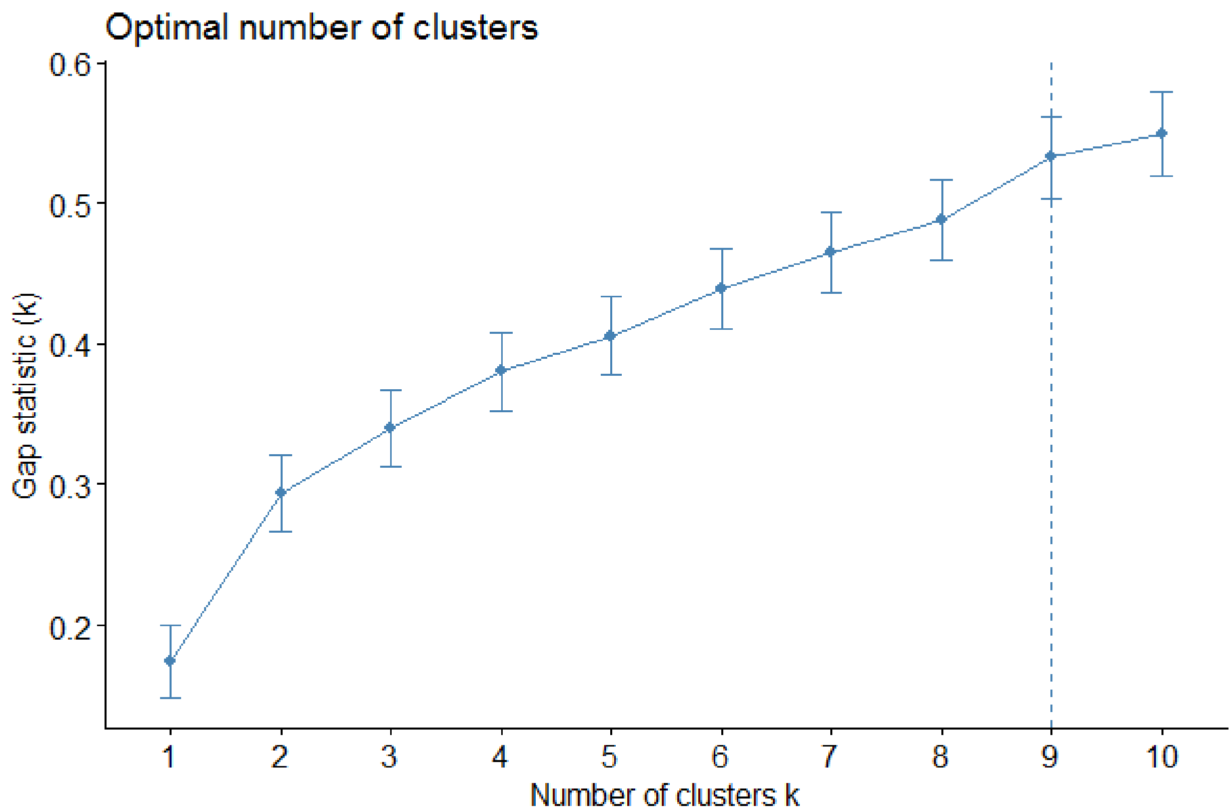

Figure A3 Plot of gap statistic values for the Salt-Stressed hierarchical clustering analysis. The vertical line indicates the optimal pruning level of nine clusters.

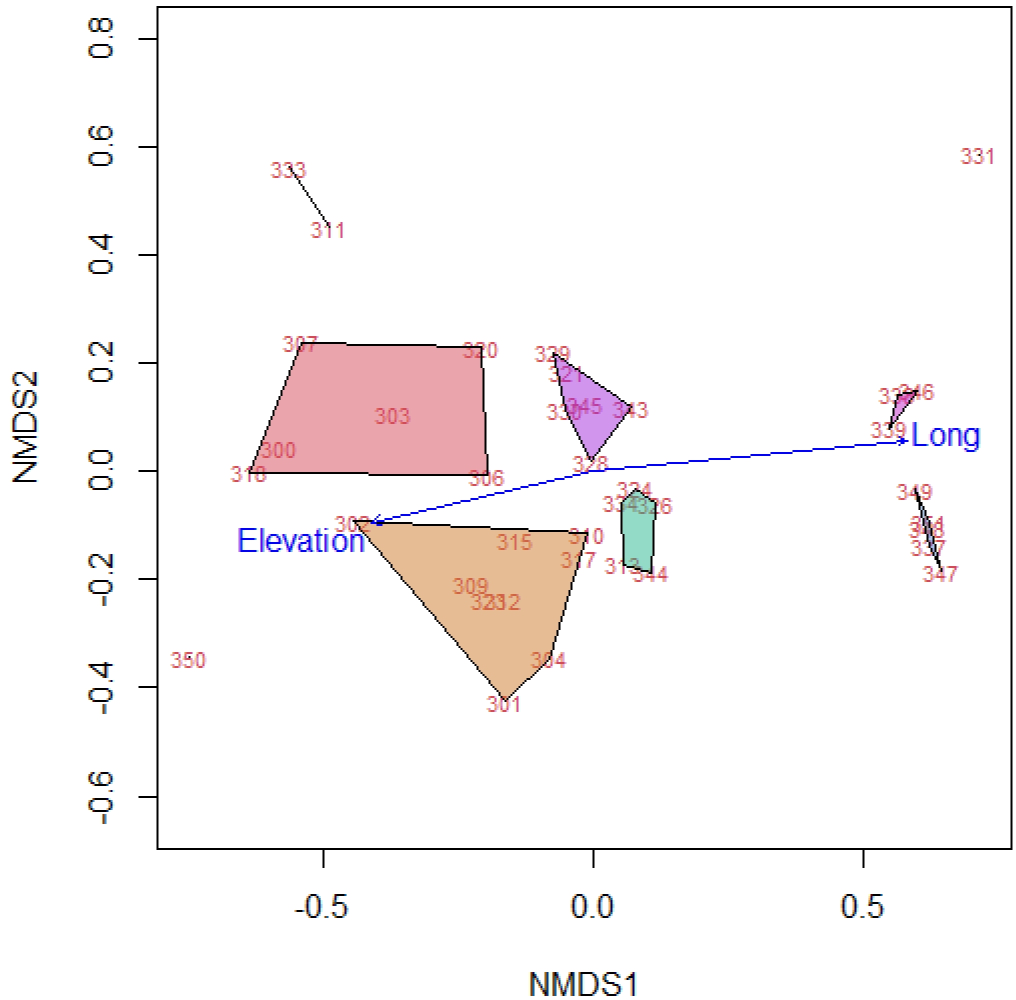

Figure A4 NMDS ordination of field plots in species space. Communities are based on the Salt-Stress Included analysis, and include: Oak/Hornbeam (red), Water Tupelo (orange), Swamp Tupelo (purple), Bald cypress (teal), Salt-stressed Tupelo (pink), Salt-stressed Bald cypress (blue), Pine (plots 311 and 333), Alder/Magnolia (plot 331), and Live Oak (plot 350). Biplot overlays indicate the relationship of elevation above NAVD88 and longitude ("Long", as a proxy for river distance) to plot ordination. Both elevation and longitude were significantly correlated with both NMDS1 (Table A2).

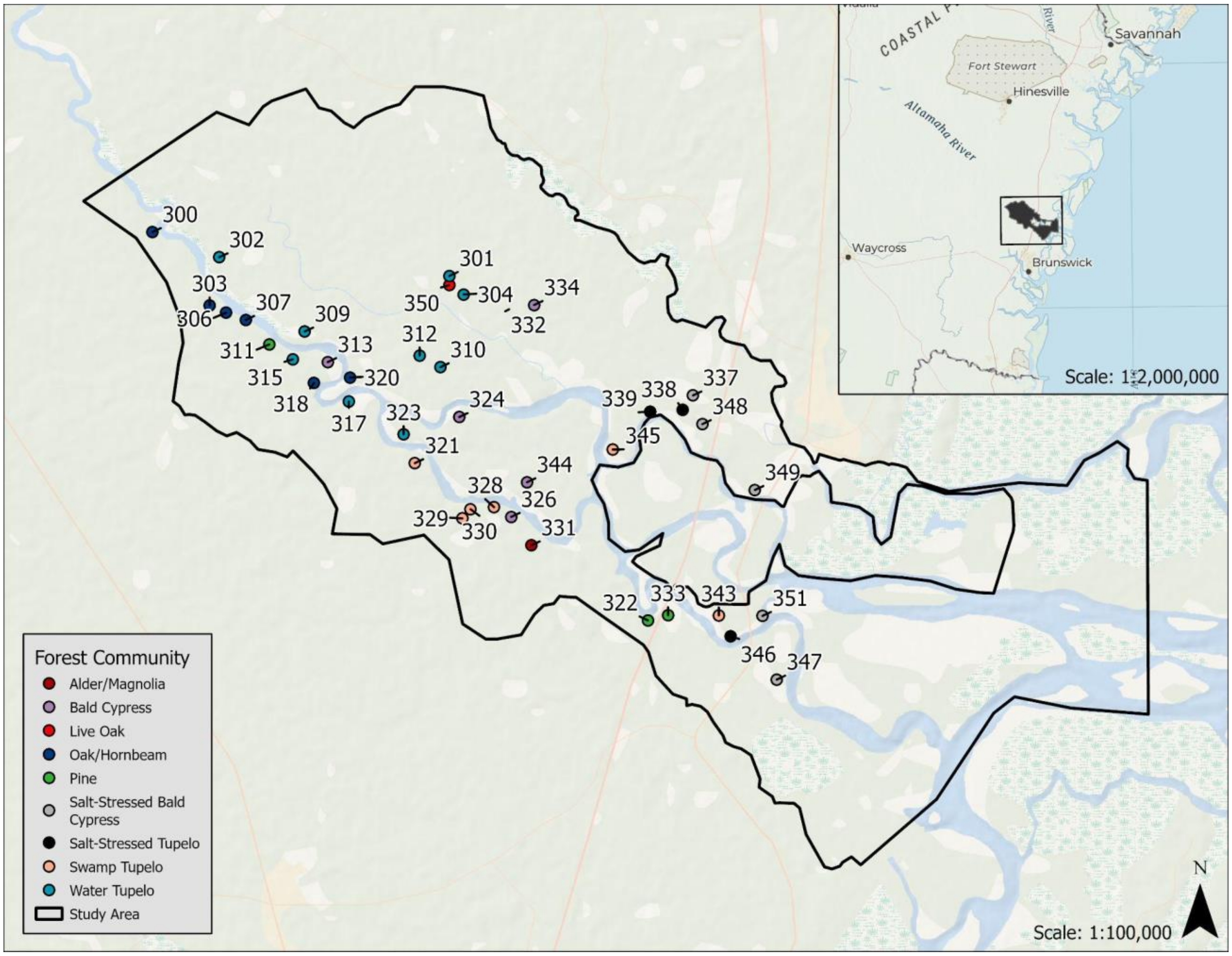

Figure A5 Study area and field sampling plot locations on the Altamaha River, Georgia. Forest communities were identified via hierarchical clustering and indicator species analysis of field plot data in our Salt-Stressed analysis (Figure A1).

Table A1 Mean importance values for trees and shrubs in each community identified from our Salt-Stressed analysis. Bolded numbers are dominant species that total more than 50% of the importance in each community.

Species	Common Name	Community								
		Oak/ Hornbeam	Water Tupelo	Pine	Bald Cypress	Swamp Tupelo	Alder/ Magnolia	Stressed Cypress	Stressed Tupelo	Live Oak
Acer rubrum	Red maple	0.05	0.02	0.01	0.05	0.04	0.00	0.01	0.06	0.00
Alnus serrulata	Hazel alder	0.01	0.05	0.00	0.02	0.05	**0.47**	0.00	0.00	0.00
Betula nigra	River birch	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Carya aquatica	Water hickory	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Carpinus caroliniana	American hornbeam	**0.19**	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cephalanthus occidentalis	Buttonbush	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
Fraxinus spp.	Ash	0.03	**0.14**	0.00	0.14	**0.23**	**0.37**	0.18	0.21	0.00
Standing dead trees		0.01	0.02	0.00	0.02	0.03	0.00	0.00	0.00	0.00
Ilex opaca	American holly	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
Ilex decidua	Possumhaw	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Liquidambar styraciflua	Sweetgum	0.12	0.07	0.09	0.07	0.10	0.00	0.00	0.00	0.00
Magnolia virginiana	Sweetbay	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00
Nyssa aquatica	Water tupelo	0.01	**0.36**	0.00	0.03	0.03	0.00	0.00	0.01	0.00
Nyssa biflora	Swamp tupelo	0.06	0.07	0.02	**0.17**	**0.38**	0.00	0.21	**0.57**	0.00
Persea borbonia	Redbay	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.04	0.00
Pinus spp.	Pine	0.05	0.00	**0.84**	0.00	0.00	0.00	0.00	0.00	0.00
Planera aquatica	Water elm	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Quercus laurifolia/nigra	Water oak / Laurel oak	**0.34**	0.09	0.01	0.01	0.06	0.00	0.00	0.00	0.04
Quercus lyrata	Overcup oak	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Quercus virginiana	Live oak	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.96**
Taxodium distichum	Bald cypress	0.05	0.13	0.00	**0.45**	0.05	0.00	**0.57**	0.10	0.00
Ulmus americana	American elm	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Number of Plots		6	9	2	5	6	1	5	3	1
Average Elevation (m above NAVD88)		1.82	1.07	2.17	1.01	1.02	0.46	1.04	1.07	6.53
Basal area ($m^2 \cdot ha^{-1}$)		41.7	73.1	33.7	66.2	58.5	12.8	21.0	24.7	10.4
Density ($stems \cdot ha^{-1}$)		1197	1196	1040	1140	1500	1340	404	1100	1100
Mean Canopy Coverage (%)		95.88	96.33	99.75	89.25	87.50	58.50	83.55	74.00	86.25

Table A2 *envfit* results for the Salt-Stressed analysis showing the correlation between NMDS axes in species space with environmental variables. Elevation is the mean plot elevation above NAVD88 derived from a USGS 3DEP DEM of the study area. Longitude is the distance in meters west of 0°, and serves as a proxy for river distance.

	NMDS 1	**NMDS 2**	**r^2**	**P**
Elevation	-0.98	-0.22	-0.31	0.001
Longitude	0.99	0.10	0.58	0.001

APPENDIX B

COMPARISON OF COMMUNITY ANALYSIS RESULTS WITH USNVC

Introduction

To facilitate comparison to other geographic areas and validate our classification, plant communities were matched with the best fitting United States National Vegetation Classification (USNVC) alliance or association. The goal of the USNVC is to provide a standardized methodology for describing plant communities to facilitate botanical research at different scales and localities (Jennings et al. 2009). The two main functional units of the USNVC are the *association* and *alliance*. Both levels are defined based on species composition, growth form, environmental gradients and site history (Jennings et al. 2009). Associations are the smallest and more specific unit, defined by the relative abundance of a few diagnostic species and a relatively narrow range of environmental conditions (Jennings et al. 2009). Alliances are the next largest unit, composed of multiple similar associations which share diagnostic species but encompass a wider range of habitats and growth forms (Jennings et al. 2009). Open data, including detailed plot data, and peer review of proposed associations/alliances maintain data integrity, and the classification is regularly reviewed and updated (Jennings et al. 2009).

Jennings et al. (2009) proposed that remote sensing studies could benefit from the consistent and well documented data of the USNVC, but in practice, sensor spatial and spectral resolutions are often too coarse to consistently discriminate between closely related plant associations (Clark 2020).

Our hierarchical clustering analyses (Chapter 2, Appendix A) were based on our field data, and our interpretation of these results was informed by indicator species analysis and our fieldwork. Post-hoc comparison of these results with communities described in the USNVC serves as an additional layer of external validation and facilitates comparison with other sites. Studies of the floral communities of the Altamaha's tidal fresh forest are few, so while two of our communities are directly comparable to those identified by Duberstein et al. (2014) (Chapter 2.3), the USNVC enables us to compare our communities with those identified by researchers at other localities. We performed keyword searches of the USNVC database (https://usnvc.org/explore-classification/) by both common and scientific names and identified the USNVC plant alliance or association that most closely corresponded to our own classes. In most cases, we found one or more close matches (Table B1).

Table B1. Most similar USNVC associations for our forest communities. The community column indicates our community. The analysis column indicates in which of our analyses the community was present. RA is the Relative Abundance Only analysis, SS is the Salt-Stress included analysis. ID is the USNVC association code, which links to the report for that association. Colloquial name is the common name from the USNVC.

Community	**Analysis**	**ID**	**Colloquial Name**
Oak/Hornbeam	RA, SS	CEGL007348	Laurel Oak Bottomland Forest
Bald Cypress	RA, SS	CEGL002420	Bald-cypress Floodplain Forest
Swamp Tupelo	RA, SS	CEGL007864	Swamp Tupelo Floodplain Forest
Water Tupelo	RA, SS	CEGL002419/ CEGL008561	Water Tupelo Swamp Forest/Water Tupelo Tidal Forest
Live Oak	RA, SS	CEGL004676	South Atlantic Swamp Island
Alder/Magnolia	RA, SS	CEGL004627	Tidal Freshwater Alder Shrubland
Salt-stressed Bald Cypress	SS	CEGL003739	South Atlantic Tidal Bald-cypress Woodland

Salt-stressed Swamp Tupelo	SS	CEGL004484	Hardwood Tidal Swamp Forest
Bald Cypress/Tupelo	RA	CEGL007431	Bald-cypress - Tupelo Brownwater Floodplain Forest
Pine	RA, SS	CEGL008462	Ruderal Loblolly Pine - Sweetgum Forest

Discussion

The communities we identified in Chapter 2 and Appendix A correspond closely with similar plant communities described in the USNVCs, which supports the ecological validity of our results. This is particularly important for our Live Oak and Alder/Magnolia communities, which were poorly represented in our field sampling, and our Salt-Stressed Swamp Tupelo and Salt-Stressed Bald Cypress communities, which were present only in the Salt Stressed analysis. In the case of our Live Oak community, the South Atlantic Swamp Island association is specifically noted as occurring on islands within the Altamaha floodplain. The USNVC description of Tidal Freshwater Alder Shrubland as “a fringing shrubland, zonal between *Zizania aquatica* tidal marshes and tidal cypress - gum forests” fits our single sampling plot perfectly, although in our case Z. miliacea was the dominant marsh plant. The South Atlantic Tidal Bald-cypress Woodland and Hardwood Tidal Swamp Forest associations are close matches for our Salt-Stressed Bald Cypress and Salt-Stressed Swamp Tupelo communities, respectively, lending support to our Salt Stressed Analysis, which identified them as separate communities. The main limitation in comparing our results to the USNVC is the detail of our ground reference data. The field sampling on which the USNVC is based is far more detailed than we undertook, encompassing all vegetation from canopy trees to the smallest herbaceous vegetation, as well as edaphic conditions. As a result there are some discrepancies between our communities and the USNVC associations they are matched with (Table B1). These differences are primarily in co-dominant or understory tree species, vines, and herbaceous vegetation and ground cover. Differences in the composition of co-dominant and understory trees may be a product of natural diversity between sites, while differences in herbaceous vegetation composition is likely due to our sampling methodology, which was focused on canopy and understory trees.

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APPENDIX C

ACCURACY ASSESSMENT FOR SATELLITE IMAGERY CLASSIFICATION

Table C1. Land cover class confusion matrices for Balanced Random Forest classification of Sentinel-2 MSI satellite imagery of the Altamaha River tidal fresh forest. (A). 10/01/2016, (B). 09/01/2017, (C).10/21/2018, (D). 09/26/2019, (E). 10/30/2020, and (F). 09/25/2021. The Balanced Random Forest classification included the following predictor rasters: DEM, MSI bands 1,2,3,4,5,6,7,8,8a,9,11, and 12, and six vegetation indices: MNDWI, NDMI, ARI 1, SGI, NDBI, GDVI, and ARI 2. Following classification, the images were smoothed using a 5 pixel minimum aggregation. Not all land cover classes were present in all images. Columns represent reference data (what the pixel actually was based on validation data) and rows represent the predicted image data (what the pixel was classified as). Shaded cells are those where the classification was accurate. Values represent the percentage of reference or predicted image pixels. Values are rounded to the nearest decimal place and may not sum to 100 percent for each cover class.

A

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.00	0.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.07	0.01	0.03	0.00	0.00	0.00	0.00	0.00
Iva frutescens / S. alterniflora	0.00	0.00	0.83	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.09	0.00	0.00	0.00	0.00
J. roemerianus	0.02	0.12	0.01	0.84	0.64	0.00	0.06	0.00	0.19	0.00	0.00	0.00	0.00	0.03	0.03	0.22	0.15	0.04	0.00	0.00	0.00	0.57	0.00
Juncus/Schoenoplectus	0.00	0.00	0.00	0.05	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.04	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
Mud	0.00	0.00	0.00	0.00	0.00	0.00	0.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Tupelo	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.00	0.00	0.00	0.02	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.03	0.00	0.00
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.21	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.00	0.01	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.40	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02
S. tabernaemontani	0.00	0.16	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.47	0.00	0.00	0.08	0.00	0.10	0.00	0.00	0.17
Salt-tolerant shrubs	0.00	0.00	0.06	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.01	0.00	0.03	0.00	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.75	0.00	0.09	0.01	0.00	0.00	0.00
S. cynosuroides	0.00	0.08	0.00	0.02	0.00	0.00	0.03	0.00	0.35	0.00	0.00	0.00	0.00	0.00	0.01	0.13	0.05	0.29	0.07	0.02	0.00	0.00	0.00
Tall *S. alterniflora*	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.70	0.00	0.00	0.00	0.00
Salt-stressed tidal forest	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.01	0.38	0.00	0.76	0.01	0.00	0.09
Bald Cypress	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.02	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.02
Wrack	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.00
Z. miliacea	0.06	0.03	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.04	0.00	0.17	0.00	0.08	0.04	0.00	0.69

B

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.10	0.65	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.02	0.00	0.04	0.00	0.01	0.00	0.00	0.03
Iva frutescens / S. alterniflora	0.00	0.00	0.90	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.07	0.00	0.00	0.00	0.00
J. roemerianus	0.00	0.00	0.00	0.88	0.02	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.10	0.07	0.01	0.06	0.00	0.00	0.08	0.00
Juncus/Schoenoplectus	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	0.67	0.00	0.06	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
Mud	0.00	0.00	0.00	0.00	0.00	0.00	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tupelo	0.01	0.00	0.00	0.00	0.00	0.08	0.00	0.85	0.00	0.00	0.00	0.14	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Pine	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.92	0.00	0.04	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.05	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.62	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.41	0.00	0.02	0.00	0.04	0.00	0.00	0.00	0.03
S. tabernaemontani	0.01	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.41	0.00	0.00	0.00	0.00	0.01	0.00	0.05	0.07
Salt-tolerant shrubs	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.43	0.01	0.06	0.05	0.03	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.00	0.00	0.02	0.00	0.00	0.06	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.09	0.84	0.05	0.23	0.04	0.00	0.02	0.00
S. cynosuroides	0.00	0.09	0.00	0.03	0.00	0.00	0.01	0.00	0.08	0.00	0.00	0.00	0.00	0.01	0.00	0.10	0.01	0.62	0.03	0.02	0.00	0.01	0.01
Tall *S. alterniflora*	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.46	0.01	0.00	0.01	0.00
Salt-stressed tidal forest	0.01	0.00	0.00	0.00	0.00	0.15	0.08	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.10	0.01	0.04	0.00	0.27	0.00	0.00	0.03
Bald Cypress	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.00	0.00
Wrack	0.00	0.00	0.10	0.03	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.84	0.00
Z. miliacea	0.02	0.11	0.00	0.00	0.00	0.00	0.13	0.01	0.14	0.01	0.00	0.00	0.00	0.00	0.03	0.10	0.03	0.16	0.03	0.60	0.00	0.00	0.82

C

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.01	0.63	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.13	0.02	0.00	0.00	0.00	0.01
Iva frutescens / S. alterniflora	0.00	0.00	0.81	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.07	0.00	0.00	0.00	0.00
J. roemerianus	0.00	0.00	0.04	0.91	0.00	0.00	0.09	0.00	0.11	0.00	0.00	0.00	0.00	0.01	0.04	0.03	0.02	0.02	0.02	0.01	0.00	0.09	0.00
Juncus/Schoenoplectus	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	0.78	0.00	0.04	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00
Mud	0.00	0.01	0.00	0.00	0.00	0.00	0.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.05	0.00
Tupelo	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.28	0.05	0.00	0.03
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Pine	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.97	0.01	0.17	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.98	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.06	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.27	0.00	0.00	0.00	0.04	0.00	0.00	0.01	0.00
S. tabernaemontani	0.00	0.19	0.00	0.00	0.00	0.00	0.01	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.48	0.00	0.01	0.04	0.00	0.05	0.00	0.00	0.14
Salt-tolerant shrubs	0.00	0.02	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.02	0.03	0.03	0.02	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.00	0.06	0.03	0.00	0.00	0.03	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.75	0.04	0.18	0.19	0.00	0.00	0.00
S. cynosuroides	0.00	0.00	0.00	0.01	0.00	0.00	0.06	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.02	0.20	0.12	0.53	0.10	0.03	0.00	0.00	0.04
Tall *S. alterniflora*	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.06	0.43	0.00	0.00	0.00	0.00
Salt-stressed tidal forest	0.01	0.00	0.00	0.00	0.00	0.17	0.06	0.04	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.05	0.04	0.01	0.20	0.01	0.00	0.05
Bald Cypress	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.86	0.00	0.02
Wrack	0.08	0.00	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.11	0.02	0.00	0.05	0.09	0.00	0.00	0.85	0.00
Z. miliacea	0.01	0.15	0.00	0.00	0.00	0.00	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.19	0.02	0.03	0.00	0.22	0.04	0.00	0.71

D

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.01	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.00	0.51	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.01	0.04	0.03	0.01	0.00	0.00	0.03
Iva frutescens / S. alterniflora	0.00	0.08	0.76	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.07	0.00	0.00	0.00	0.00
J. roemerianus	0.01	0.12	0.01	0.90	0.12	0.00	0.03	0.00	0.08	0.01	0.00	0.00	0.00	0.01	0.02	0.10	0.02	0.00	0.05	0.00	0.00	0.11	0.00
Juncus/Schoenoplectus	0.00	0.00	0.00	0.05	0.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	0.75	0.00	0.03	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
Mud	0.00	0.00	0.11	0.00	0.00	0.00	0.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.04	0.00	0.00	0.34	0.01
Tupelo	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.93	0.00	0.00	0.00	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
Pine	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.01	0.45	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.97	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.04	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00
S. tabernaemontani	0.00	0.07	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.00	0.02	0.02	0.00	0.01	0.00	0.00	0.19
Salt-tolerant shrubs	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.51	0.00	0.00	0.04	0.04	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.00	0.04	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.75	0.03	0.19	0.09	0.00	0.01	0.00
S. cynosuroides	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00	0.03	0.07	0.10	0.53	0.02	0.03	0.00	0.00	0.00
Tall *S. alterniflora*	0.00	0.01	0.06	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.41	0.00	0.00	0.03	0.01
Salt-stressed tidal forest	0.00	0.04	0.00	0.00	0.00	0.15	0.07	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.07	0.02	0.63	0.02	0.00	0.07
Bald Cypress	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.00	0.01
Wrack	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.03	0.00	0.03	0.00	0.00	0.52	0.00
Z. miliacea	0.00	0.17	0.00	0.00	0.00	0.00	0.05	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.06	0.13	0.03	0.26	0.02	0.19	0.01	0.00	0.67

E

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	*Z. miliacea*
Bare or paved	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.00	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.04
Iva frutescens / S. alterniflora	0.00	0.00	0.79	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.01	0.00	0.07	0.00	0.00	0.00
J. roemerianus	0.05	0.01	0.01	0.84	0.22	0.00	0.12	0.00	0.08	0.00	0.00	0.00	0.00	0.01	0.04	0.10	0.04	0.01	0.03	0.00	0.00	0.02
Juncus/Schoenoplectus	0.00	0.00	0.00	0.07	0.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	0.92	0.00	0.04	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00
Mud	0.00	0.04	0.03	0.00	0.00	0.00	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.15	0.27	0.03	0.00	0.03
Tupelo	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.34	0.05	0.00
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.27	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	1.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.53	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.98	0.17	0.00	0.00	0.00	0.04	0.00	0.00	0.00
S. tabernaemontani	0.00	0.19	0.00	0.01	0.00	0.00	0.01	0.03	0.19	0.00	0.00	0.00	0.00	0.01	0.70	0.00	0.05	0.03	0.01	0.03	0.00	0.10
Salt-tolerant shrubs	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.48	0.01	0.01	0.02	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.00	0.10	0.06	0.01	0.00	0.01	0.12	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.76	0.06	0.08	0.00	0.00	0.00
S. cynosuroides	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.12	0.73	0.06	0.03	0.00	0.00
Tall *S. alterniflora*	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.41	0.00	0.00	0.00
Salt-stressed tidal forest	0.00	0.15	0.00	0.00	0.00	0.05	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.24	0.04	0.08
Bald Cypress	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.84	0.01
Z. miliacea	0.02	0.05	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.03	0.00	0.00	0.00	0.28	0.03	0.70

F

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald cypress	*Z. miliacea*
Bare or paved	0.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00
C. jamaicense	0.00	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.01	0.04	0.00	0.00	0.00	0.01
Iva frutescens / S. alterniflora	0.00	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.08	0.00	0.00	0.00
J. roemerianus	0.00	0.00	0.00	0.92	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.04	0.00	0.01	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.91	0.00	0.08	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00
Mud	0.00	0.02	0.04	0.00	0.00	0.89	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.10	0.00	0.00	0.01
Tupelo	0.00	0.00	0.00	0.00	0.08	0.00	0.88	0.00	0.00	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.01
P. virgatum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.04	0.00	0.00	0.00	0.00
Pine	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.99	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oak/Hornbeam	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.65	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Live Oak	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
S. americanus	0.01	0.02	0.00	0.02	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.98	0.30	0.00	0.00	0.00	0.17	0.00	0.00	0.09
S. tabernaemontani	0.00	0.05	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.56	0.00	0.01	0.04	0.00	0.01	0.00	0.11
Salt-tolerant shrubs	0.00	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.49	0.00	0.04	0.00	0.00	0.00	0.00
Medium *S. alterniflora*	0.00	0.09	0.10	0.04	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.81	0.12	0.13	0.00	0.00	0.00
S. cynosuroides	0.00	0.22	0.04	0.00	0.00	0.00	0.00	0.35	0.00	0.00	0.00	0.00	0.00	0.03	0.14	0.11	0.52	0.06	0.01	0.00	0.01
Tall *S. alterniflora*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.44	0.00	0.00	0.00
Salt-stressed tidal forest	0.00	0.08	0.00	0.00	0.00	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.72	0.02	0.03
Bald cypress	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.91	0.01
Z. miliacea	0.00	0.15	0.00	0.00	0.00	0.04	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.07	0.09	0.01	0.09	0.01	0.26	0.00	0.72

Table C2. Land cover class Producer's Accuracy and Overall Accuracy for Balanced Random Forest classification of Sentinel-2 MSI satellite imagery of the Altamaha River tidal fresh forest. Producer's Accuracy indicates how well reference pixels of a given cover type are classified. The Balanced Random Forest classification included the following predictor rasters: DEM, MSI bands 1,2,3,4,5,6,7,8,8a,9,11, and 12, and six vegetation indices: MNDWI, NDMI, ARI 1, SGI, NDBI, GDVI, and ARI 2. Following classification, the images were smoothed using a 5 pixel minimum aggregation. Not all land cover classes were present in all images, absent classes are indicated by "-".

	Landcover Class Producer's Accuracy						
Landcover Class	10/1/2016	9/1/2017	10/21/2018	9/26/2019	10/30/2020	5/28/2021	9/25/2021
Bare or paved	0.92	0.84	0.84	0.97	0.93	1.00	0.97
C. jamaicense	0.61	0.65	0.63	0.51	0.39	0.45	0.36
Iva frutescens / S. alterniflora	0.83	0.90	0.81	0.76	0.79	0.76	0.79
J. roemerianus	0.84	0.88	0.91	0.90	0.84	0.94	0.92
Juncus/Schoenoplectus	0.36	0.98	0.99	0.88	0.77	-	-
Mixed broadleaf swamp	0.96	0.67	0.78	0.75	0.92	0.97	0.91
Mud	0.54	0.48	0.49	0.74	0.81	0.53	0.89
Tupelo	0.92	0.85	0.88	0.93	0.77	0.82	0.88
P. virgatum	0.43	0.70	0.38	0.68	0.41	0.27	0.49
Pine	0.96	0.92	0.97	0.97	0.96	0.96	0.96
Pine/Sweetgum	1.00	0.99	0.98	0.97	1.00	1.00	0.99
Oak/Hornbeam	0.56	0.62	0.70	0.40	0.53	0.77	0.65
Live Oak	0.88	0.82	0.89	0.95	0.86	0.83	0.92
S. americanus	0.95	0.94	0.97	0.99	0.98	0.93	0.98
S. tabernaemontani	0.47	0.41	0.48	0.77	0.70	0.42	0.56
Salt-tolerant shrubs	0.36	0.43	0.40	0.51	0.48	0.46	0.49
Medium S. alterniflora	0.75	0.84	0.75	0.75	0.76	0.75	0.81
S. cynosuroides	0.29	0.62	0.53	0.53	0.73	0.62	0.52
Tall S. alterniflora	0.70	0.46	0.43	0.41	0.41	0.63	0.44
Salt-stressed tidal forest	0.76	0.27	0.20	0.63	0.24	0.82	0.72
Bald Cypress	0.90	0.92	0.86	0.93	0.84	0.82	0.91
Wrack	0.43	0.84	0.85	0.52	-	-	-
Z. miliacea	0.69	0.82	0.71	0.67	0.70	0.73	0.72
Overall Accuracy	0.82	0.83	0.84	0.84	0.83	0.85	0.86

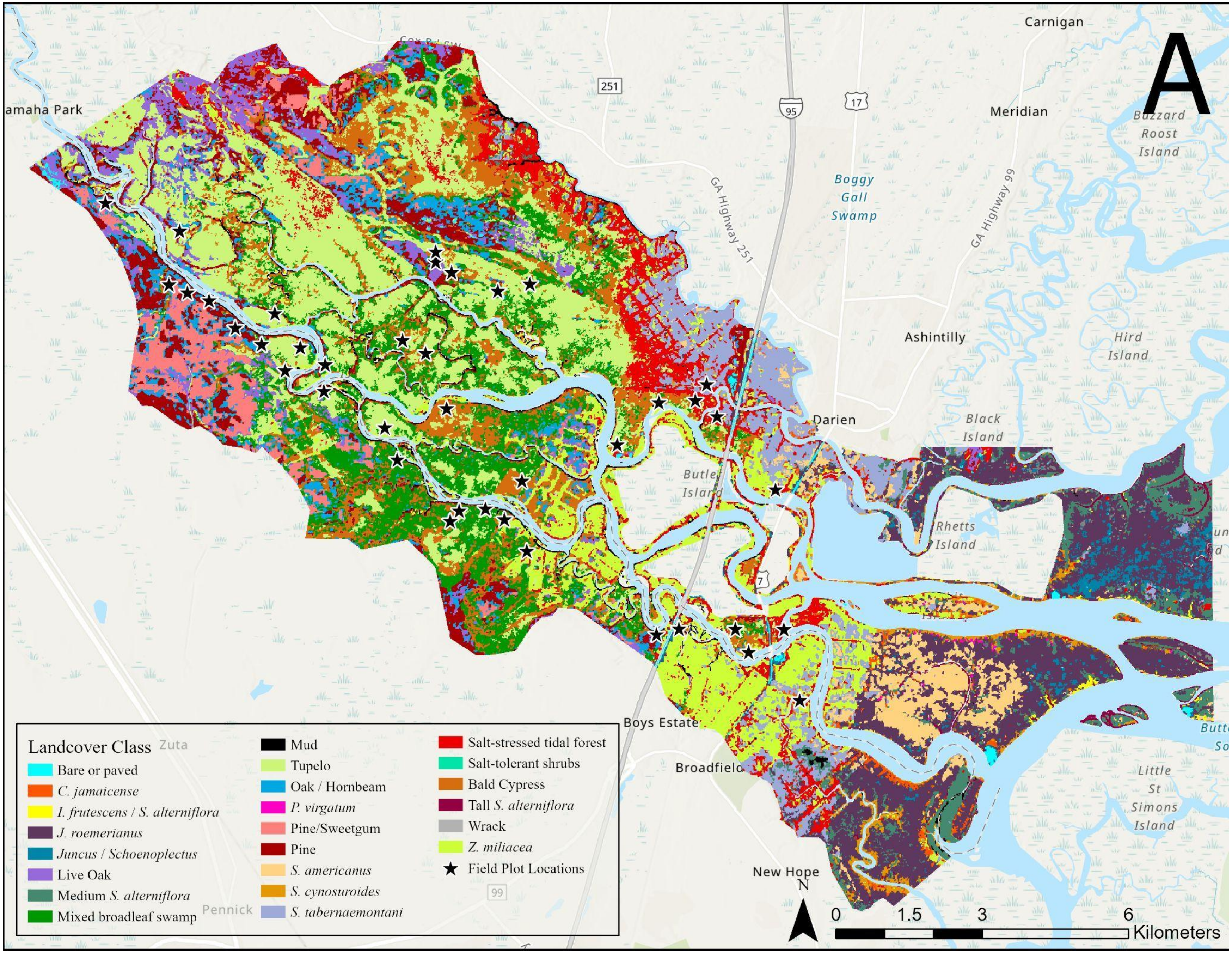
Table C3. Mean Decrease in Accuracy for predictor variables in our Balanced Random Forest classifications as calculated by *randomForest*'s *importance* function. Values are the mean decrease in accuracy for each predictor variable for all classes, divided by their standard errors. Larger values indicate that a predictor variable was more important to the classification. Bolded and shaded cells are the five most important predictor variables for each classification date.

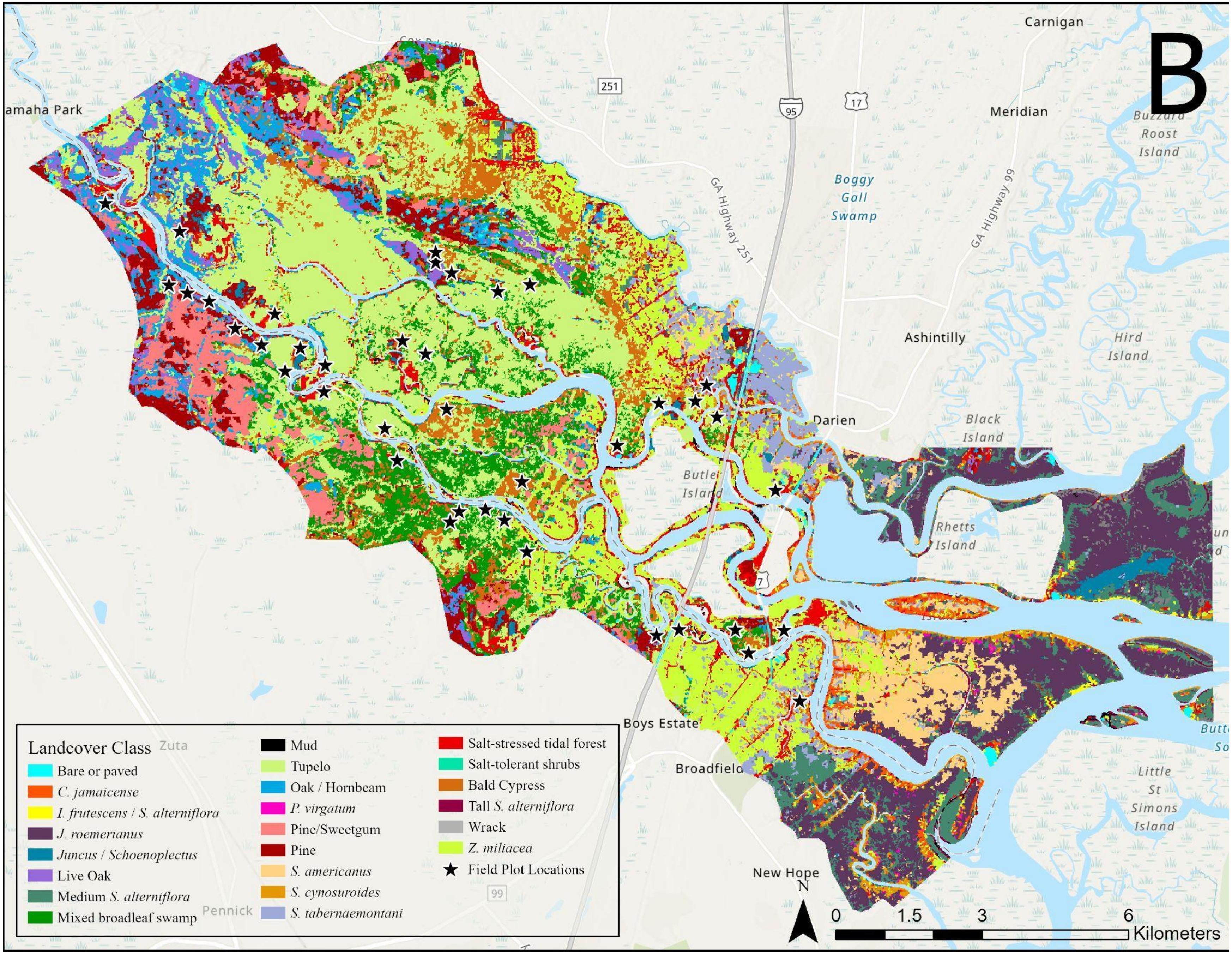
	Mean Decrease in Accuracy					
Predictor Variable	2016*	2017	2018*	2019*	2020*	2021
DEM	**274.78**	**315.94**	**308.52**	**249.53**	**258.51**	**218.75**
S-2 MSI Band 1	**248.11**	**257.85**	**245.60**	**201.62**	**228.11**	**227.11**
S-2 MSI Band 2	79.50	99.31	74.86	73.39	76.76	80.04
S-2 MSI Band 3	74.98	86.70	70.59	75.99	76.31	69.95
S-2 MSI Band 4	105.18	104.30	102.36	129.78	112.31	97.79
S-2 MSI Band 5	**159.65**	**159.90**	**164.65**	**164.97**	**180.56**	126.32
S-2 MSI Band 6	81.64	66.81	88.90	74.60	68.74	60.92
S-2 MSI Band 7	81.59	59.25	88.14	71.92	67.40	66.90
S-2 MSI Band 8	78.38	61.36	86.51	75.35	67.36	60.45
S-2 MSI Band 8a	90.22	62.07	96.68	72.03	81.81	61.66
S-2 MSI Band 9	**181.77**	122.47	**199.44**	**146.27**	**159.25**	**177.08**
S-2 MSI Band 11	134.97	**163.43**	145.88	122.35	122.23	141.77
S-2 MSI Band 12	127.51	145.37	129.52	143.64	128.73	146.60
MNDWI	131.67	**181.20**	134.06	145.63	122.33	**157.45**
NDMI	**150.95**	142.06	**163.75**	**167.88**	**168.29**	**150.41**
ARI1	80.99	104.23	90.57	89.88	91.27	88.45
SGI	78.43	87.30	71.48	74.45	77.79	68.75
NDBI	98.96	78.46	105.07	116.76	98.12	76.07
GDVI	89.43	63.28	95.90	70.07	81.36	61.34
ARI2	63.00	97.20	63.12	57.37	57.00	79.79

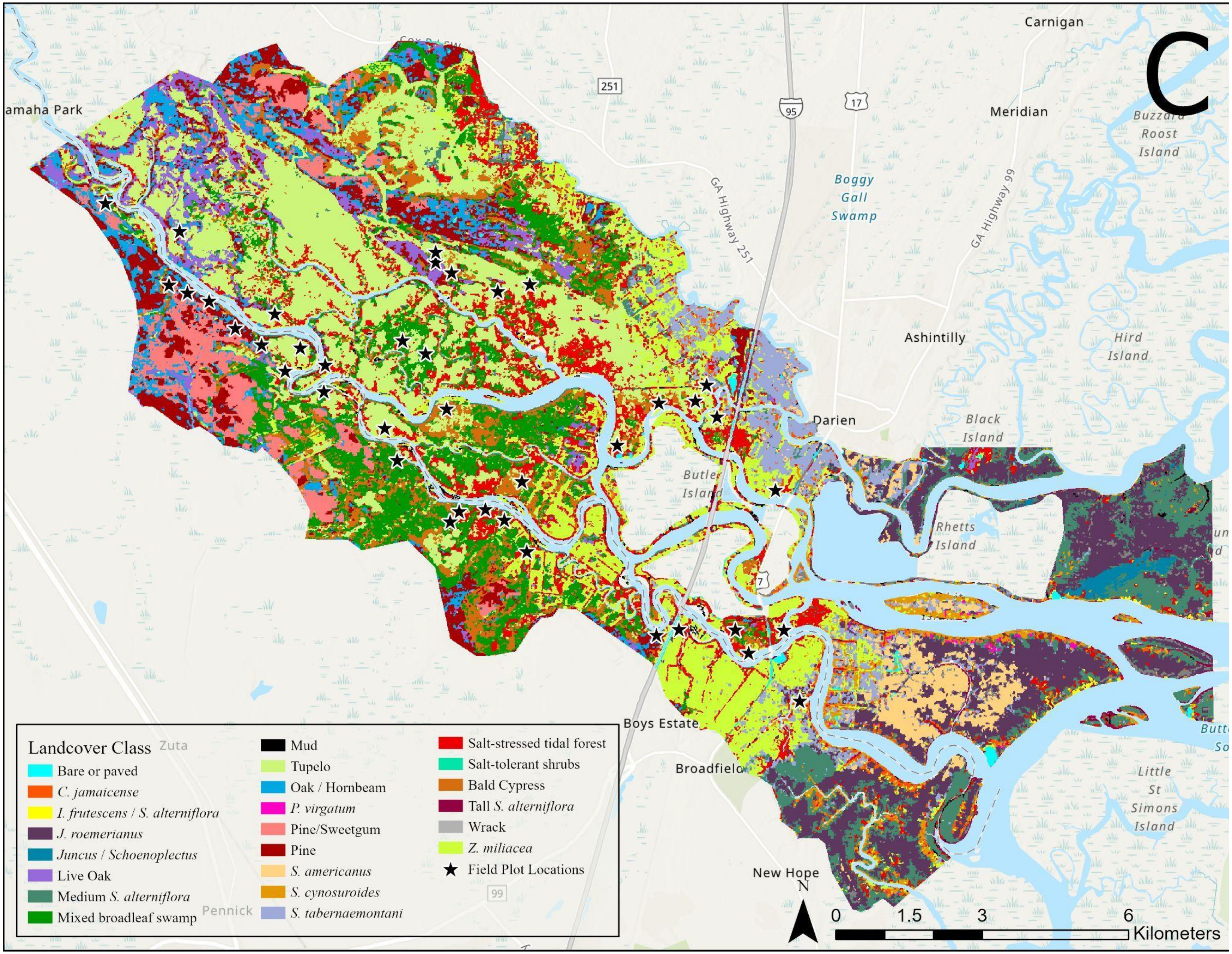
APPENDIX D

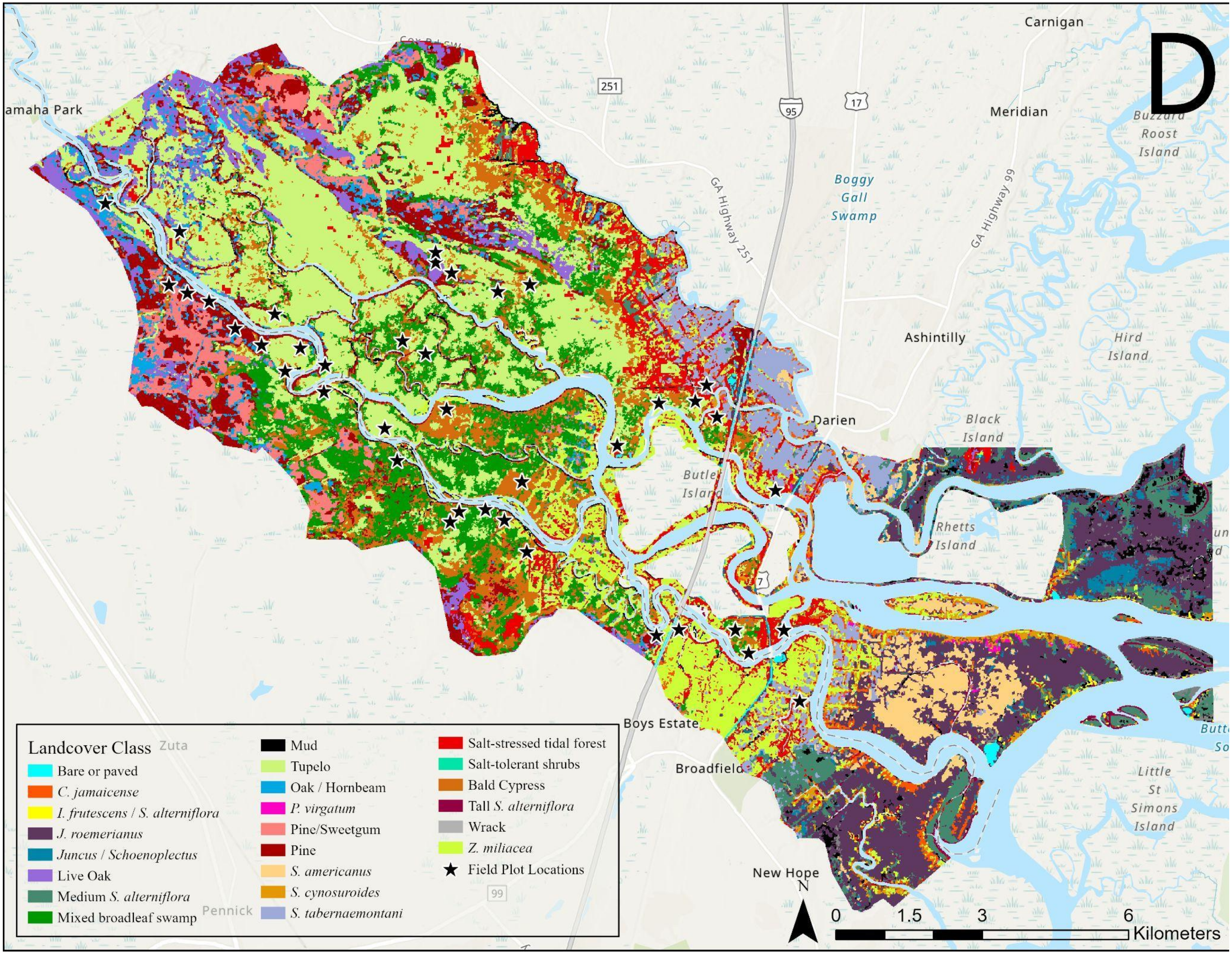
TEMPORAL CHANGE

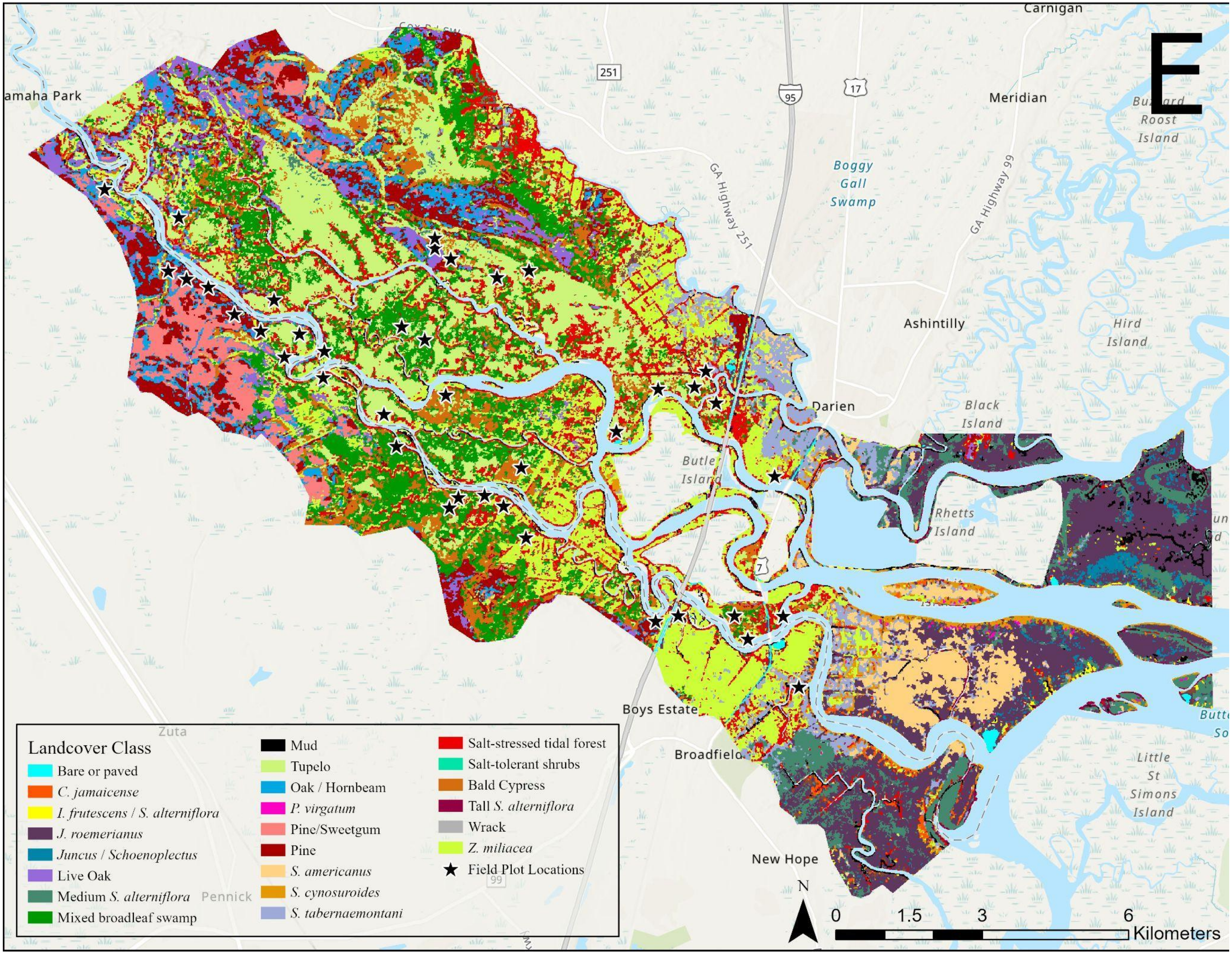
Figure D1. Final Balanced Random Forest classified images used for temporal change analysis. (A). 10/01/2016, (B). 09/01/2017, (C).10/21/2018, (D). 09/26/2019, (E). 10/30/2020, (F). 09/25/2021. The Balanced Random Forest classification included the following predictor rasters: DEM, MSI bands 1,2,3,4,5,6,7,8,8a,9,11, and 12, and six vegetation indices: MNDWI, NDMI, ARI 1, SGI, NDBI, GDVI, and ARI 2. Following classification, the images were smoothed using a 5 pixel minimum aggregation.


A
Landcover Class
Bare or paved
C. jamaicense
I. frutescens / S. alterniflora
J. roemerianus
Juncus / Schoenoplectus
Live Oak
Medium S. alterniflora
Mixed broadleaf swamp
Mud
Tupelo
Oak / Hornbeam
P. virgatum
Pine/Sweetgum
Pine
S. americanus
S. cynosuroides
S. tabernaemontani
Salt-stressed tidal forest
Salt-tolerant shrubs
Bald Cypress
Tall S. alterniflora
Wrack
Z. miliacea
Field Plot Locations
N
0 1.5 3 6 Kilometers
Carnigan
Meridian
Boggy Gall Swamp
GA Highway 251
GA Highway 99
Ashintilly
Darien
Hird Island
Black Island
Rhetts Island
Boys Estate
Broadfield
New Hope
Little St Simons Island
Pennick
Zuta


B
Landcover Class
Bare or paved
C. jamaicense
I. frutescens / S. alterniflora
J. roemerianus
Juncus / Schoenoplectus
Live Oak
Medium S. alterniflora
Mixed broadleaf swamp
Mud
Tupelo
Oak / Hornbeam
P. virgatum
Pine/Sweetgum
Pine
S. americanus
S. cynosuroides
S. tabernaemontani
Salt-stressed tidal forest
Salt-tolerant shrubs
Bald Cypress
Tall S. alterniflora
Wrack
Z. miliacea
Field Plot Locations
N
0 1.5 3 6 Kilometers
Carnigan
Meridian
Buzzard Roost Island
Boggy Gall Swamp
GA Highway 251
GA Highway 99
Ashintilly
Hird Island
Darien
Black Island
Butler Island
Rhetts Island
Boys Estate
Broadfield
Little St Simons Island
New Hope
Pennick
Zuta
251
95
17
99


C
Landcover Class
Bare or paved
C. jamaicense
I. frutescens / S. alterniflora
J. roemerianus
Juncus / Schoenoplectus
Live Oak
Medium S. alterniflora
Mixed broadleaf swamp
Mud
Tupelo
Oak / Hornbeam
P. virgatum
Pine/Sweetgum
Pine
S. americanus
S. cynosuroides
S. tabernaemontani
Salt-stressed tidal forest
Salt-tolerant shrubs
Bald Cypress
Tall S. alterniflora
Wrack
Z. miliacea
Field Plot Locations
N
0 1.5 3 6 Kilometers
Carnigan
Meridian
Buzzard Roost Island
Boggy Gall Swamp
GA Highway 251
GA Highway 99
Ashintilly
Hird Island
Darien
Black Island
Butler Island
Rhetts Island
Boys Estate
Broadfield
New Hope
Little St Simons Island
Zuta
Pennick


D
Landcover Class
Bare or paved
C. jamaicense
I. frutescens / S. alterniflora
J. roemerianus
Juncus / Schoenoplectus
Live Oak
Medium S. alterniflora
Mixed broadleaf swamp
Mud
Tupelo
Oak / Hornbeam
P. virgatum
Pine/Sweetgum
Pine
S. americanus
S. cynosuroides
S. tabernaemontani
Salt-stressed tidal forest
Salt-tolerant shrubs
Bald Cypress
Tall S. alterniflora
Wrack
Z. miliacea
Field Plot Locations
N
0 1.5 3 6
Kilometers
Carnigan
Meridian
Boggy Gall Swamp
Ashintilly
Darien
Hird Island
Black Island
Rhetts Island
Butler Island
Boys Estate
Broadfield
New Hope
Little St Simons Island
GA Highway 251
GA Highway 99
Pennick
Zuta


E
Landcover Class
Bare or paved
C. jamaicense
I. frutescens / S. alterniflora
J. roemerianus
Juncus / Schoenoplectus
Live Oak
Medium S. alterniflora
Mixed broadleaf swamp
Mud
Tupelo
Oak / Hornbeam
P. virgatum
Pine/Sweetgum
Pine
S. americanus
S. cynosuroides
S. tabernaemontani
Salt-stressed tidal forest
Salt-tolerant shrubs
Bald Cypress
Tall S. alterniflora
Wrack
Z. miliacea
Field Plot Locations
N
0
1.5
3
6
Kilometers
Carnigan
Meridian
Boggy
Gall
Swamp
GA Highway 251
GA Highway 99
Ashintilly
Hird
Island
Darien
Black
Island
Butler
Island
Rhetts
Island
Boys Estate
Broadfield
New Hope
Little
St
Simons
Island
Zuta
Pennick
Roost
Island

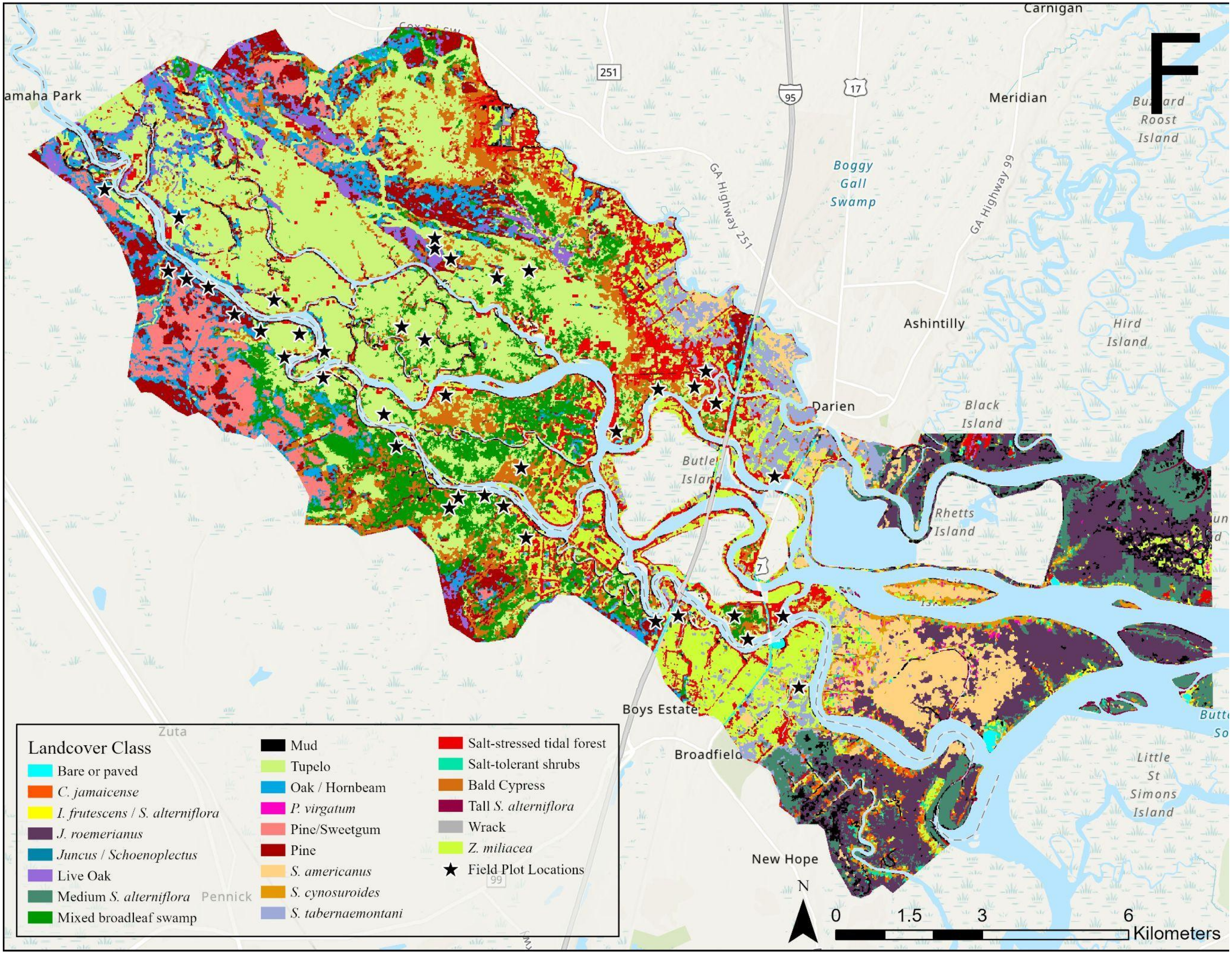

F
Landcover Class
Bare or paved
C. jamaicense
I. frutescens / S. alterniflora
J. roemerianus
Juncus / Schoenoplectus
Live Oak
Medium S. alterniflora
Mixed broadleaf swamp
Mud
Tupelo
Oak / Hornbeam
P. virgatum
Pine/Sweetgum
Pine
S. americanus
S. cynosuroides
S. tabernaemontani
Salt-stressed tidal forest
Salt-tolerant shrubs
Bald Cypress
Tall S. alterniflora
Wrack
Z. miliacea
Field Plot Locations
N
0 1.5 3 6 Kilometers
Carnigan
Meridian
Boggy Gall Swamp
GA Highway 251
GA Highway 99
Ashintilly
Darien
Black Island
Hird Island
Butler Island
Rhetts Island
Boys Estate
Broadfield
New Hope
Little St Simons Island
Zuta
Pennick
251
95
17
99

Table D1. Land cover class change statistics for Balanced Random Forest classifications of the various Sentinel-2 MSI images of the Altamaha River tidal fresh forest. (A). 2016-2017, (B). 2017-2018, (C). 2018-2019, (D). 2019-2020, (E). 2020-2021, (F). 2016-2021, and (G). 2016-2021 with merged marsh classes. Land cover indicates the dominant type of vegetation in that pixel. Not all land cover classes were present in all images. Columns represent the initial state classes (what the pixel was classified as in the initial image (T_1)), and rows represent the final state classes (what the pixel was classified as in the final image (T_2)). For each initial state class (columns), the table shows how these pixels were classified in the final state image (rows). Shaded cells are the proportion of pixels that did not change between the initial and final image dates. Values represent the proportion of initial or final image pixels. Proportions are rounded to the nearest decimal place and may not sum to 100% for each cover class. Class Changes are the percent of pixels that changed class between T_1 and T_2. Net Change is the area in square kilometers by which the class has increased or decreased between T_1 and T_2.

A

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium*S. alterniflora*	*S. cynosuroides*	Tall*S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	69.58	0.26	0.04	0.30	2.35	0.03	0.16	0.33	0.00	0.49	0.07	0.19	1.33	0.40	0.71	0.38	0.24	0.24	0.70	0.72	0.11	1.58	1.20
C. jamaicense	2.91	40.14	2.46	1.93	2.65	0.00	0.11	0.10	4.52	0.11	0.06	0.12	0.07	0.59	1.36	11.37	0.52	8.09	1.35	1.92	0.01	3.50	6.21
Iva frutescens / S. alterniflora	0.00	0.28	51.51	0.14	0.09	0.00	0.04	0.01	0.00	0.07	0.00	0.03	0.00	0.05	0.01	2.86	0.39	0.33	1.06	0.12	0.00	0.00	0.00
J. roemerianus	0.82	2.77	4.05	72.99	55.04	0.00	0.07	0.07	11.48	0.03	0.00	0.03	0.02	9.46	6.06	3.52	17.43	10.05	2.04	1.64	0.02	74.03	0.20
Juncus/Schoenoplectus	0.26	0.66	0.73	2.11	20.08	0.62	23.78	0.50	0.00	1.68	0.16	0.17	0.09	0.05	1.10	0.52	0.39	1.22	0.24	0.79	0.74	0.66	0.56
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	50.10	1.21	2.02	0.00	2.39	2.95	8.87	7.06	0.00	0.00	0.00	0.00	0.00	0.00	0.90	12.04	0.00	0.86
Mud	0.42	0.22	1.47	0.01	0.00	0.01	11.39	0.00	0.00	0.04	0.00	0.00	0.01	0.01	0.02	0.45	0.25	1.05	7.58	0.46	0.03	0.00	0.48
Tupelo	2.54	0.53	0.09	0.05	1.67	36.15	5.86	80.86	0.00	5.93	3.11	5.90	8.00	0.02	0.07	0.09	0.01	0.22	0.10	10.02	36.44	0.00	5.87
P. virgatum	0.00	0.65	0.00	0.89	0.01	0.00	0.00	0.00	32.64	0.00	0.00	0.00	0.00	0.06	0.01	1.92	0.18	1.92	0.27	0.06	0.00	0.00	0.05
Pine	1.93	0.20	0.00	0.02	0.30	1.51	0.80	1.66	0.00	51.77	4.20	12.13	8.30	0.00	0.02	0.02	0.00	0.01	0.00	0.53	3.14	0.48	0.29
Pine/Sweetgum	0.05	0.00	0.00	0.00	0.00	3.66	0.02	0.03	0.00	6.82	72.58	24.97	7.35	0.00	0.00	0.00	0.00	0.00	0.00	0.07	1.06	0.00	0.13
Oak/Hornbeam	0.73	0.00	0.00	0.00	0.01	0.82	0.34	1.94	0.00	15.73	11.06	34.91	29.83	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.21	0.00	0.18
Live Oak	7.30	0.04	0.00	0.07	0.40	0.09	0.18	2.41	0.00	5.47	3.89	7.66	34.86	0.00	0.02	0.00	0.00	0.00	0.00	1.35	0.25	0.00	0.25
S. americanus	0.00	3.02	0.00	3.85	0.66	0.00	0.00	0.00	11.57	0.00	0.00	0.00	0.01	72.26	11.77	0.61	1.08	0.45	0.66	0.37	0.00	1.05	0.47
S. tabernaemontani	0.10	6.36	0.00	0.74	0.82	0.00	1.15	0.00	4.34	0.00	0.00	0.00	0.00	10.80	42.33	0.66	2.19	0.75	0.42	1.30	0.00	0.22	2.23
Salt-tolerant shrubs	0.02	1.83	0.60	0.27	0.03	0.00	0.23	0.03	0.72	0.04	0.00	0.02	0.04	0.02	0.02	17.56	1.21	1.93	1.52	0.71	0.01	0.00	0.15
Medium *S. alterniflora*	0.03	4.27	15.17	9.02	3.51	0.00	3.12	0.00	13.11	0.01	0.00	0.00	0.02	3.20	14.36	19.48	60.35	18.81	27.37	5.51	0.00	0.35	0.58
S. cynosuroides	0.40	8.44	3.32	1.47	0.17	0.00	3.91	0.01	14.92	0.05	0.00	0.00	0.01	0.26	1.01	12.24	2.62	38.69	11.24	3.18	0.01	0.96	0.93
Tall *S. alterniflora*	0.40	1.84	5.99	0.21	0.26	0.00	3.98	0.00	0.18	0.07	0.00	0.00	0.00	0.25	0.42	7.22	1.40	4.42	32.18	0.46	0.01	0.13	0.28
Salt-stressed tidal forest	1.60	5.21	0.00	0.61	1.66	2.49	20.42	3.31	2.26	2.98	0.64	0.66	1.50	0.18	3.04	3.91	3.28	1.70	3.69	25.75	4.10	0.00	7.59
Bald Cypress	0.00	0.00	0.00	0.00	0.00	3.98	3.86	5.39	0.00	5.27	1.04	3.99	0.22	0.00	0.00	0.00	0.01	0.00	0.00	4.27	38.80	0.00	0.85
Wrack	1.48	0.87	13.32	2.49	6.55	0.01	0.05	0.00	0.81	0.03	0.00	0.00	0.00	0.92	0.89	1.43	4.00	2.24	5.82	0.11	0.00	16.69	0.05
Z. miliacea	9.41	22.41	1.25	2.84	3.75	0.51	19.30	1.33	3.44	1.01	0.24	0.35	1.27	1.46	16.79	15.78	4.45	7.90	3.75	39.36	1.99	0.35	70.59
Class Changes (%)	30.42	59.86	48.49	27.01	79.92	49.90	88.61	19.14	67.36	48.23	27.42	65.09	65.14	27.74	57.67	82.44	39.65	61.31	67.82	74.25	61.20	83.31	29.41
Net Change (km2)	0.51	1.27	-0.01	-1.04	0.23	-4.11	-1.43	9.37	0.15	-1.56	2.04	0.85	-2.16	0.49	-3.42	-0.07	2.35	0.16	-0.12	-2.37	-5.41	0.83	3.78

B

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	34.18	2.02	0.50	0.03	0.23	0.00	0.04	0.09	0.00	0.15	0.01	0.13	0.61	0.58	0.12	0.00	0.02	0.09	0.26	0.29	0.00	0.07	0.32
C. jamaicense	1.36	46.44	0.82	0.73	0.52	0.00	0.59	0.02	11.11	0.01	0.00	0.00	0.00	1.23	2.89	2.63	0.68	4.52	2.85	0.37	0.00	0.94	1.31
Iva frutescens / S. alterniflora	0.04	0.14	41.74	0.05	0.07	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.33	0.47	0.66	0.00	0.00	0.90	0.02
J. roemerianus	1.94	3.32	6.40	69.53	0.71	0.00	0.63	0.00	18.31	0.00	0.00	0.00	0.01	10.25	4.12	1.63	13.83	3.79	2.12	0.17	0.00	45.67	0.54
Juncus/Schoenoplectus	0.00	0.00	0.00	0.38	31.63	0.01	0.00	0.05	0.00	0.11	0.00	0.02	0.09	0.02	0.02	0.08	0.43	0.19	0.00	0.34	0.01	0.17	0.07
Mixed broadleaf swamp	1.21	0.05	0.14	0.01	4.06	58.06	0.41	13.88	0.00	2.56	11.12	2.89	0.56	0.00	0.00	0.03	0.00	0.02	0.03	4.85	10.07	0.11	0.72
Mud	0.00	0.31	0.82	0.10	1.19	0.02	40.07	0.06	0.00	0.01	0.03	0.02	0.00	0.01	0.03	1.33	0.47	2.85	7.37	1.36	0.12	1.16	0.80
Tupelo	6.99	1.19	1.41	0.13	6.32	4.02	0.39	55.67	0.00	4.66	0.03	4.49	8.77	0.16	0.26	3.24	0.14	0.36	0.25	14.03	26.06	0.15	6.38
P. virgatum	0.01	0.68	0.27	0.21	0.04	0.00	0.00	0.00	17.46	0.00	0.00	0.00	0.00	0.14	0.17	0.17	0.27	2.14	0.03	0.08	0.00	0.01	0.12
Pine	5.62	0.42	2.00	0.01	2.13	2.00	0.87	1.58	0.00	63.03	9.63	22.61	12.55	0.00	0.00	0.50	0.01	0.25	0.48	2.62	3.81	0.33	0.34
Pine/Sweetgum	0.38	0.09	0.00	0.00	0.44	2.12	0.00	0.43	0.00	4.35	60.06	7.96	2.29	0.00	0.00	0.00	0.00	0.00	0.00	0.56	1.34	0.00	0.11
Oak/Hornbeam	2.94	0.37	0.00	0.01	0.46	2.06	0.00	0.58	0.00	11.43	12.78	34.90	24.13	0.00	0.00	0.08	0.00	0.04	0.03	0.48	2.25	0.00	0.13
Live Oak	11.77	0.25	0.23	0.04	1.54	1.22	0.17	2.06	0.00	5.00	2.02	22.73	46.69	0.00	0.01	0.06	0.00	0.07	0.03	1.72	0.10	0.01	1.02
S. americanus	0.06	1.02	0.00	1.59	0.08	0.00	0.00	0.00	0.35	0.00	0.00	0.00	0.00	57.28	5.97	0.11	1.03	0.43	1.37	0.15	0.00	0.75	0.23
S. tabernaemontani	5.59	10.17	0.23	1.22	2.29	0.00	0.31	0.03	3.25	0.00	0.00	0.00	0.00	19.55	61.71	0.83	7.19	3.71	5.34	1.42	0.01	5.35	4.87
Salt-tolerant shrubs	0.09	0.80	10.71	0.11	0.10	0.00	0.85	0.00	3.52	0.00	0.00	0.00	0.00	0.01	0.00	24.46	0.77	3.89	1.77	0.43	0.00	0.19	0.19
Medium *S. alterniflora*	2.18	2.52	8.98	18.59	27.79	0.15	7.73	0.63	14.17	0.48	0.00	0.15	0.14	1.34	6.08	12.49	59.48	15.57	14.53	7.52	1.09	22.73	2.09
S. cynosuroides	1.02	30.12	9.44	0.79	0.80	0.00	3.62	0.02	21.76	0.04	0.00	0.00	0.03	0.79	0.61	14.16	4.44	36.98	7.21	1.42	0.00	4.24	2.19
Tall *S. alterniflora*	0.88	1.27	3.77	0.12	0.29	0.00	15.41	0.01	0.19	0.00	0.00	0.00	0.00	0.07	0.32	2.22	1.91	4.78	38.78	0.56	0.00	3.26	0.36
Salt-stressed tidal forest	3.21	2.59	1.45	1.56	5.58	16.26	10.52	12.38	2.90	1.56	0.95	1.57	2.31	0.30	1.10	23.52	4.41	4.83	5.48	35.42	6.26	2.25	10.09
Bald Cypress	0.86	0.05	0.32	0.00	5.13	11.27	1.11	6.92	0.00	5.75	2.40	1.67	0.80	0.00	0.00	0.89	0.00	0.15	0.13	4.90	45.17	0.00	1.04
Wrack	5.05	6.37	5.58	4.17	0.68	0.00	1.46	0.02	2.83	0.00	0.00	0.00	0.00	5.28	1.98	2.16	2.15	2.84	3.00	0.36	0.00	10.03	0.55
Z. miliacea	14.36	15.18	2.95	0.48	5.85	2.75	12.14	5.51	4.14	0.75	0.96	0.72	0.84	2.91	14.48	7.04	1.74	8.42	5.07	19.53	3.53	0.49	66.09
Class Changes (%)	65.56	78.91	55.99	30.34	66.30	41.89	56.51	44.27	82.54	36.86	39.93	64.96	53.14	42.64	38.18	73.77	39.83	59.41	58.00	63.16	54.66	88.78	33.49
Net Change (km2)	-0.46	-0.96	-0.06	-2.10	-1.18	2.69	0.25	-9.84	-0.06	1.58	-1.17	-0.95	1.13	-1.55	1.40	0.02	3.06	0.74	0.10	5.88	0.26	0.68	0.46

C

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	53.21	0.65	0.00	0.11	0.00	0.01	0.10	0.05	0.91	0.09	0.00	0.17	1.06	0.02	0.01	0.43	0.03	0.21	0.38	0.13	0.01	2.32	0.46
C. jamaicense	1.05	16.48	0.32	0.47	0.00	0.00	0.55	0.00	2.03	0.00	0.00	0.00	0.00	0.21	5.20	6.94	0.52	11.06	2.49	0.41	0.00	3.62	2.59
Iva frutescens / S. alterniflora	0.10	0.18	48.68	0.09	0.00	0.00	0.27	0.00	0.35	0.00	0.00	0.00	0.00	0.00	0.02	4.47	0.41	1.22	1.60	0.10	0.00	0.88	0.03
J. roemerianus	14.13	16.40	5.27	77.94	31.68	0.00	0.67	0.01	20.39	0.00	0.00	0.00	0.03	5.01	8.80	9.02	26.00	9.51	6.33	2.39	0.00	34.38	1.60
Juncus/Schoenoplectus	4.34	0.30	0.00	4.72	52.85	0.00	0.18	0.00	0.00	0.03	0.00	0.00	0.11	0.32	1.28	0.11	2.43	0.70	1.07	0.19	0.00	1.43	0.31
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.13	61.42	0.23	2.18	0.00	2.01	6.30	3.74	4.36	0.00	0.00	0.00	0.15	0.00	0.00	20.50	16.67	0.00	2.55
Mud	0.44	0.53	10.54	4.44	2.61	0.14	41.48	0.25	1.27	0.27	0.00	0.03	0.06	0.27	0.82	1.33	9.15	3.31	11.13	2.36	0.90	16.85	1.42
Tupelo	0.22	0.02	0.00	0.01	1.99	17.85	0.37	81.97	0.00	3.52	0.23	1.20	18.62	0.00	0.16	0.19	2.01	0.00	0.02	27.81	15.92	0.00	9.72
P. virgatum	0.00	0.20	0.00	0.10	0.00	0.00	0.00	0.00	33.62	0.00	0.00	0.00	0.00	0.00	0.26	0.03	0.21	0.56	0.00	0.01	0.00	0.20	0.06
Pine	0.46	0.00	0.00	0.00	5.64	1.48	0.43	0.47	0.00	71.25	6.14	17.19	6.84	0.00	0.00	0.00	3.62	0.00	0.03	0.73	6.80	0.00	0.40
Pine/Sweetgum	0.32	0.00	0.00	0.00	0.00	0.87	0.00	0.01	0.00	3.18	68.17	18.22	1.08	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.34	0.00	0.03
Oak/Hornbeam	0.13	0.00	0.00	0.00	0.00	0.80	0.09	0.06	0.00	7.36	13.39	33.95	10.84	0.00	0.00	0.00	0.02	0.00	0.00	0.42	0.48	0.00	0.20
Live Oak	8.26	0.00	0.00	0.00	0.09	0.69	0.20	0.67	0.00	8.08	2.11	23.54	54.13	0.00	0.00	0.00	0.01	0.00	0.00	0.94	0.23	0.00	0.59
S. americanus	3.85	0.43	0.00	3.04	0.00	0.00	0.06	0.00	1.67	0.00	0.00	0.00	0.00	86.79	7.73	0.56	0.09	0.61	1.51	0.02	0.00	15.48	0.08
S. tabernaemontani	0.46	16.21	0.00	1.86	0.00	0.00	0.31	0.05	8.06	0.00	0.00	0.00	0.01	6.60	61.81	0.05	2.04	2.41	1.44	0.50	0.00	5.63	6.06
Salt-tolerant shrubs	0.00	0.98	0.38	0.02	0.00	0.00	0.72	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.00	29.41	0.16	2.08	1.73	0.57	0.00	0.15	0.24
Medium *S. alterniflora*	0.14	3.85	13.30	3.37	2.97	0.00	3.22	0.06	4.06	0.00	0.00	0.00	0.00	0.10	4.28	8.11	39.43	7.78	5.48	1.75	0.00	4.48	1.32
S. cynosuroides	0.29	8.80	2.89	0.36	0.19	0.00	5.33	0.03	23.43	0.00	0.00	0.00	0.00	0.04	0.81	13.51	2.66	28.75	4.69	0.63	0.00	1.50	1.30
Tall *S. alterniflora*	1.73	1.16	10.41	0.15	0.00	0.00	10.19	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.42	4.81	1.39	4.18	42.35	0.63	0.00	1.80	0.16
Salt-stressed tidal forest	4.19	5.65	0.56	0.16	0.35	1.46	11.97	4.64	1.06	0.54	0.02	0.10	1.74	0.05	3.24	7.37	3.96	4.27	3.61	19.80	1.87	1.03	15.69
Bald Cypress	0.00	0.00	0.00	0.00	0.56	15.01	3.20	8.25	0.00	3.49	3.63	1.78	0.80	0.00	0.00	0.05	1.77	0.01	0.21	12.40	56.04	0.00	3.75
Wrack	0.00	0.71	6.21	2.69	0.54	0.00	2.85	0.00	0.30	0.00	0.00	0.00	0.00	0.21	0.32	0.77	1.83	2.27	8.14	0.07	0.00	7.55	0.01
Z. miliacea	4.11	13.39	1.00	0.32	0.38	0.23	14.38	1.30	2.43	0.15	0.02	0.06	0.28	0.03	4.52	12.18	1.70	18.94	3.30	7.21	0.71	1.70	51.05
Class Changes (%)	44.21	69.47	50.88	21.89	47.12	38.57	55.31	18.02	66.13	28.73	31.83	66.03	45.84	13.17	37.86	69.92	60.16	69.12	53.16	79.78	43.92	91.45	48.58
Net Change (km2)	-0.02	0.51	0.08	2.63	0.78	0.58	2.60	6.21	-0.05	0.77	-0.22	-1.63	0.32	0.75	-0.10	-0.03	-4.57	-0.88	0.12	-4.60	3.41	-0.82	-5.66

D

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium S. alterniflora	*S. cynosuroides*	Tall S. alterniflora	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	67.22	0.22	0.08	0.29	1.37	0.00	0.04	0.00	0.00	0.04	0.00	0.01	0.40	0.01	0.04	0.00	0.00	0.02	0.09	0.15	0.00	0.66	0.07
C. jamaicense	0.00	20.57	0.00	0.60	1.09	0.00	0.01	0.00	0.40	0.00	0.00	0.00	0.00	0.12	0.99	3.68	0.45	4.17	0.56	0.62	0.00	0.09	1.59
Iva frutescens / S. alterniflora	0.02	0.12	33.28	0.09	0.01	0.00	0.55	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	1.33	0.19	0.28	1.65	0.00	0.00	4.46	0.01
J. roemerianus	5.24	15.61	17.26	76.71	44.01	0.00	13.75	0.02	17.01	0.01	0.00	0.00	0.01	3.61	1.82	13.25	18.32	15.27	5.13	1.32	0.00	28.34	2.76
Juncus/Schoenoplectus	0.00	0.05	0.00	3.36	23.42	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	1.51	0.34	0.06	0.02	0.00	0.17	0.07
Mixed broadleaf swamp	0.68	0.00	0.00	0.00	0.00	54.37	0.16	16.28	0.00	1.52	1.99	1.44	2.31	0.00	0.01	0.00	0.00	0.00	0.00	3.58	22.39	0.00	0.36
Mud	0.96	2.01	7.63	1.04	0.36	0.04	40.55	0.05	0.47	0.36	0.00	0.10	0.01	0.36	0.79	9.07	3.51	9.61	15.93	3.20	0.56	11.97	1.80
Tupelo	0.22	0.70	0.71	0.14	0.00	3.05	1.63	52.88	1.41	1.73	0.04	0.34	1.18	0.00	1.67	1.78	1.51	0.93	0.05	13.03	8.32	0.02	2.52
P. virgatum	0.00	0.04	0.00	0.10	0.08	0.00	0.04	0.00	28.72	0.00	0.00	0.00	0.00	0.06	0.23	0.00	0.11	1.36	0.00	0.00	0.00	0.38	0.01
Pine	1.37	0.00	0.00	0.01	0.03	2.68	0.11	1.43	0.00	66.81	6.21	17.77	17.23	0.00	0.00	0.00	0.00	0.00	0.00	0.71	2.44	0.00	0.10
Pine/Sweetgum	0.08	0.00	0.00	0.00	0.00	1.16	0.00	0.03	0.00	2.49	57.24	19.44	3.23	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.77	0.00	0.02
Oak/Hornbeam	0.58	0.00	0.00	0.00	0.00	1.99	0.18	0.26	0.00	10.24	29.43	41.74	12.01	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.93	0.00	0.04
Live Oak	6.17	0.00	0.00	0.00	0.31	2.91	0.04	0.90	0.00	3.66	2.91	12.21	52.62	0.00	0.01	0.06	0.01	0.00	0.00	1.28	0.38	0.00	0.12
S. americanus	0.17	2.05	0.21	3.08	1.42	0.00	0.42	0.00	3.56	0.00	0.00	0.00	0.00	84.06	6.93	0.18	0.18	0.62	1.69	0.07	0.00	2.35	0.11
S. tabernaemontani	0.08	18.74	0.46	3.64	6.38	0.00	0.76	0.07	11.57	0.00	0.00	0.00	0.00	9.10	51.92	1.81	3.48	5.52	3.30	1.87	0.00	1.52	2.84
Salt-tolerant shrubs	0.00	2.16	5.35	0.28	0.04	0.00	0.17	0.04	0.20	0.00	0.00	0.00	0.00	0.00	0.11	26.86	1.34	3.79	1.47	1.43	0.00	0.49	0.78
Medium *S. alterniflora*	0.00	1.18	14.15	7.36	16.02	0.00	14.58	0.88	15.94	0.00	0.00	0.00	0.01	1.55	5.96	4.30	58.04	9.36	13.34	1.49	0.03	31.19	0.46
S. cynosuroides	0.13	13.17	9.63	1.47	0.36	0.00	1.44	0.00	18.43	0.00	0.00	0.00	0.00	0.39	2.92	7.32	2.02	32.01	10.07	1.46	0.00	13.54	2.36
Tall *S. alterniflora*	0.00	0.55	4.69	0.14	0.18	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.03	5.57	0.94	2.19	37.99	0.28	0.02	3.32	0.14
Salt-stressed tidal forest	1.22	3.77	4.27	0.80	1.10	10.71	20.56	10.42	0.20	5.66	0.33	1.73	2.70	0.08	3.59	16.87	4.10	7.00	6.37	36.25	13.06	0.56	9.15
Bald Cypress	0.02	0.00	0.00	0.00	0.00	8.69	0.72	7.68	0.00	6.87	0.70	1.34	1.15	0.00	0.02	0.18	0.01	0.04	0.00	2.80	41.51	0.00	0.47
Wrack	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Z. miliacea	15.85	24.95	2.28	1.00	4.33	14.40	3.72	9.06	2.08	0.61	1.16	3.87	7.14	0.36	22.94	7.74	4.29	7.48	2.29	30.18	9.59	0.96	74.22
Class Changes (%)	32.78	85.32	66.72	23.39	77.12	45.63	59.45	47.12	71.28	33.19	42.76	58.26	47.38	15.94	48.08	73.14	41.96	67.99	62.01	63.75	58.49	100.00	25.78
Net Change (km2)	-0.07	-0.99	-0.05	0.19	-0.55	2.04	-0.39	-11.94	-0.04	0.15	-0.79	1.33	-0.75	0.35	-0.58	0.25	1.05	0.30	-0.34	5.02	-2.48	-0.91	9.19

E

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	77.83	0.10	0.46	0.46	0.00	0.04	0.21	0.01	0.00	0.09	0.01	0.06	1.34	0.07	0.03	0.00	0.00	0.01	0.08	0.08	0.01	0.00	0.70
C. jamaicense	0.09	25.37	0.36	1.15	0.24	0.00	0.23	0.04	0.26	0.00	0.00	0.00	0.00	0.02	0.86	5.40	0.45	2.66	0.08	0.30	0.00	0.00	0.35
Iva frutescens / S. alterniflora	0.04	0.23	42.73	0.12	0.00	0.00	0.68	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	2.45	0.31	1.12	2.04	0.05	0.00	0.00	0.01
J. roemerianus	0.56	5.72	8.98	69.63	70.65	0.00	4.96	0.11	18.80	0.00	0.00	0.00	0.00	3.04	5.44	8.88	17.80	3.73	1.74	0.72	0.00	0.00	0.25
Juncus/Schoenoplectus	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.00	0.00	0.00	0.00	0.00	39.07	0.25	1.24	0.00	1.53	0.68	1.30	9.68	0.00	0.00	0.00	0.00	0.00	0.00	10.09	7.04	0.00	10.50
Mud	0.57	0.62	12.81	5.38	2.90	0.04	53.23	0.23	0.00	0.09	0.00	0.23	0.14	0.18	0.50	1.95	9.16	6.00	14.98	5.22	0.35	0.00	0.86
Tupelo	0.00	0.03	0.00	0.03	0.00	44.98	0.83	83.23	0.00	3.90	0.04	1.10	7.23	0.00	0.54	3.26	3.44	0.00	0.00	29.34	28.36	0.00	15.08
P. virgatum	0.00	0.74	0.00	0.59	0.00	0.00	0.00	0.00	29.61	0.00	0.00	0.00	0.00	0.34	1.74	0.15	0.13	2.50	0.07	0.00	0.00	0.00	0.03
Pine	1.20	0.00	0.00	0.00	0.00	0.84	0.48	0.73	0.00	67.12	1.25	14.77	8.31	0.00	0.00	0.00	0.00	0.00	0.00	2.19	7.35	0.00	0.35
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	2.22	85.13	16.09	2.50	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.52	0.00	0.20
Oak/Hornbeam	0.91	0.00	0.00	0.00	0.00	0.95	0.11	0.10	0.00	15.73	11.81	58.94	25.19	0.00	0.00	0.00	0.00	0.00	0.00	0.48	1.32	0.00	2.47
Live Oak	3.30	0.00	0.00	0.01	0.00	0.21	0.03	0.21	0.00	6.39	0.77	5.56	43.23	0.00	0.00	0.00	0.01	0.00	0.00	0.89	0.42	0.00	0.75
S. americanus	5.63	3.19	1.02	3.03	0.01	0.00	1.17	0.00	11.42	0.00	0.00	0.00	0.01	92.00	26.22	0.26	0.82	10.01	2.23	0.21	0.00	0.00	1.13
S. tabernaemontani	0.09	5.44	0.56	0.55	0.00	0.00	1.21	0.22	7.82	0.00	0.00	0.00	0.01	2.65	45.18	0.36	4.03	9.10	0.31	1.43	0.00	0.00	6.31
Salt-tolerant shrubs	1.56	4.37	4.08	1.11	0.30	0.00	0.50	0.02	0.00	0.00	0.00	0.00	0.00	0.04	0.23	15.97	0.15	1.89	3.05	0.45	0.00	0.00	0.34
Medium *S. alterniflora*	0.11	1.49	9.49	10.60	25.59	0.00	7.34	0.22	13.97	0.00	0.00	0.00	0.00	0.45	4.41	11.21	55.36	7.12	15.60	0.71	0.00	0.00	0.15
S. cynosuroides	0.74	18.91	11.79	2.15	0.14	0.00	4.42	0.02	18.01	0.00	0.00	0.00	0.00	0.52	2.57	14.08	2.37	34.74	6.86	0.79	0.00	0.00	0.73
Tall *S. alterniflora*	0.13	0.17	4.34	0.22	0.05	0.00	3.21	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.32	1.88	1.53	4.66	44.48	0.17	0.00	0.00	0.02
Salt-stressed tidal forest	1.94	2.92	0.71	0.90	0.09	0.88	10.29	8.42	0.00	0.30	0.01	0.18	1.52	0.02	1.77	9.29	3.31	1.50	4.50	30.30	2.22	0.00	13.06
Bald Cypress	0.00	0.00	0.00	0.00	0.00	12.68	1.56	4.66	0.00	2.58	0.27	1.75	0.57	0.00	0.00	0.09	0.16	0.00	0.00	9.31	52.37	0.00	4.02
Wrack	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Z. miliacea	5.30	30.69	2.65	4.05	0.04	0.03	9.30	0.54	0.09	0.04	0.03	0.01	0.29	0.48	10.18	24.78	0.98	14.93	3.96	7.24	0.05	0.00	42.69
Class Changes (%)	22.17	74.63	57.27	30.37	100.00	60.93	46.77	16.77	70.39	32.88	14.87	41.06	56.77	8.00	54.82	84.03	44.64	65.26	55.52	69.70	47.63	0.00	57.31
Net Change (km2)	0.21	-0.09	0.01	-1.99	-1.01	-5.23	1.44	15.26	0.20	-0.49	0.69	1.96	-1.45	2.18	-0.66	-0.03	-0.07	0.01	0.07	-3.22	0.77	0.00	-8.56

F

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	*Juncus/Schoenoplectus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	Wrack	*Z. miliacea*
Bare or paved	61.05	1.85	0.48	0.46	2.78	0.01	0.03	0.02	0.00	0.08	0.03	0.07	0.68	0.09	0.00	0.28	0.00	0.16	0.44	0.42	0.00	1.14	1.04
C. jamaicense	0.00	17.20	0.39	0.96	0.51	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.95	3.37	0.33	4.11	0.14	0.84	0.00	0.00	0.67
Iva frutescens / S. alterniflora	0.04	0.36	43.21	0.21	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	3.75	0.33	0.66	1.28	0.08	0.00	0.00	0.02
J. roemerianus	1.59	5.32	7.40	67.35	62.65	0.00	0.12	0.00	10.04	0.00	0.00	0.00	0.00	5.21	3.55	7.66	13.09	11.69	2.44	1.98	0.00	80.98	0.30
Juncus/Schoenoplectus	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mixed broadleaf swamp	0.14	0.00	0.00	0.00	0.00	50.71	1.31	3.53	0.00	1.66	3.45	10.89	9.01	0.00	0.00	0.00	0.00	0.00	0.00	0.71	7.70	0.00	1.04
Mud	1.10	0.86	9.49	7.16	7.93	0.14	60.58	0.08	0.00	1.06	0.00	0.04	0.13	0.86	3.06	4.78	8.80	10.43	21.47	2.16	0.62	5.65	1.55
Tupelo	0.14	0.03	0.00	0.01	0.00	32.06	2.30	87.10	0.00	2.54	0.13	1.67	9.50	0.00	0.16	0.00	0.09	0.01	0.00	12.80	31.67	0.13	4.65
P. virgatum	0.07	1.33	0.26	0.65	0.73	0.00	0.00	0.00	23.87	0.00	0.00	0.00	0.00	0.49	0.32	1.05	0.15	1.45	0.02	0.01	0.00	0.44	0.50
Pine	1.54	0.00	0.00	0.00	0.01	2.65	2.80	0.43	0.00	69.17	1.45	15.37	11.15	0.00	0.01	0.00	0.00	0.00	0.00	0.99	4.84	0.31	0.27
Pine/Sweetgum	0.00	0.00	0.00	0.00	0.00	1.58	0.08	0.08	0.00	2.55	75.34	12.92	5.82	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.48	0.00	0.03
Oak/Hornbeam	3.84	0.00	0.00	0.00	0.00	2.53	0.36	0.42	0.00	13.17	18.90	49.40	26.75	0.00	0.00	0.00	0.00	0.00	0.00	0.49	0.77	0.00	0.57
Live Oak	13.45	0.00	0.00	0.06	0.24	0.16	0.03	0.98	0.00	4.90	0.23	7.19	33.34	0.00	0.01	0.00	0.00	0.00	0.00	0.94	0.06	0.00	0.36
S. americanus	4.94	14.40	0.09	6.28	4.13	0.00	0.02	0.00	27.31	0.00	0.00	0.00	0.00	82.27	14.88	4.10	2.55	2.87	3.57	0.21	0.00	6.53	2.34
S. tabernaemontani	0.91	5.67	0.00	0.37	0.43	0.00	0.08	0.00	0.81	0.00	0.00	0.00	0.00	5.29	40.86	0.23	0.68	1.32	0.05	2.75	0.00	0.00	5.79
Salt-tolerant shrubs	0.39	5.41	2.92	0.89	0.97	0.00	0.02	0.00	0.36	0.00	0.00	0.00	0.01	0.19	0.05	17.60	0.62	4.55	2.50	0.41	0.00	0.48	0.55
Medium *S. alterniflora*	0.02	2.86	20.34	9.64	4.98	0.00	2.02	0.00	6.69	0.00	0.00	0.00	0.01	3.06	11.15	13.92	62.48	16.26	18.95	2.65	0.00	0.66	0.34
S. cynosuroides	0.12	21.87	5.36	2.16	0.56	0.00	0.18	0.00	28.39	0.00	0.00	0.00	0.00	0.70	0.68	25.54	2.44	33.21	3.57	1.29	0.00	0.83	3.27
Tall *S. alterniflora*	0.42	0.45	7.71	0.21	0.09	0.00	0.67	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.13	7.38	1.59	4.35	42.49	0.16	0.00	0.26	0.07
Salt-stressed tidal forest	4.52	1.22	0.96	0.57	1.06	1.45	20.08	3.91	0.18	1.01	0.06	0.19	2.57	0.14	7.09	1.03	4.50	2.32	1.62	47.13	4.01	0.00	14.81
Bald Cypress	0.00	0.00	0.00	0.00	0.00	8.70	5.80	3.39	0.00	3.85	0.38	2.26	0.89	0.00	0.01	0.00	0.12	0.00	0.00	6.40	49.73	0.00	1.72
Wrack	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Z. miliacea	5.73	21.17	1.39	3.04	12.94	0.02	3.52	0.04	2.35	0.01	0.02	0.00	0.13	1.51	17.09	9.30	2.23	6.61	1.48	17.53	0.10	2.59	60.10
Class Changes (%)	38.95	82.80	56.79	32.65	100.00	49.29	39.42	12.90	76.13	30.83	24.66	50.60	66.66	17.73	59.14	82.40	37.52	66.79	57.51	52.87	50.27	100.00	39.90
Net Change (km2)	0.18	-0.26	-0.02	-2.36	-1.74	-4.02	2.35	9.04	0.20	0.40	0.55	1.55	-2.91	2.24	-3.37	0.13	1.81	0.33	-0.21	0.65	-3.49	-0.23	-0.81

G

	Bare or paved	*J. roemerianus*	Mixed decicuous forest	Mud	Tupelo	Pine	Pine/Sweetgum	Oak/Hornbeam	Live Oak	Mesohaline Marsh	Salt Marsh	Salt-stressed tidal forest	Bald cypress	Tidal fresh marsh	Wrack
Bare or paved	66.39	0.61	0.00	0.01	0.02	0.05	0.01	0.06	0.50	0.30	0.07	0.35	0.00	0.66	1.15
J. roemerianus	1.15	68.74	0.00	0.06	0.00	0.00	0.00	0.00	0.00	5.68	10.22	2.16	0.00	1.46	81.20
Mixed decicuous forest	0.09	0.00	54.30	0.81	2.95	1.41	3.34	10.66	9.23	0.00	0.00	0.66	6.35	0.51	0.00
Mud	1.11	6.90	0.08	67.10	0.06	0.87	0.00	0.01	0.08	2.87	10.31	2.01	0.47	1.96	5.76
Tupelo	0.09	0.00	30.35	1.56	88.95	1.87	0.07	1.13	8.26	0.00	0.06	11.95	30.79	2.71	0.15
Pine	0.79	0.00	2.39	2.07	0.34	72.55	1.16	13.68	10.73	0.00	0.00	0.87	4.37	0.15	0.30
Pine/Sweetgum	0.00	0.00	1.59	0.07	0.06	2.23	76.96	12.74	5.62	0.00	0.00	0.06	0.42	0.01	0.00
Oak/Hornbeam	3.36	0.00	2.25	0.30	0.32	12.17	17.88	52.75	27.38	0.00	0.00	0.43	0.54	0.31	0.00
Live Oak	13.03	0.07	0.12	0.00	0.80	4.58	0.16	6.90	34.91	0.00	0.00	0.85	0.04	0.19	0.00
Mesohaline Marsh	3.98	9.16	0.00	0.12	0.00	0.00	0.00	0.00	0.00	72.52	5.31	3.53	0.00	10.54	7.52
Salt Marsh	0.41	8.88	0.00	2.38	0.00	0.00	0.00	0.00	0.01	7.28	66.77	3.72	0.00	4.59	0.90
Salt-stressed tidal forest	3.61	1.39	1.35	18.29	3.67	0.95	0.06	0.15	2.47	2.43	4.70	49.37	3.84	11.28	0.60
Bald cypress	0.00	0.00	7.57	4.63	2.82	3.32	0.34	1.92	0.73	0.00	0.06	6.12	53.09	0.93	0.00
Tidal fresh marsh	5.99	4.25	0.00	2.59	0.02	0.00	0.02	0.00	0.08	8.92	2.50	17.91	0.06	64.70	2.41
Wrack	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Class Changes (%)	33.61	31.26	45.70	32.90	11.05	27.45	23.04	47.25	65.09	27.48	33.23	50.63	46.91	35.30	100.00
Net Change (km2)	0.17	-4.00	-3.86	2.27	8.73	0.36	0.54	1.55	-2.89	2.54	1.57	0.73	-3.39	-4.13	-0.20

APPENDIX E

SPECTRAL SEPARABILITY

For accurate supervised classification of remote sensing data, user-designated classes must have distinct spectral signatures. We evaluated the spectral separability of our land cover classes using Jeffries-Matusita distance, which measures the average distance between two class density functions (Richards and Jia 2006). Testing was implemented using the Spectral Separability tool in ENVI 5.6.1, using Sentinel-2 MSI bands 1-12 as input. Values range from 0 to 2, with higher values indicating better separability (Richards and Jia 2006). Testing of separability was iterative. With each iteration we removed poorly-performing classes, combined them with spectrally and ecologically similar classes, or adjusted our regions of interest (ROIs) to reduce ambiguity. Table E1 shows the final results for the training data used in our Balanced Random Forest classification of the May 28, 2021 Sentinel-2 MSI image. Most classes have excellent spectral separability (greater than 1.9) (Richards and Jia 2006). Some marsh classes (e.g., *C. jamaicense*, *Iva frutescens/S. alterniflora*, and Salt-tolerant shrubs) have poor spectral separability from other marsh classes. This spectral similarity frequently resulted in classifier error between these classes. For example, *C. jamaicense* and *S. tabernaemontani* had a separability score of just 1.6, and 20% of C. jamaicense pixels were misclassified as S. tabernaemontani (Table 3.3). Overall classification accuracy could likely be improved by removing some of the smaller classes with lower separability scores and Producer's accuracies.

References

Richards, J.A., & Jia, X. (2006). Remote sensing digital image analysis. Berlin: Springer

Table E1. Jeffries-Matusita spectral separability of training data for the May 28, 2021 Sentinel-2 MSI image. Values range from 0 to 2, with higher values indicating better spectral separability (greater differences between a pair of classes). Values above 1.8 are considered good. Shaded cells indicate pairs of classes with separability lower than 1.8. The table is symmetrical, so only half of the values are shown.

	Bare or paved	*C. jamaicense*	*Iva frutescens / S. alterniflora*	*J. roemerianus*	Mixed broadleaf swamp	Mud	Tupelo	*P. virgatum*	Pine	Pine/Sweetgum	Oak/Hornbeam	Live oak	*S. americanus*	*S. tabernaemontani*	Salt-tolerant shrubs	Medium *S. alterniflora*	*S. cynosuroides*	Tall *S. alterniflora*	Salt-stressed tidal forest	Bald Cypress	*Z. miliacea*
Bare or paved																					
C. jamaicense	1.99822																				
Iva frutescens / S. alterniflora	1.99935	1.87026																			
J. roemerianus	1.99951	1.99861	1.99995																		
Mixed broadleaf swamp	1.99658	1.96433	1.95731	1.86838																	
Mud	1.99996	2.00000	2.00000	2.00000	2.00000																
Tupelo	1.99995	1.99998	1.99995	2.00000	1.80082	2.00000															
P. virgatum	1.99978	1.92947	1.99683	1.99984	2.00000	1.99885	1.99984														
Pine	1.99927	1.99997	2.00000	2.00000	1.97678	1.99999	1.98544	1.99907													
Pine/Sweetgum	2.00000	2.00000	2.00000	2.00000	1.99207	2.00000	1.98873	2.00000	1.96829												
Oak/Hornbeam	1.99989	2.00000	2.00000	2.00000	1.96825	2.00000	**1.78969**	1.99947	**1.34418**	1.85475											
Live oak	1.99907	1.98987	1.99904	2.00000	1.95119	1.99992	1.88570	1.96655	**1.62598**	1.86053	**1.30986**										
S. americanus	1.99964	1.97482	1.99985	1.90480	2.00000	1.97347	2.00000	1.99515	1.99993	2.00000	2.00000	1.99996									
S. tabernaemontani	1.99894	**1.55029**	1.94850	1.96272	2.00000	1.85420	1.99988	1.94787	1.99999	2.00000	1.99999	1.99604	1.81412								
Salt-tolerant shrubs	1.99900	**1.67623**	**1.73842**	1.99997	1.99931	1.98828	1.99257	1.88201	1.99369	2.00000	1.99754	1.94935	1.99960	1.87669							
Medium *S. alterniflora*	1.99920	**1.68974**	**1.67464**	1.97526	2.00000	1.82247	2.00000	1.98549	2.00000	2.00000	2.00000	1.99941	1.98999	**1.58582**	**1.76570**						
S. cynosuroides	1.99809	**1.69584**	1.89338	1.99719	1.99987	1.92241	1.99778	**1.76675**	1.97562	1.99994	1.99370	1.94794	1.99378	**1.78596**	**1.40601**	**1.73775**					
Tall *S. alterniflora*	1.99894	1.92232	**1.79335**	1.99984	2.00000	1.90667	1.99999	1.99924	1.99955	2.00000	2.00000	1.99836	1.99649	1.94200	1.94775	1.94448	**1.68115**				
Salt-stressed tidal forest	1.99586	**1.77674**	**1.77474**	1.99989	1.99966	1.95458	1.98837	1.97494	1.99979	1.99998	1.99867	1.96980	1.99925	1.88577	**1.59664**	1.81546	**1.73571**	**1.76024**			
Bald Cypress	1.99987	1.99988	1.99761	2.00000	1.90631	2.00000	**1.70852**	1.99948	1.96416	1.98529	1.92338	1.92126	2.00000	1.99918	1.98011	1.99992	1.99459	1.99925	1.96151		
Z. miliacea	1.99703	**1.44234**	1.86694	1.98993	2.00000	1.80383	1.99994	1.98984	1.99999	2.00000	2.00000	1.99720	1.99430	**1.75084**	**1.78921**	**1.61681**	1.86917	1.98071	1.99959	1.99959	