MARSH HABITAT MAPPING AND CLASSIFICATION SYNTHESIS FOR THE FLORIDA PENINSULA

Final Report

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Abstract

A project to inventory, map, and synthesize coastal marshes for conservation and environmental management. This effort acquired Landsat 8 satellite data, field training data, and contributed ancillary information to classify and map salt marshes from southern coastal Georgia, northeast Florida, and the Gulf Coast and Panhandle of Florida for multi-purpose habitat management. Emphasizing maps of high marsh and associated habitats, the project also delivers source imagery, vector and raster datasets, and report accuracy assessment.

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I. Executive Summary

A. Purpose

This report documents the creation of salt marsh habitat maps and associated geospatial data products for the Atlantic Coast Joint Venture (ACJV) spanning the Florida Peninsula and Panhandle. The document details the literature background, methods, and pertinent accuracy and inherent constraints towards conservation planning and management.

Specifically, this report focuses on the following:

1. Application of remote sensing to salt marsh classification across southern coastal Georgia, northeast Florida, and west Gulf Coast and Panhandle regions of Florida, including exhaustive and mutually exclusive classes allowable by synoptic satellite remote sensing.

2. Provision of raster and vector marsh maps and supporting field observations and remotely sensed imagery to allow for future marsh habitat monitoring and assessment.

B. Significance

Numerous efforts over recent decades have sought to inventory and monitor wetlands and land use/land cover along the coastal plain of the Gulf of Mexico and Eastern Seaboard of the United States. Advances in satellite sensors and image classification methodologies have established that new approaches can replicate or surpass traditional techniques of manual aerial photointerpretation for efficient regional mapping. The approach taken is documented in detail that could be replicated in the future or applied to other marsh landscapes or regions.

The project is geographically extensive, using satellite-based remote sensing to extend prior mapping of the Southeast (South Atlantic region from North Carolina to Georgia) in this project through northeast Florida, the western Gulf of Mexico coast of Florida, including the Panhandle. The primary product provides a synoptic spatial resolution map with thematic detail of salt marsh classes as compared to prior satellite land use/land cover products or localized aerial and field-based mapping projects. The combination of synoptic spatial scale and improved thematic detail (especially as compared to only localized data or coarse land use/ land cover class definitions) should improve conservation planning and management in the region, particularly for low versus high marshes and adjoining upload ecotopes.

C. Broader Effort

The methodology and data developed in this study have garnered interest and ensuing discussions among other Landscape Conservation Cooperatives as well as states and non-governmental organizations. NASA and the European Space Agency (ESA) have also developed new satellites and software applications to facilitate greater use of satellite information for such mapping. The project applied available Landsat 8 Optical Land Imager (OLI) sensor (operational since 2013) and proven successful for the Southeast in 2018. In addition to a comprehensive inventory of high and low marshes, the project provides extensive coverage of other landscape units, including salt pans, mudflats, mangroves, and adjoining coastal riparian wetland forests. These additional classes and the imagery used can provide a baseline for assessing future marsh conditions and biophysical characteristics.

D. Approach

This project maps salt marshes using Landsat 8 Optical Land Imagery (OLI) satellite sensor in the coastal zone using Object-Oriented Image Analysis (OBIA) techniques. Using a set of Intensive Study Areas (ISAs) scattered across the region with supporting field and ancillary data, sparse access to sites in some areas, and collaborative personnel on the ground and familiar with various area marshes, the region was masked and classified into coastal marsh classes. The approach incorporated secondary and disturbed marshes, riverine tidal marshes, and reclaimed and emergent marsh areas as best practicable in order to avoid omission errors of salt marshes. Intensive study areas were also utilized as test areas, before finalizing the classification scheme and collection of separate training and accuracy assessment verification data (photographs, GPS coordinates, and species identification notes.)

E. Organization

This report is divided into five major Sections followed by Appendices containing additional maps.

1. The **First Section**, *Introduction*, provides information on literature guiding the work, key data, assumptions, errors and uncertainty, and the relationship of these factors to potential conservation planning and actions. The literature review in this Section evaluates the most recent information on salt marsh remote sensing, key factors in sea level rise and marsh responses, and processing methods undertaken for quality assurance.
2. The **Second Section**, *Approach*, provides more detailed information on the approach, including study region, intensive study areas, field survey methods, image classification techniques, and particular *a priori* areas of concern.
3. The **Third Section**, *Results*, reports findings and details the products created. This section includes an overview of maps (examples presented in appendices) and tabular and statistical summaries and discussion of accuracy assessment.
4. The **Fourth Section**, *Conclusions*, presents a concise list of application recommendations as well as future studies or monitoring that may improve marsh habitat management and conservation planning.
5. The **Fifth Section**, *References*, provides references supporting the approach and methods.
6. **Appendices** include examples of regional maps and NDX composites, field site keys and descriptions, and a sample of field site photographs.

F. Report Deliverables

Five core deliverables are contained within this report or provided digitally:

1. Maps for the region and each intensive study area, including raster and vector formats and metadata (provided digitally.)
2. Imagery depicting derived Normalized Differences Indices (NDX) composites used in classification with consideration for interpretation and future change detection (provided digitally.)

3. Tabulated summary and accuracy of the classified marsh maps, including an error matrix in this report. Webmaps are also provided in a digital format online at https://arcg.is/1CbSmT0 and within an explanatory story map here: https://arcg.is/0C4LHz.
4. Summary data collected and links to other resources provided in references.
5. Appendices include additional field site information, interpretation, and example photos.

G. Findings

Key Takeaway 1

The distribution of salt marshes follows expected trends in tidal frame, temperature and hydroclimatology, and salinity that differentiates north Florida and the Gulf Coast, yet marked localized patterns also emerged owing to land use and human hydrologic alterations, mangrove colonization, localized landform influences, and intermittent as well as disturbances aligned with sea level rise and climate change.

Key Takeaway 2

In zones of reduced tidal range, interdigitation of *Juncus* and other marshes tends to occur at a fine scale. In southwest Florida where mangroves become more extensive, these stands tend to occupy a similar tidal prism that would otherwise support salt marshes. West of the Big Bend, mangroves are rarer, yet the tidal prism and barrier island and estuarine landforms provide less accommodation space for the extensive *Juncus* platform marshes seen to the southeast.

Key Takeaway 2

The adopted classification scheme provides a seamless, mutually exclusive categorization inclusive of inundation, salinity, and substrate and autochthonous processes in marshes. The range of classes provides for the inclusion of tidal fresh and brackish marshes that are extensive in the tidal riverine zones, mudflats in the lower intertidal zone, salt flats and pans in the upper tidal frame and interfluve platform marshes in the south. Capturing these zones in mapping may allow for consideration of marsh transgression/invasion (or mangroves) with sea level rise.

Key Takeaway 3

Landsat 8 OLI multispectral data proved capable for high vs. low marsh differentiation, with the caveat previously noted about spatial resolution, yet tidal fresh and brackish marshes, marshes disturbed by burning, and mudflats or exposed dredge spoils with variable tidal conditions in available imagery limit accuracy in these areas. For site specific area management, this study augments rather than replaces high-resolution airborne and in situ mapping. New advances in small Unmanned Aerial Systems (sUAS) even since this study initiated provide additional applied research avenues for inventorying and managing habitats at the scale of individual reserves and refuges.

Table of Contents

I. Executive Summary 2

1.INTRODUCTION 8

1.1 Study Objectives 8

1.2 Literature Synthesis 9

1.2.1 Regional Remote Sensing of Salt Marshes 9

1.2.2 Rationale for Marsh Regional Classification Typology 14

1.2.3 Hypsometry of Salt Marshes 18

1.3 Key Data 19

1.4 Assumptions and Limitations 20

2.APPROACH 22

2.1 Study Area 22

2.2 Image Search Criteria and Acquisition 23

2.3 Field Site Visits 24

2.4 Remote Sensing Methods 26

2.4.1. Mosaic and Masking 26

2.4.2 Image Compositing and Normalized Difference Indices (NDX) 28

2.4.3 Field Work and Training in Intensive Study Areas 30

2.5 Image Classification 31

2.5.1 OBIA Classification 31

2.5.2 Segmentation, Training and Classification 32

2.5.3 Accuracy Assessment 35

3 RESULTS 36

3.1 Map Results and Comparison 36

3.2 Accuracy Assessment Results 37

3.3 Mapping Limitations 40

4 CONCLUSIONS 42

5 REFERENCES 44

Appendices 48

Appendix A. Northeast FL and Georgia NDX Composite and Classification Maps 48

Appendix B. Gulf Coast Peninsula and Panhandle Extent NDX Composite and Classified Maps 50

Appendix C. Marsh Classification Scheme and Field Sites 53

Appendix D. Field Marsh Photos and Descriptions..56

1. INTRODUCTION

1.1 Study Objectives

Coastal marshes are widely regarded for the crucial habitat and ecosystem services they provide to society, including avian and faunal habitats, fish and wildlife nurseries, pollution filtration and nutrient uptake, storm surge damage mitigation, and serving as sinks for atmospheric carbon. Uncertainty of marsh response to sea level rise is a grave concern to coastal conservation and management and communities that surround them. Recent advances in satellite remote sensing and image classification are poised to improve the inventorying, monitoring, scientific understanding and management of coastal marshes. In particular, the improved spectral and radiometric resolution of Landsat 8 and advanced object-based image analysis (OBIA) classification techniques are primed for application to regional inventory of salt marshes. Such data and algorithms can improve on the classification thematic detail as compared to past inventories (e.g., marsh zonation and floristic or physiognomic detail) as well as cost-effectively providing a regional mapping process (also providing for more currency by updating these maps in dynamic coasts more frequently.)

Salt Marsh Maps

The primary objective of the study was to map high and low marshes with high resolution satellite imagery, including delineating ecotones between high- and low marshes. Utilizing Intensive Study Areas (ISAs) with higher resolution aerial imagery and field data, the classification would provide a seamless and exhaustive snapshot of the distribution of salt marshes across peninsular Florida and the Panhandle. In particular, the classification would delineate salt marsh habitats that are oftentimes aggregated in traditional schemes such as the National Wetland Inventory (NWI) or the National Estuarine Research Reserves' (NERRs) estuarine classifications or that are highly species-specific and prone to high classification error in locally produced field mapping. Hence, the synthesis marsh map product sought to create a marsh classification with improved thematic detail- separating high and low marsh classes into commonly recognized ecotopes while also retaining adequate spatial resolution for landscape conservation management.

Methodological and Biophysical Products

The third objective of the study was meta-level, to produce documentation of the methodological approach for regional classification, including detailing the classification scheme typology, data acquisition and preprocessing, and image classification and accuracy assessment techniques. A derivative of this objective also incorporates a continuous biophysical product in the form of multi-band Normalized Difference Indices (NDX) composite images. NDX composites of Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Soil Index (NDSI) derived from calibrated Landsat 8 OLI bands comprise complementary characteristics of salt marshes in a gradational, continuous sense. Such continuous biophysical measurements augment the discrete marsh classification and aid managers interested in relative composition or monitoring future trends in marsh conditions. Similar to widely applied NDVI vegetation mapping or Tasseled Cap Transformation (Kauth and Thomas 1976; Crist and Ciccone 1984), these biophysical indices capture a set of spectrally identifiable characteristics. NDWI allows for assessment of the water background absorption and is sensitive to marsh dieback and reduced vegetative cover extent relative to tidal inundation. NDWI relies particularly on the absorption of middle-infrared reflectance by water. NDVI, as is commonly used in forest, grassland and agricultural monitoring, reflects the cover and biomass vigor, being a normalized difference of the short-wave infrared and red visible wavelengths. NDSI summarizes the normalized difference between middle-infrared and near-infrared reflectance, a relationship that is sensitive to soil background reflectance, which in the case of salt marshes can include wrack, mud, and salt pan/sandy substrates. Since all three indices are normalized and rescaled to the range 0-1, they also provide for a baseline for multi-temporal monitoring and change detection since radiometric calibration and atmospheric correction have been applied to the imagery used in this study.

1.2 Literature Synthesis

1.2.1 Regional Remote Sensing of Salt Marshes

This study was predicated on the proven capabilities of Landsat multispectral data for regional, synoptic scale mapping. As compared to prior LCLUC data products such as NOAA C-CAP or USGS NLCD and MRLC, the higher radiometric and spectral fidelity of Landsat 8 combined with a narrower range of cover types for classification points to a strong feasibility to distinguish and classify ecological marsh zones. Although trends toward ultra-fine resolution imagery continue to advance (Digital Globe, WorldView, and airborne and unmanned aerial vehicle sensors), the suitability of Landsat remains very relevant. Landsat continues to provide a long time series of synoptic scale land cover observations. The temporal resolution of 16 days allows for capturing sufficient cloud-free imagery in the region to avoid total cloud contamination, to capture phenological trends, and to select from various tidal stages in the cloud-free imagery that are available.

Marsh Elevation

Elevation is a fundamental factor affecting the extent of tidal flooding and, consequently, species distribution and patterns in marshes (Hladik and Alber, 2012). The elevation of *Spartina alterniflora* relative to mean sea level also affects their stability (Morris et al. 2002). Owing to the relatively flat topography, elevation differences of less than 10 cm can drive variability in marsh species patterns. Thus, there is a need for accurate elevation mapping in salt marshes to identify vulnerable habitat and predict how marshes will respond to perturbations that might alter plant distributions, such as sea level rise (Hladik and Alber 2012). In recent years, LiDAR has been used to ascertain ground elevation and vegetation structure for developing digital elevation models (DEMs). LiDAR has been used to determine elevation in tidal areas with vertical resolution as fine as 16 cm in North Carolina (Poulter and Halpin 2008). However, an accuracy assessment of LiDAR models in salt marshes showed that they overestimate marsh ground elevations, with mean errors increasing with increased vegetation density and plant height (Hladik and Alber 2012). These errors may result from inadequate horizontal and vertical sensor resolution that, given the small topographic variability in salt marshes, makes it difficult to detect meaningful differences in elevation. Another source of error may be the inability of LiDAR to differentiate between vegetation types with heights less than 2m, which describes much of salt marsh vegetation (Hladik and Alber 2012). Such wide area “marsh correction” of LiDAR is complex given that regional variation of sea-level, tidal frame, and according gradient of marshes over the SALCC region varies dramatically in the vertical. Moreover, the vertical height of a given marsh species may vary longitudinally and laterally along the riverine-estuarine axis as a function of the tidal prism. Hence, marsh-corrected LiDAR was ultimately not implemented in this study. While this has strong future potential, a dedicated field campaign and tidal-controlled LiDAR or imagery may be necessary. Marsh-corrected elevations would have value in spatially explicit marsh response modeling (e.g., SLAMM and MEM) for sea level rise studies. Having a mrsh classification is a first step toward such correction, since regression or other empirical modeling could then be applied to DEMs in a distributed fashion. Future investigation of Interferometric satellite SAR (IfSAR) could potentially augment this, or even bridge this gap, but may also entail having a robust and extensive marsh type classification.

Object vs. Pixel-based Classification

Traditional image classification focuses on the implicit topology of raster cells, or pixels, in satellite imagery, the use of supervised or sometimes hierarchical image classification procedures, and pixel-based accuracy assessment. A recent trend oftentimes used in ultra-high resolution remote sensing involves a new alternative, Object-Based Image Analysis (OBIA). Approaching the mapping purpose from the standpoint of patches of homogenous cover types, objects are groups of adjacent pixels with similar reflectance characteristics that signify homogenous on the ground entities (species, cover types, or zones.) These two approaches offer distinct advantages and disadvantages. This project adopted OBIA methods for a few significant reasons, even if the use of OBIA in synoptic classification (e.g., Landsat 30m resolution) is less widely demonstrated.

OBIA classification provides for the inclusion of diverse spatial information and topology in the creation of features, the use of powerful computational algorithms for classifying discrete objects, and the inherent vector data structure for compact and efficient analysis and data dissemination via GIS. Classification algorithms include parametric and non-parametric multivariate cluster and classification models as well as regression trees, support vector machines, and random forests. Polygon segments are also inherent to discrete, patchy ecotopes such as salt marshes. The capability of OBIA to measure and include spatial shape metrics in classification can capitalize on pattern and shape characteristics of marshes (e.g., long perimeter-area ratio of fringing marshes such as Juncus or creekbank levee Spartina and compact, circular shapes prominent in colonial patches of invasive *Phragmities* or adjacent *Typha.*) A measure of efficiency is also gained by the use of vector polygon objects for training (allowing for fewer target training sites as compared to pixels) and the consequent easier field reconnaissance and accuracy assessment access.

With increasing spatial resolution satellite data, alternatives to pixel-based classification are being developed. A major drawback of pixel-based classification is that a pixel's spatial extent may not match the extent of the cover type feature of interest (Aplin and Smith 2008). This results in mixed pixels, whereby a pixel represents more than a single type of land cover. High resolution images support several scales within their images. Object-based image analysis (OBIA), on the other hand, uses spatially explicit information to derive objects that are made up of several pixels. OBIA builds on older segmentation, edge-detection, feature extraction and classification concepts that have been used in remote sensing image analysis for decades, but were not used extensively in geospatial applications until the past decade (Blaschke 2010). Segments are regions which are generated by one or more criteria of homogeneity in one or more dimensions of a feature space (Blaschke 2010). Segments have more spectral information than single pixels; more importantly, they have more spatial information (e.g., distances, neighborhood, topology) that is crucial to OBIA methods. Grouping pixels into image objects mitigates the "salt and pepper effect" that occurs with misclassification of pixels caused by shadow, mixed species, and differences in reflectance values (Kelly et al. 2011). Some object-based image classification techniques attempt to replicate traditional pixel-based classification techniques using the spatial scale of the object instead of the pixel. For instance, the maximum likelihood classification algorithm has been used for object-based classification, either (i) by classifying objects directly (e.g., by comparing each object's group of pixels as a whole against the training classes, or (ii) by first classifying pixels individually and then grouping these to populate each object (Aplin and Smith 2008). The efficacy of OBIA techniques has been demonstrated in several studies. Platt and Rapoza (2008) compared results from a maximum likelihood classification with results from OBIA and found that the combination of segmentation into image objects, use of the nearest neighbor classifier, and the integration of expert knowledge yielded substantially improved classification accuracy compared to a per-pixel method. Kamal and Phinn (2011) compared pixel-based and object-based mapping techniques using spectral angle mapper (SAM) and linear spectral unmixing (LSU) for the pixel-based approaches, and multi-scale segmentation for the OBIA approach. They found that OBIA mapping produced the most accurate results (overall accuracy 76%, Kappa 0.67). Riggan and Weih (2010) obtained similar results comparing three methodologies (object-based, and supervised and unsupervised pixel-based classifications) to determine if an object-based analysis of remotely sensed imagery would produce a statistically more accurate LULC classification than a pixel-based analysis applied to the same imagery. Results showed that when merging high-spatial resolution aerial imagery with medium-spatial resolution satellite imagery, the object-based classification outperformed both supervised and unsupervised pixel-based methods.

OBIA has also illustrated robustness for multi-scale mapping, expanding beyond its initial focus on ultra-high resolution imagery to extend to landscape mapping. Phinn et al. (2012) demonstrate the multi-scale mapping for coral reef benthic habitats and geomorphology, highlighting the value of hierarchical classification. Using high-resolution color- and near-infrared imagery, Kelly et al. (2011) note that care should be taken in multi-scale analyses for marsh vegetation undergoing restoration, as pattern metrics such as patch statistics can be sensitive to scale. Kim et al. (2011) also find that multi-scale OBIA classification produces higher map accuracies in marshes. Nonetheless, some coastal ecosystem zones, such as fringing mangroves, may present a challenge to even ultra-high resolution imagery. Heumann (2011) achieved accuracy exceeding 94% for mangroves in the Galapagos but describes limitations for OBIA and WorldView-2 imagery of mixed zonation or sparse vegetation. Timm and McGarigal (2012) document the classification of 1m resolution coastal dune and marsh vegetation at Cape Cod, crediting success to a supervised random forest classification algorithm. These studies collectively affirm that very fine spatial resolution coastal marshes are able to be accurately mapped, and moreover that advanced image segmentation and classification algorithms are able to efficiently handle landscape extents. A prevailing challenge cited remains the standardization of imagery, acquisition and environmental factors, and the portability of OBIA parameters, rule sets, and resulting variation in accuracy.

NDX Composites for Classification and Interpretation

Multispectral imagery includes a measure of inherently redundant spectral information across the various wavebands of a sensor such as Landsat OLI. Although the moderate spectral resolution allows for an easier classification as compared to hyperspectral (and high redundancy), the capability to interpret spectral information and weight them (and balance spectral versus spatial information) are reduced when a large number of redundant, correlated bands are used in image classification. Hence, there is an efficiency gained by deriving fewer, biophysically distinct spectral derivatives for classification and image interpretation alike. Further, advanced image classification techniques such as spectral unmixing to discern fractional composition of wetlands undergoing change (e.g., Rogers and Kearney 2004) and hydrologic simulation modeling have also provided additional input data for classification. For instance, floodplain inundation models have been incorporated into classification (Townsend and Walsh 1998) and such data integration has an analogous history of success at improving forest classification in complex montane environments. Accordingly, the aforementioned NDX composites are thus adopted for classification purposes and subsequent biophysical image analysis.

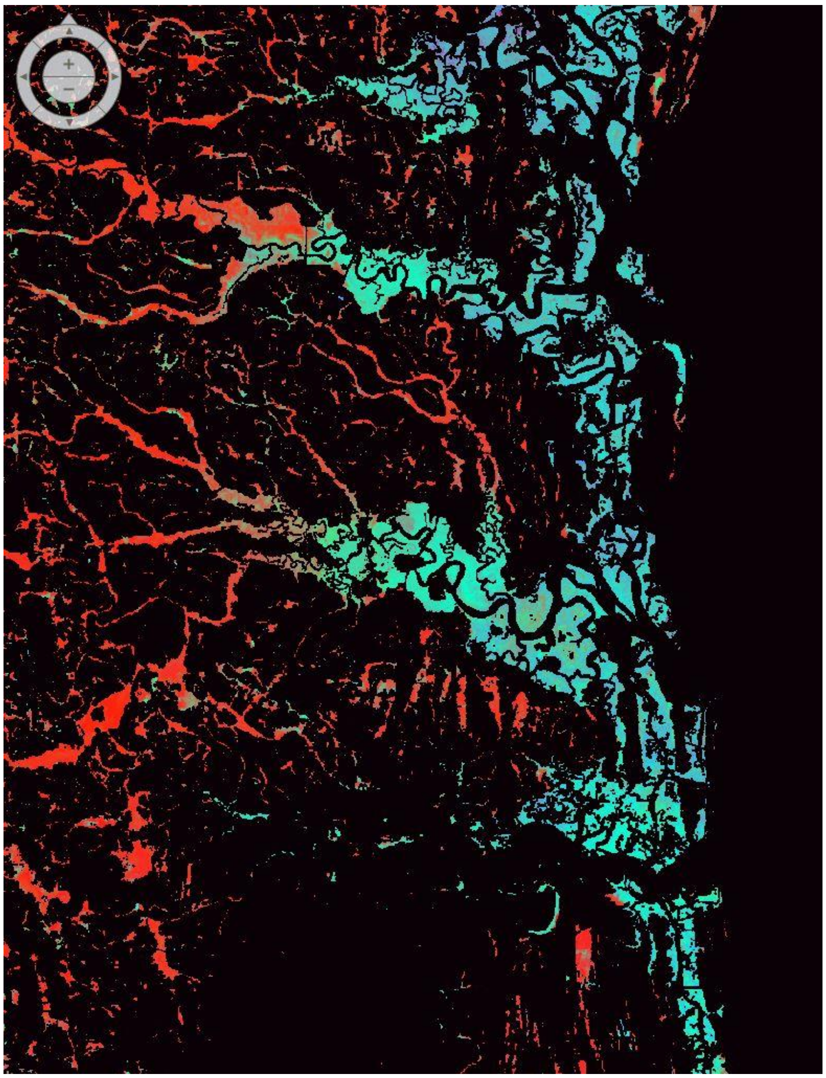

Figure 1 Composite NDX image showing red, green, blue indices for NDVI, NDSI, and NDWI bands (as red, green, blue, respectively) for northeast Florida.

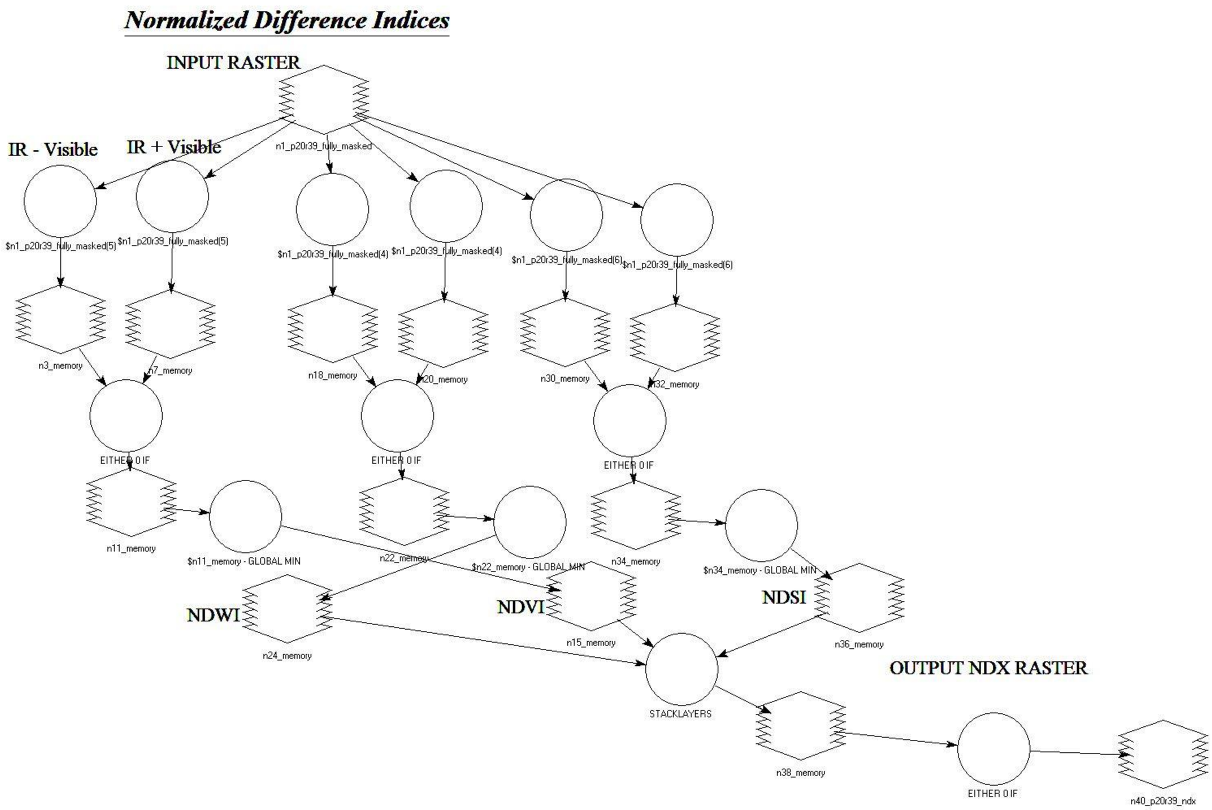

Figure 2 Erdas IMAGINE model created to compute the NDX composite images from masked and atmospherically corrected Landsat 8 OLI imagery.

Support Vector Machines Classifier

Support Vector Machines (SVM), a machine-learning algorithm, was adopted as the classifier tool of the training site polygons identified in the intensive ISAs. Training required image interpretation and use of ultra-high resolution orthophotography, field work, consulting ancillary maps and oftentimes discussion with local NERRs or reserve staff and academic scientists (e.g., GA Southern, USF, and UFL.) Training of 100s of target polygons in this manner created a spectral-statistical dataset that the SVM algorithm could subdivide. We aimed generally for 30-40 target polygons per class of highly representative spectral purity or homogeneity in each Landsat scene.

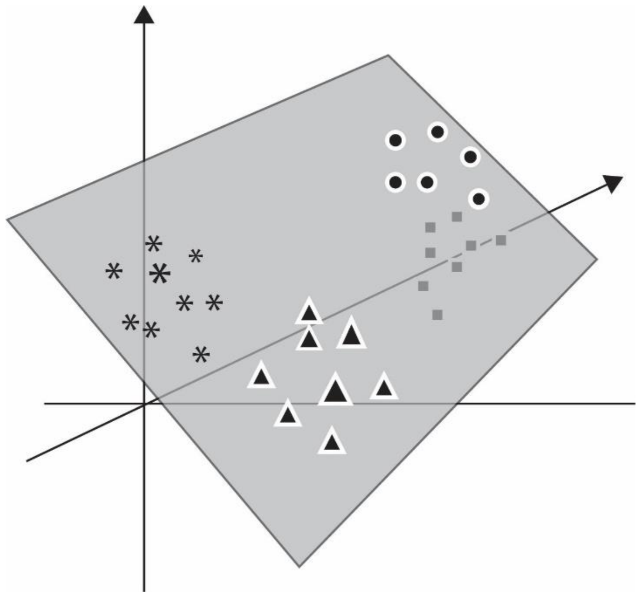

Figure 3 SVM classification graphical view. One of several hyperplanes separates four possible training classes shown in three band spectral space.

The training site image keys used with aerial orthoimagery include several factors: color/tone, canopy, shape, pattern, and texture. The OBIA and SVM approach provided the advantage of high accuracy potential and reduced interaction as in supervised, unsupervised or hybrid classification techniques. The OBIA use of vector polygons also provides managers useful spatial objects, preserving spatial characteristics of marsh patches while still allowing for rasterization and use with modeling and other programs. Both OBIA image segmentation and SVM are suitable to large datasets. The SVM technique, shown in Fig. 2 in a generalized diagram, searches for optimal hyperplanes in multidimensional spectral space to differentiate thematic classes (training sites.) The method used combines the sequence of steps: 1) Derive vector polygons from image segmentation, 2) identify the best, purest representative training polygons and 3) classify the full set of segmented polygons after the separating spectral characteristics of SVM are derived. In the prior South Atlantic LCC project, Monteverdi Toolbox open source software was used to train and classify the imagery. For this project, the same algorithm was adapted to use in ArcGIS Pro v. 2.3x and implemented for each Landsat 8 scene.

1.2.2 Rationale for Marsh Regional Classification Typology

Salt marshes are among the most productive ecosystems on earth, providing benefits to coastal communities by filtering pollutants from surface waters, buffering storm energies, and providing nursery and habitat for coastal wildlife and fisheries. These functions also provide economic benefits to coastal communities that provide services and supplies for recreational hunting and fishing. Salt marshes also provide highly effective sinks for atmospheric carbon dioxide, and efforts are emerging to use salt marsh preservation or restoration in carbon offset programs (Chmura 2013). Salt marshes are threatened by increasing rates of sea level rise. In many areas, the vegetation responsible for marsh soil accretion may not survive increased flooding periods, resulting in submergence of the marsh in its present location or inability to restore a marsh at its previous elevation.

Confronting the challenge of applying marsh inventories to conservation, a myriad set of geospatial data exist, with advantages and disadvantages for managers. The National Wetland Inventory (NWI) is a long-standing and reputable product based upon Cowardin's (1979) hierarchical classification scheme and available at fine spatial resolution (originally designed for mapping and distribution via 1:24,000 topographic quadrangles.) NWI is also widely available and digitally accessible in GIS formats as well as webmap services. However, NWI mapping lacks some fine thematic differentiation now recognized as vital to coastal marsh habitat management and planning. In particular, NWI was not developed with some avian and estuarine faunal habitats and lacks some floristic details in high and brackish marshes, such as predominantly *Juncus* marshes.

The classification scheme of the Sea Level Affecting Marshes Model (SLAMM) (Clough et al. 2012; Warren Pinnacle 2016) is a widely used derivative of NWI maps. One of few landscape to regional marsh response models that is spatially continuous (although often run in distributed areas), SLAMM utilizes an approximation and crosswalk of NWI classes to a scheme more closely resembling salt marsh zonation for habitat management. However, SLAMM inherits some of the aggregation of marsh classes, and even exacerbates this to some ecological applications (e.g., defining brackish vs. transitional marshes.) As may be expected, SLAMM also does not include a *Phragmites* class in its scheme. However, SLAMM does use mangroves and we included this class separate from salt marshes and coastal riparian or swamp forests.

Across the South Atlantic and Gulf Coast, a network of National Estuarine Research Reserves (NERRs), state-managed coastal reserves, and sporadic private reserves offer a range of marsh habitat maps. The NERRs, in particular, achieve a systematic classification owing to management from NOAA and participating reserve staff. Several of these NERRs and coastal reserves in the South Atlantic and Florida would ultimately provide important intensive study areas, and their wetland classification maps provided a helpful guide to field work for training classifications. However, the NERRs maps themselves typically only characterized salt marshes quite generally (no differentiation of high, low, or fringing marshes, typically no *Phragmites*, and only occasionally brackish or tidal fresh marshes in the few cases where aerial imagery was classified manually.) For instance, Fig. 4 shows the limited thematic detail of existing land cover for North Inlet-Winyah Bay, South Carolina, where our typology was first tested and compared. Nonetheless, the general classification was useful, and oftentimes included delimited extent of mud and salt flats. One notable exception in this area was the Georgia Marine Ecosystems Long-Term Ecological Research (L-TER) site that is more directly relevant to this project. This area was mapped using high spatial and hyperspectral imagery and provided a critical southern detailed map for our classification by Hladik and Alber (2012). Another exception was fine-resolution mapping products from the Skidaway Institute of Oceanography for Groves Creek, including corrected LiDAR and field RTK elevation points (Alexander and Hladik 2015.) The project examined the products and methods of a fine-scale vegetation map for Rookery Bay NERR by Barry et al. (2013). This map and report, however, revealed that oftentimes marshes were very finely-interdigitated with mangroves. Even at the fine-scale of aerial orthoimagery manual digitization, such areas were mapped as scrub mangroves.

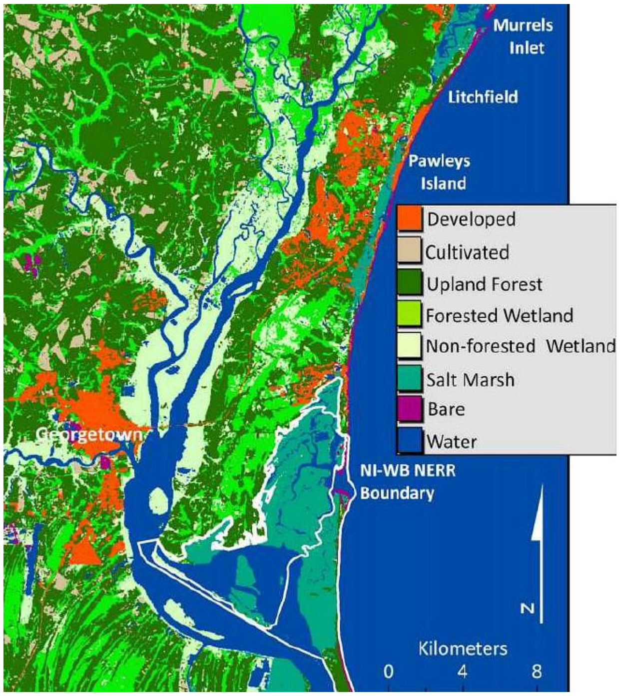

Figure 4 Sample NERR classification for North Inlet-Winyah Bay, SC. Note the limited thematic detail in salt marshes but the useful inclusion of bare flats, open water, and uplands as well as the parallel spatial resolution compatible with Landsat 8. (NERR 2016a)

Finer resolution habitat classifications in Fig. 4 are some improvement in detail for intertidal cover types and provided a standard for comparison across NERRs sites. However, the classification does not differentiate between marsh zones or species within the hydrogeomorphic gradients.

Few other satellite remote sensing classifications approached the necessary detail in thematic or spatial resolution. However, NOAA Coastal Change Analysis Program (C-CAP) and USGS National Land Cover Data (NLCD) classifications provided valuable non-marsh classifications, allowing the project to reliably mask uplands, most open water, forests, and urban developed areas. In

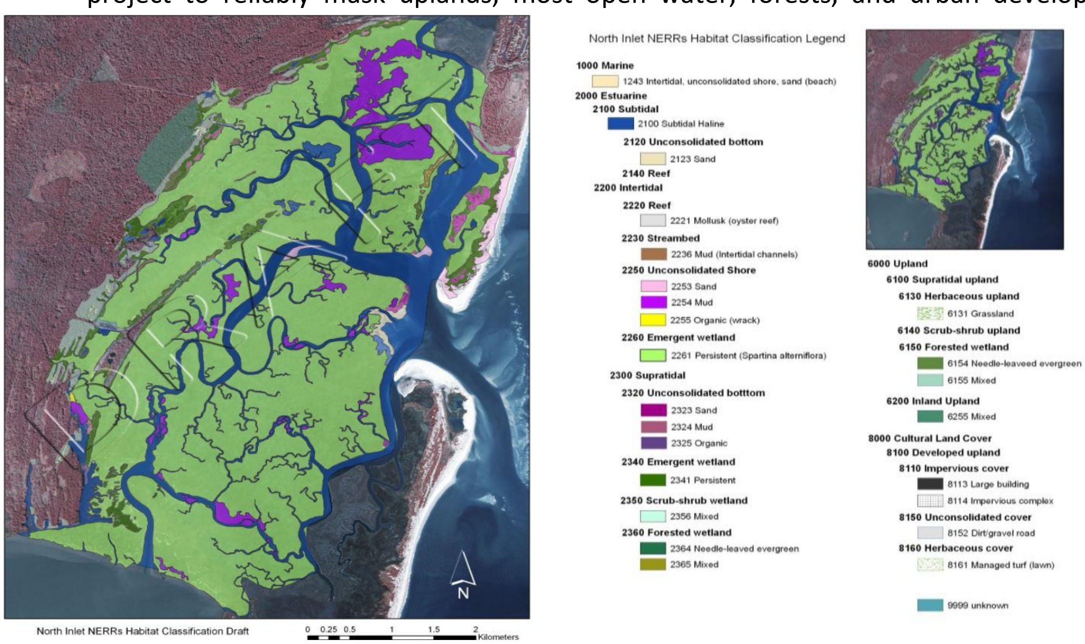

Figure 5 North Inlet-Winyah Bay NERR habitat classification (NERR 2016b.)

addition, C-CAP and NLCD are also based on prior Landsat sensors, sharing similar spatial resolution and carefully documented accuracy assessment.

Ecologic Considerations in Classification

The distribution of salt marsh communities is governed by the magnitude, frequency, and duration of tidal inundation (Donnelly and Bertness 2001). Salt marshes in southeastern North Carolina typically comprise three parts – high marsh, low marsh, and creekbank marsh. Creekbank marsh and low marsh are flooded twice a day. High marsh forms where trapped sediment has built up over time; while flooded periodically it may be dry for several days at a time. Different species of vegetation, each important to the provision of ecosystem services, inhabit the different zones. Low marsh and creekbank marsh are dominated by smooth cordgrass (*Spartina alterniflora*), an important producer in the estuarine food web. High marsh plants include spikegrass (*Distichlis spicata*), Black needlerush (*Juncus roemerianus*), salt meadow cordgrass (*Spartina patens*), sea ox-eye and glasswort (*Salicornia species*) (Hladik and Alber 2012). Vegetation at this level provides much of the pollutant filtering and storm surge protection services. In addition, salt marsh ecosystems have relatively high rates of carbon sequestration. Carbon burial rates within a salt marsh may be affected by variability in hydroperiod, salinity, and suspended sediment supply (McLeod et al. 2011). The alteration of the demarcations among species is an indicator of sea level and environmental changes within a salt marsh (Lee et al. 2012). Changes in distribution patterns can alter erosion and accretion rates in marshes, increasing their vulnerability to sea level rise. Therefore, conservation of marsh communities at each level is critical to the continued provision of ecosystem services.

Schematic Representation and Gradients

Schematic figures were developed to guide the classification scheme following field visits and early testing in ISAs. In Georgia (Fig. 6), salt marsh zonation reflects a wider tidal range thatn to the north in NC and SC, with a correspondingly wider extent of low marsh and high salinity salt pans. Brackish and lower tidal fresh zones also see an increase in some areas of three-sword and sawgrass. Low marsh is more widely stratified in recognizable short, and sometimes differentiated in medium vs. tall forms (the latter prominent in creekbank levees.) This pattern continues southward into Florida. However, a higher wave climate, welded (and developed) barrier islands, and narrower, relatively fresh to brackish coastal lagoon systems in Florida tend to reduce the available accommodation space for salt marshes. In sum, the classification scheme is considered to be a benefit for conservation management with the thematic detail as compared to traditional physiognomic classification and coarser satellite remote sensing schemes of the past. The scheme is complete yet mutually exclusive. The classes are readily identifiable in the field and aerial orthoimagery (particularly 4-band NIR composites) and the number and diversity of classes is not so detailed as to raise classification errors to a level that would undermine confidence and user accuracy (e.g., < 75-80%.)

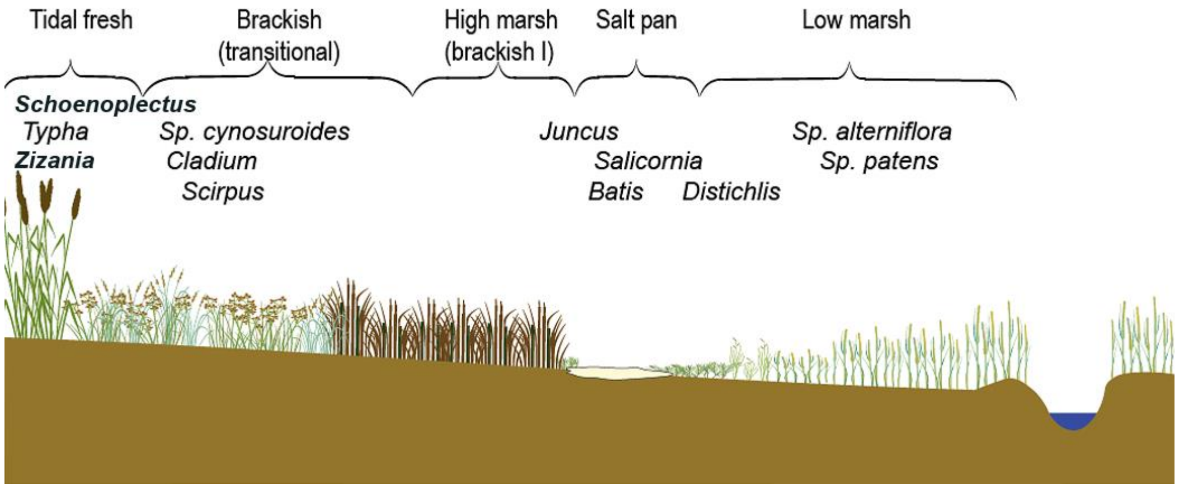

Figure 6 Schematic representation of salt marsh habitats in Georgia and NE Florida, north of mangroves and controlling for localized development.

For the Gulf of Mexico and Panhandle, the project consulted prior research and reports on the distribution of marsh species and adjoining communities. These include a profile graph from University of Florida extension, developed to portray marshes based on reports from Stout (1984), Mullahey et al. (n.d.), Mitsch (2000) and the Florida Marine Research Institute (op cit. 2002.) Figure 7 from the UFL Extension depicts a generalized cross-section that shows narrow fringe of *Spartina alterniflora*, a wider zone of high marsh *Juncus roemerianus* with varying height, and landward patchy zones of *Distichlis spp*., *Spartina patens*, and eventually supratidal brackish marsh or shrub (e.g., *Baccharus, Iva…*) and upload coastal forests.

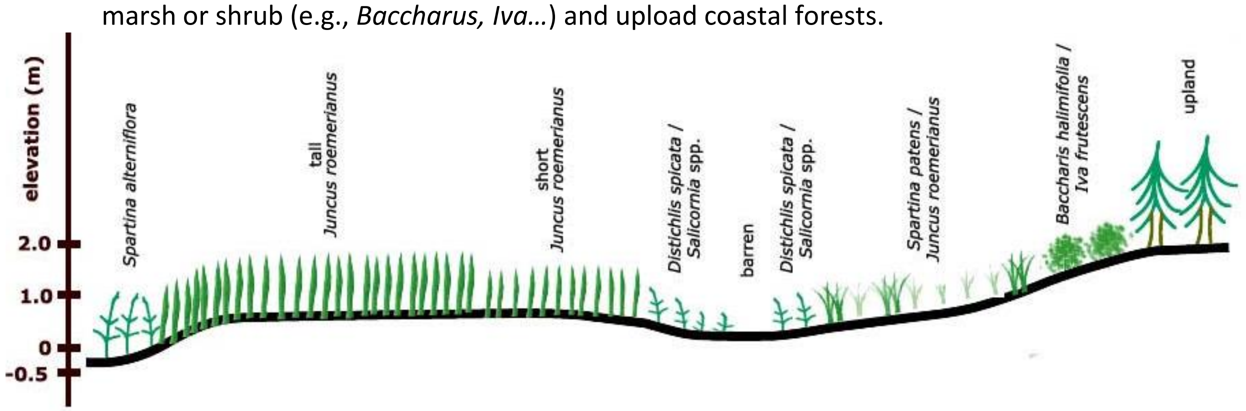

Figure 7 Composite cross-section of Gulf Coast salt marshes from the U. Florida Extension. *https://soils.ifas.ufl.edu/wetlandextension/types/gulfcoastmarsh.htm*

1.2.3 Hypsometry of Salt Marshes

High and low marsh (and shoreline) boundaries have been mapped using a variety of remote sensing and other techniques. While remote sensing for vegetation classification is the priority of this project, inundation time (using hydrography and digital elevation data) may also provide a means for evaluating the theoretical high and low marsh distribution. An extensive spatial analysis of marsh historical extent and is infeasible in this project, yet site history and available trends of marshes in intensive study areas are valuable information products for modeling and planning. Recent aerial orthophotography at fine-scale is collated in this project as a guide to training and subsequent accuracy assessment. For each ISA, 1m or finer orthoimagery is acquired and used for field work, digitizing training sites, and (outside of original training areas) a reference for identifying classification accuracy.

The vulnerability of high and low marshes to sea-level rise is also an objective dependent on the success of marsh mapping. Marshes can be evaluated in a spatially explicit analysis for relationships between their hypsometry and tidal inundation. Strahler (1952) developed the use of hypsometry (area-elevation measurement) for assessing the age and stages of drainage basins. Integrated area-elevation was interpreted to show morphometric characteristics of distinct shapes. Oertel (2001) have also applied similar morphometrics to hydro-hypsometry in estuaries, coastal lagoons and paleochannels. Hypsometry is also often utilized in glacier mass balance studies (deAngelis 2014), tectonic geomorphology (Cheng et al. 2003), and sometimes sea level rise (Smith et al. 2016.)

With the new marsh habitat maps produced, it is possible to measure hypsometric curves and assess marsh vulnerability to rising sea-level, focusing on the zones lowest on the tidal frame. Hence, we will systematically measure and plot the major marsh vegetation types (e.g., High Marsh *Juncus roemerianus* and Low marsh *Spartina alterniflora*) as the normalized, modal elevation of its intertidal area. The modal elevation (Em) can be normalized to the dimension of the tidal frame (En), and then expressed as -1 to 1 where 0=MSL and 1=MHW, or En = (Em – MSL)/(MHW-MSL), and this statistic can be estimated for high and low marshes and visualized with GIS. The actual range of the tide will also be factored into our analysis to account for situation on the tidal frame (at MHW) (a macrotidal estuary marsh is inherently more stable than a microtidal marsh, which must be situated in a narrow tidal frame), by scaling En by tidal amplitude (Ta).

1.3 Key Ancillary Data

Diverse data were necessary for this analysis. While abbreviated for reporting, the following list denotes key information sources and datasets. Landsat 8 OLI 2015-2018 from the USGS Earth Explorer

1. Georgia Marine Ecosystems L-TER Sapelo Island vegetation classification and high-resolution vegetation mapping of Georgia (Hladik and Alber 2012)
2. NOAA C-CAP Coastal Change Analysis Program Landsat Land Use/Land Cover data (2006, 2010)
3. USGS NLCD and MRLC Landsat Land Cover (2010, 2016)
4. Water masking from a water-land mask developed by Pekel et al. (2016) using Landsat.

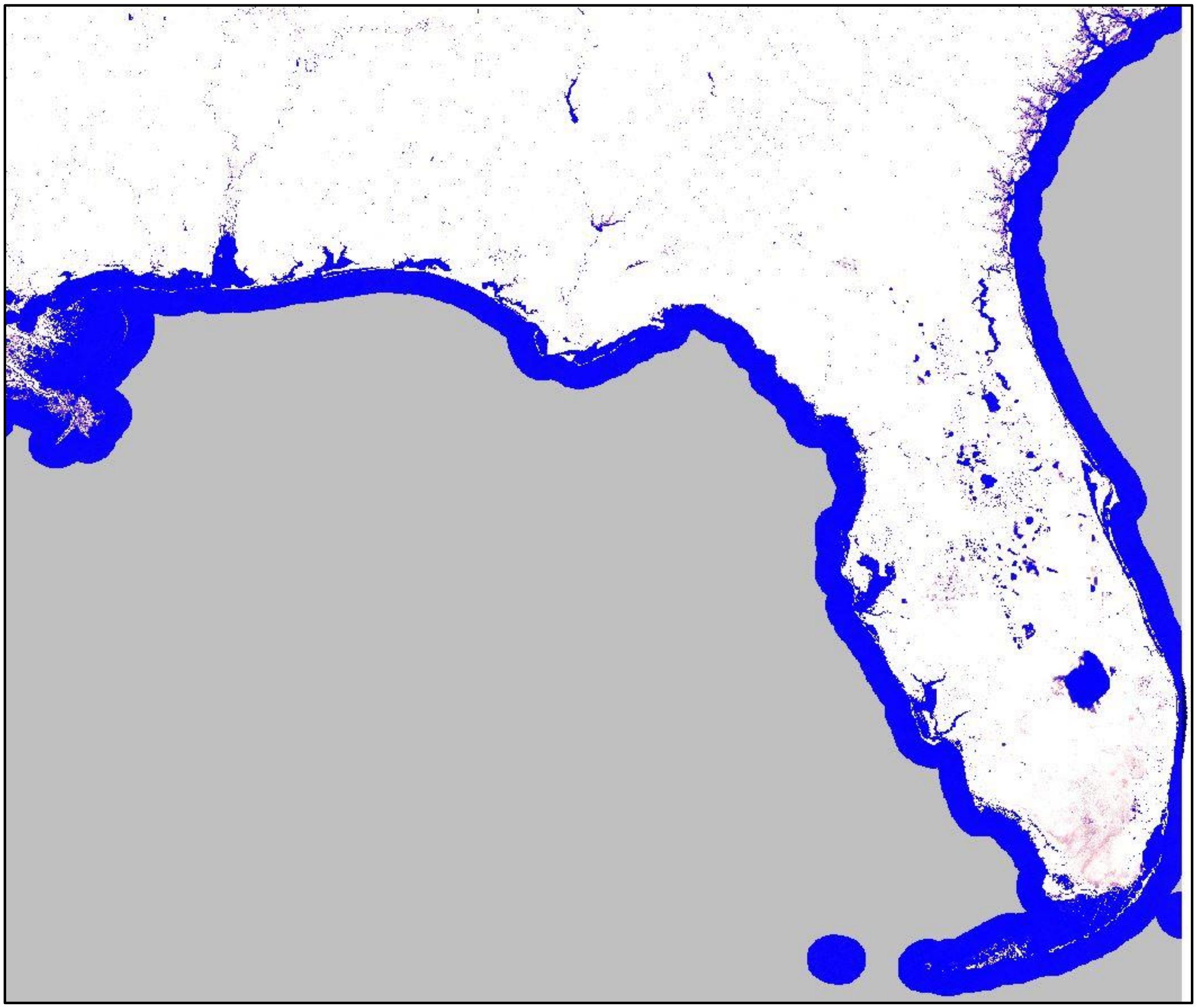

Figure 8 Water mask for eliminating subtidal and perennial water areas from Landsat imagery after Pekel et al. (2016).

1.4 Assumptions and Limitations

A number of assumptions were made owing to practical limitations on the project such as available field data, remote sensing imagery, and inherent dynamics of the coastal ecosystems under study.

Remote Sensing Data

Although care was taken in preprocessing steps, our radiometric calibration and within scene geometric accuracy inherit the accuracy and precision of the prior processing by USGS. No significant errors visually detected in the atmospheric correction or mosaicking, and no spurious edge matching or other spatial artifacts were noticed in the training or field work. The first series of scenes acquired (also in the first year of Landsat 8 operation, were impacted by poor radiometric calibration, which was subsequently corrected with new imagery and recalibration coefficients issued.) Handling of this problem delayed the project, yet fortuitously, we were able to acquire newer imagery in the following growing season which was superior and closer timing of dates between successive paths.

Another limitation inherent to Landsat imagery is the fine spatial resolution. Although it could be desirable to inventory and monitor salt marshes at much finer resolution, costs primarily prohibited this option. Pan-sharpening or multi-sensor fusion to modestly improve the spatial resolution was not determined to yield a significant improvement in the thematic detail or spatial accuracy of a marsh product and may actually have reduced the replicability and continuity of the study. As such, the products rely solely on Landsat 8 OLI for image classification, which provides for the greater long-term and continual observation. Our application of the normalized difference index (NDX) composites also provides for this continuity with historical and future sensors matching the Landsat spectral resolution.

1.4.2 Marsh Floristic and Physiognomic Constraints

The prior literature on wetland mapping does not especially highlight assumptions and limitations this study encountered, with its regional, biogeographic scale. Unlike wetland mapping studies of inland lakes and riverine marshes, this study exhibited a wide range of tidal inundation, with marshes segregating themselves in large part along hydrogeomorphic gradients, especially Atlantic versus Gulf Coast. To obtain a complete and mutually exclusive classification without diluting thematic detail for any given subregion, we broke down some of the low marshes into subclasses that may not have full expression in particular areas or may exist but only be resolved at much finer spatial resolution. Key limitations in these areas may be found in the following circumstances on the landscape:

- Narrow, fringing *Juncus* marshes along ridges or banks that are too fine scale or are shadowed or mixed with upload shrubs, trees, or in tight edges along hammocks or even mangroves in the southwest.
- Disturbed areas of *Juncus* marshes owing to burning or storm wrack deposition. Although efforts were made to include and generalize fine-scale patterns, some of these areas may introduce fine-scale patches within the classification that could recovery or transition to other states of marshes or landforms. A few areas of these were noted along the Gulf Coast near Cedar Key but could not be verified as having been burned, the date, nor the prior marsh type identified (in fact, they could have been forested.)
- Marsh species growth forms. Interdigitation of classes of short-, medium-, and tall- growth form *Spartina alterniflora*. While small patches can be discerned, our limited mapping units would be difficult to overlay on field transects or nested plots of marsh cover and density. Overall patterns at a generalized scale will be evident, but finer-scale patchiness and emphemeral conditions should be expected. In general, we found two classes to be moderately differentiated on the east coast (a standard short vs. medium-tall Spartina) but could not differentiate these in the Gulf/Panhandle. In addition, Juncus marshes on the Gulf/Panhandle would occasionally take a short vs. medium growth form. However, these could not be adequately captured in training site data to allow their separate classification. In addition, it is highly unlikely they could be spectrally distinguished with confidence.
- *Spartina spp.* can be found along narrow fringes of *Juncus* and creekbanks finer than the resolution of Landsat.
- Disturbed, unvegetated areas such as **dredge spoils** as well as **mudflats** and exposed or shallow **sand bars** were generally included in the classification, yet these dynamical features could be vegetated at times, rapidly colonized in subsequent seasons, or equally, eroded and disturbed. In addition, mudflats were potentially missed owing to variable tidal and water level conditions in available imagery. Cloud-free growing season conditions, favorable for salt marsh mapping, were prioritized.
- **Mangrove** forests, previously noted with increasing extent further south in Florida, were also mapped albeit secondarily in this project. Primarily along coastal areas of the Gulf Coast in proximity of St. Pete and north to the Big Bend, mangroves could also be found to a lesser

extent on the southern fringe of the NE Florida region, including St. Johns River and isolated areas of Cape Canaveral.

1.4.3 Temporal Considerations

Timing of image acquisition, training and field work was critical to obtaining valid representative signatures for marsh classes and developing the image classification. In addition, there was a year of accuracy assessment and solicited feedback from field experts across the region *in the year and a half after the image acquisition*. Hence, there is the possibility of state changes in some areas between the imagery and the observations. A key take-home is that dynamic landform areas, disturbance, and gradual processes alike may impart differences between the classified maps and any subsequent user application of them. Due caution should thus be taken in areas such as barrier island inlets and channels, areas known for ongoing and episodic marsh loss to erosion (as well as migration into higher areas with sea level rise), and areas prone to human disturbance (dredge spoil islands), fire scars, development, or invasive species.

2. APPROACH

2.1 Study Area

The initial study area of the project comprised focus areas across Florida's coastal landscape. These were subsequently expanded to cover the footprint of available Landsat imagery, dividing the study into thirds (northeast Florida, which also had requirements of an earlier deadline map product), and two Gulf coast sites, western Peninsular Florida from approximately Tampa north to Big Bend, and the Panhandle, from Big Bend west to Alabama (as far west insofar as imagery and project resources allowed.) Figure 9 depicts the study area with Landsat satellite scene path/row extents and location of potential key field sites.

Within the imagery scenes and stratified north-south along the region, Intensive Study Areas (ISAs) were selected. The latitudinal and hydrogeomorphic variability within the region was a driving factor in the selection of ISAs, so as to incorporate floristic, structural and physiognomic variation in marshes, yet also allow for a mutually exclusive and complete scheme of classes. For instances, low-form *Spartina spp*. marshes south coastal Georgia (and even South Carolina) are similar to those of northeast Florida, even if the absolute elevation ranges or physiognomy are relatively different owing to the different tidal regimes.

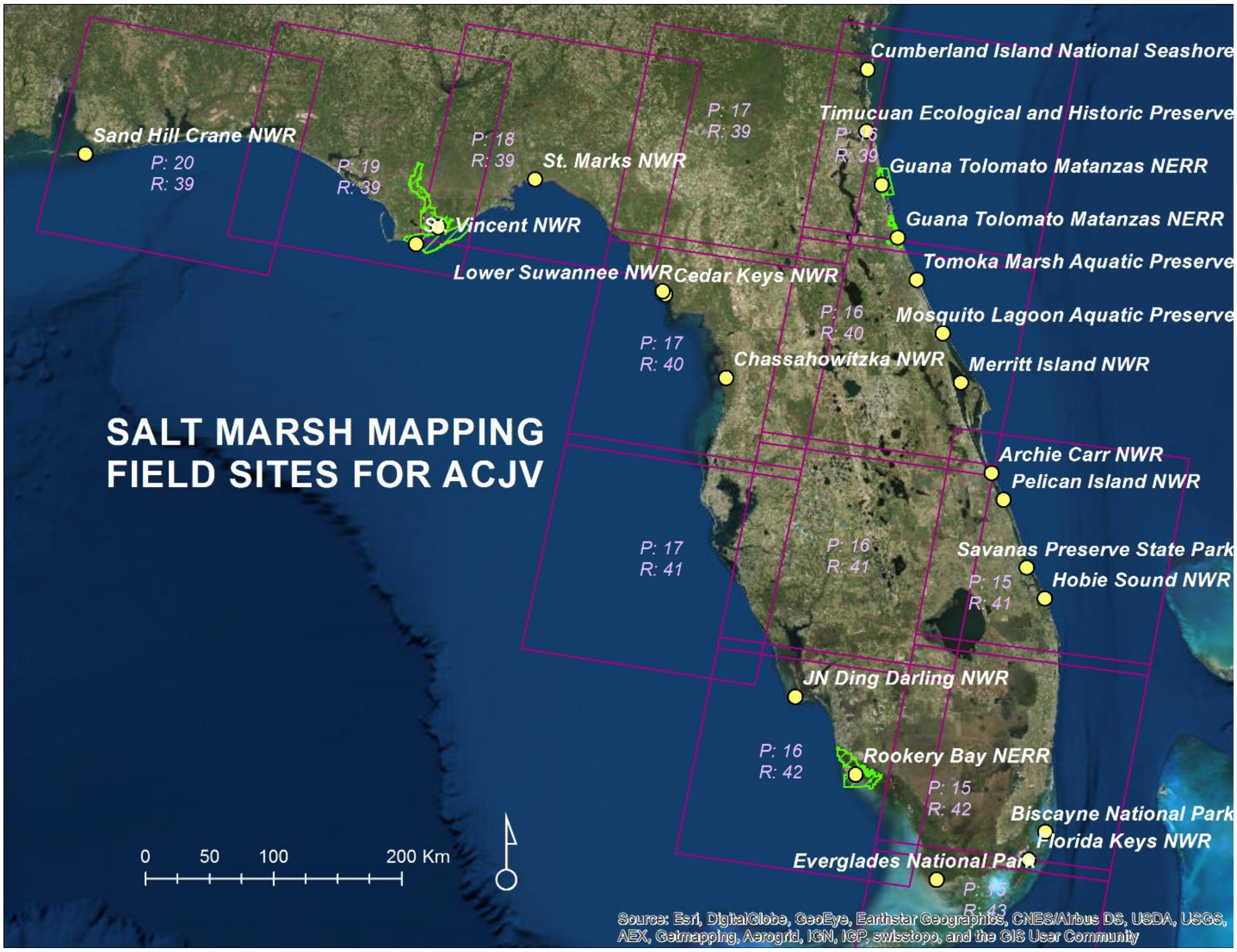

Figure 9 Study area initial extent showing Landsat WRS path-rows and targeted field sites. Early in the project owing to limited spatial marsh extent and satellite resolution, paths 15-16 rows 41-42 southward were eliminated by consensus agreement.

2.2 Image Search Criteria and Acquisition

Using the ***USGS Earth Explorer***, we searched for imagery between 2015 and 2018 along WRS-2 paths 15-20 and rows 39-42. Primary criteria included the available of level 1G (georeferenced) imagery with radiometric calibration and the lowest extent possible cloud cover. In addition, images were prioritized to coincide with seasonal growth to enhance vegetation discrimination and field identification. Lower cloud cover was evident in the greenup period late April through mid-June. Additional attention was given to tidal state at the time of image acquisition, as well as the tidal stage across the scenes. Results focused on images spanning as short a time interval as possible between scenes and were universally acquired at a time of day at or below mean tide level (evaluated by the last tidal epoch reported range from the nearest NOAA tide gage.)

After screening and visually assessing more than 70 images, we arrived at a subset of 16 candidate scenes covering the region. This group was further reduced to select scenes at mean tide or lower and with < 10% cloud cover. Further, we narrowed a candidate set of imagery collected by USGS in May 2017. Path 16 had two successive rows (39 and 40) that adjoined each other on the same date (May 9, 2017) and met our cloud and tidal requirements. Further, these scenes were within two weeks of an adjoining scene to the west (path 17 row 39) collected on May 16, 2017. Two weeks in the late spring to early summer was a realistic constraint to minimize spectral variation between scenes with late spring or early summer greenup, and these scenes were within one week. This provided an important efficiency to the project, since scenes could be mosaicked after atmospheric correction rather than processed independently and merged, post-classification, later. In that event, post-classification editing would be required, yet also likely with the result of imparting residual edge-matching accuracy issues. Moreover, only a small extent of the path 17 row 39 coverage was realistically available to tidal influence, such that most of this scene could be masked as upland, riparian and fresh marshes.

Table 1 Selected Landsat 8 OLI Imagery

Zone	Path	Row	Scene Date
Northeast FL-GA	16	39	9-May-2017
	16	40	9-May-2017
	17	39	16-May-2017
Gulf	17	40	17-Apr-2018
	17	41	17-Apr-2018
Panhandle	18	39	7-May-2017
	19	39	09-Apr-2016
	20	39	25-Aug-2017

Figure 9 and Table 1 summarize the Landsat 8 path-row scene extents and dates, respectively, of acquired images selected for classification. The range spans 9 April 2016 to 17 April 2018 Although this would present an appreciable spectral-phenological response range between images if all were mosaicked and classified, our use of path-specific mosaicking and classification, as well as a reliance on normalized indices on atmospherically corrected images, alleviates this issues to a great degree.

2.3 Field Site Visits

Field work incorporated a variety of methods of data collection to provide training "ground truth" for the image classification (*a priori*), validation reference for accuracy assessment, and process observations and measurements to better understand potential changes in marshes. Measurements included ground photography, visual species, sediment, and wrack deposit identification, GPS measures and photographs. A dedicated webapp "Geoform" was created to provide background basemap imagery and a template to collect marsh type, notes, and photographs at each site. Since training sites were not always "pure" in marsh coverage, notes and photographs were vital to capturing variability. No all of the hundreds of sites were ultimately used for training, as spectral homogeneity was critical to training a classifier. Nonetheless, all data were retained and stored, and sites that were not used for training purposes supported later accuracy assessment. All field site data are stored in the webmap data and summarized in the appendices (see Fig. 10.)

NE Florida Field Mapping GeoForm:

http://odu-gis.maps.arcgis.com/apps/GeoForm/index.html?appid=d7ad462484344909a679439aa454c4c3

Gulf and Panhandle Field Mapping Geoform:

https://odu-gis.maps.arcgis.com/apps/GeoForm/index.html?appid=68718be8c7c7495f81c555bf8a860282

Field data layer:

https://services.arcgis.com/2DbqGRRQS9wbBetw/arcgis/rest/services/TampaMarshPoints/FeatureServer

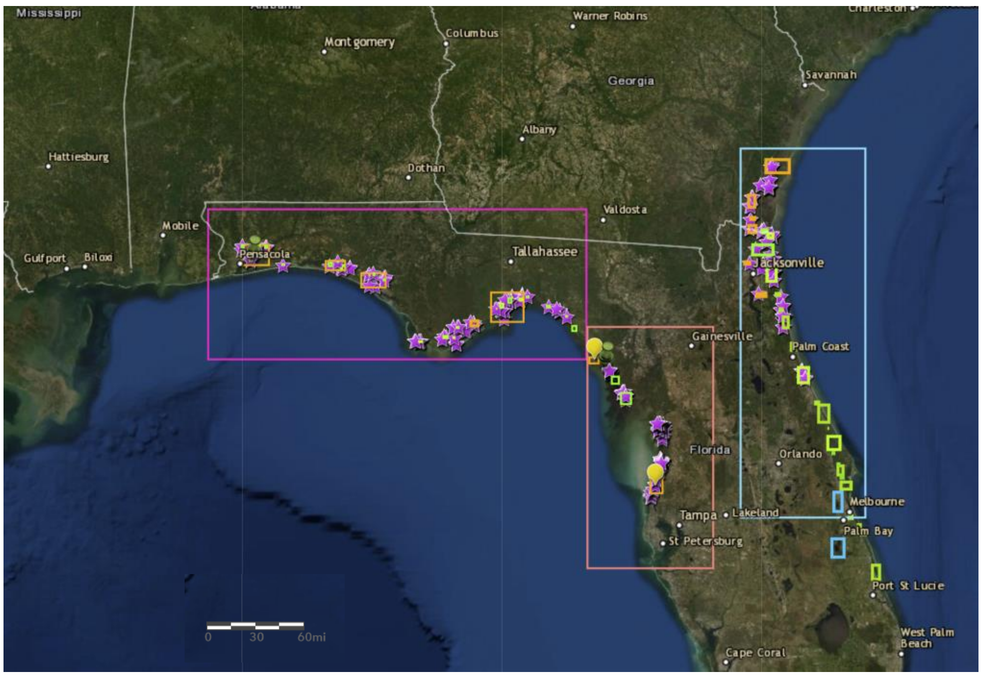

Figure 10 Study area map depicting the 3 zones for mapping, Northeast Florida (including Georgia), West Peninsula Gulf Coast, and the Panhandle. Polygons and points within each zone depict intensive study areas and targeted field sites locations for training data collection. A total of 4 trips were taken to collect data, supplementing the training data sites opportunistically.

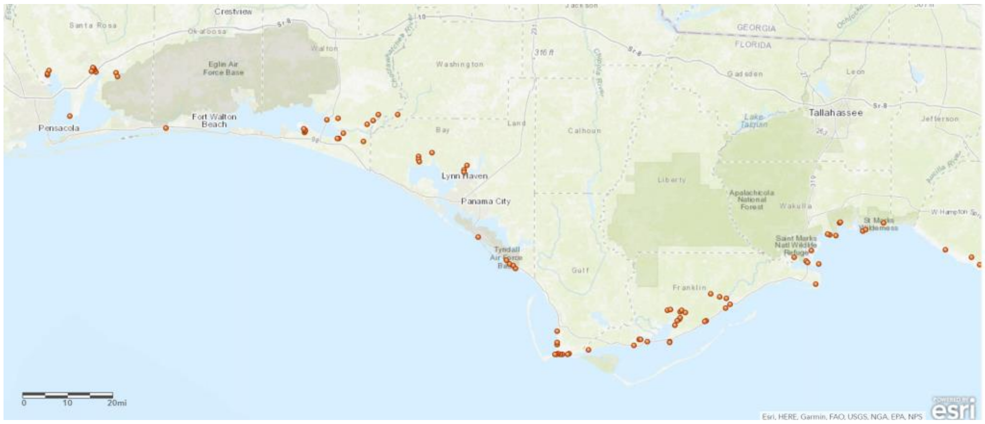

Figure 11 Pre-field trip targeted field sites in the Panhandle west of the Big Bend. Pre-identified sites with access and potential training sites were identified prior to each trip. These sites were loaded into a webmap with basemaps to guide the trip, using mobile phone or ipad with GPS.

2.4 Remote Sensing Methods

Remote sensing methods are summarized in Figure 16. Following image acquisition and conversion from GeoTIFF to Erdas Imagine file format, images were subset to the multispectral bands covering blue, green, red, near-infrared and two bands of middle-infrared. The thermal, pan, and blue band for haze and water were not utilized for their lack of aiding the spectral differentiation of marshes and the need to remove water areas. Adjoining scenes on the same path were mosaicked to seamless images. Early approaches sought to temporally normalize scenes and produce a seamless southeast mosaic. This was accomplished but the scene presented residual artifacts of brightness, owing to differences in the timing of rapid greenup and phenology (and possibly the subtle inter-scene tidal stages). Hence, images for NE Florida on the same path/date were first mosaicked and subsequently analyzed. Images for the west Gulf peninsula from Big Bend south to Tampa were similarly collected on the same date in successive images. However, images for the Panhandle crossed multiple Landsat paths, with intervening 16-day lag time and cloud cover impeding collection of imagery with same spectral and phenological conditions. Hence, the Panhandle scenes were all separately classified and later mosaicked after classification.

2.4.1. Mosaic and Masking

After mosaicking scenes, water masking was done to remove completely water-covered pixels from the imagery. A binary mask was created by setting a visual threshold in the near-IR band of the mosaic image and reclassifying this band to a mask raster. This mask was also supplemented with a global water mask also developed by Pekel et al. (2016). Then, the mask layer was overlaid with the mosaic multispectral images to remove water pixels and produce a new image. This output was visually inspected at full-zoom resolution with orthoimagery in geolinked viewers to ensure marsh areas would not accidentally be omitted. This process was implemented for each of the mosaick scenes, NC, SC, and GA.

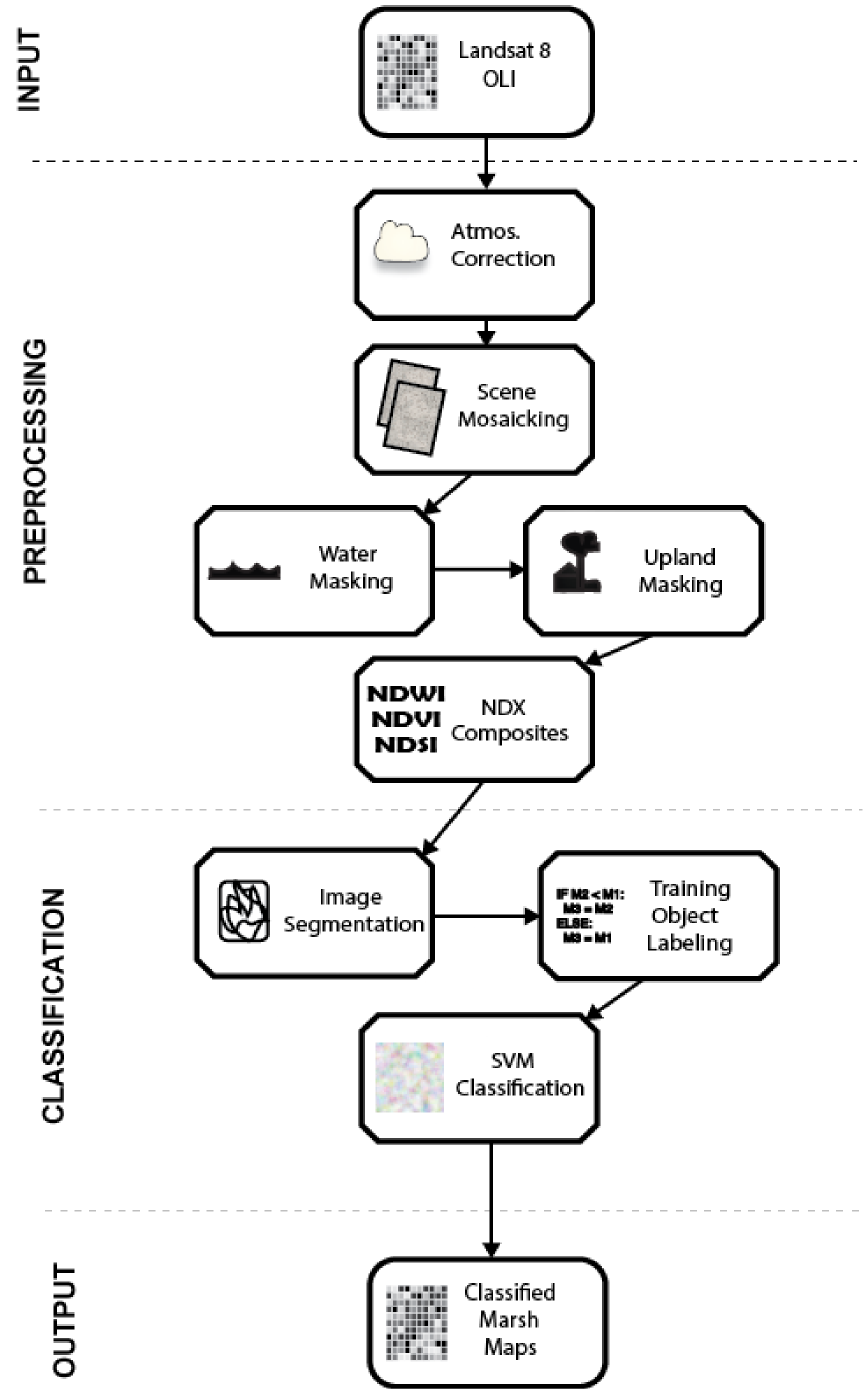

Figure 9. Overview of remote sensing methodology.

To further reduce potential classification confusion, upland land cover types that could not be potential salt marshes were also systematically masked. This process involved using a 30m NED digital elevation model (NED) set to mask areas above 2m above mean high water (MHW) for each mosaic scene. In addition, we further removed pixels classified as upland in the NOAA C-CAP land cover classification product of 2010. Overlay of these two masks for a combined mask resulted in removing all upland land cover pixels. In addition, vector editing was done after visual comparison against orthoimagery in geolinked viewers. There exists potential to have inherited some classification errors from C-CAP exists, such as confusion or mixed pixels in freshwater wetlands, scrub-shrub areas near the MHW shoreline, and shadowed or disturbed areas. In order to minimize omission and commission errors in the marsh classification, the classification scheme adopted a small number of wetland and related low elevation classes with the aim of classifying isolated areas that were misclassified by C-CAP.

2.4.2 Image Compositing and Normalized Difference Indices (NDX)

After the above procedures, a multi-band image of potential salt marshes was available for analysis. Rather than classify the multispectral image set, the NDX composite bands (Eqn. 1) were computed to allow for better visual interpretation across the region and to provide for possible temporal, sub-pixel or mixture analysis as described in the background and work by Rogers and Kearney (2004.) These indices were also recently effective at identifying marsh change and response to sea level rise (Ramsey and Rangoonwala 2017.)

$$\text{Normalized Difference Water Index } NDWI = \frac{Red - MIR}{Red + MIR} \qquad \textit{Eqn. 1}$$

$$\text{Normalized Difference Vegetation Index } NDVI = \frac{NIR - Red}{NIR + Red}$$

$$\text{Normalized Difference Soil Index } NDSI = \frac{MIR - NIR}{NIR + NIR}$$

NDWI is known to strongly relate to plant water content and sometimes as a surrogate for water stress (Gao 1996.) NDVI characterizes vegetation greenness and for plants with high productivity and leaf area provides an index of vigor. NDSI captures the normalized difference relationship between middle and near infrared and capability to differentiate bare soils and sediments from other cover types. A conceptual visualization of the segregation of hypothetical intertidal cover and marsh classes along these spectral indices is shown in Fig. 13., depicting the NDX indices as composite RGB bands of soil, greenness, and water content, respectively, and Figures 14-16.

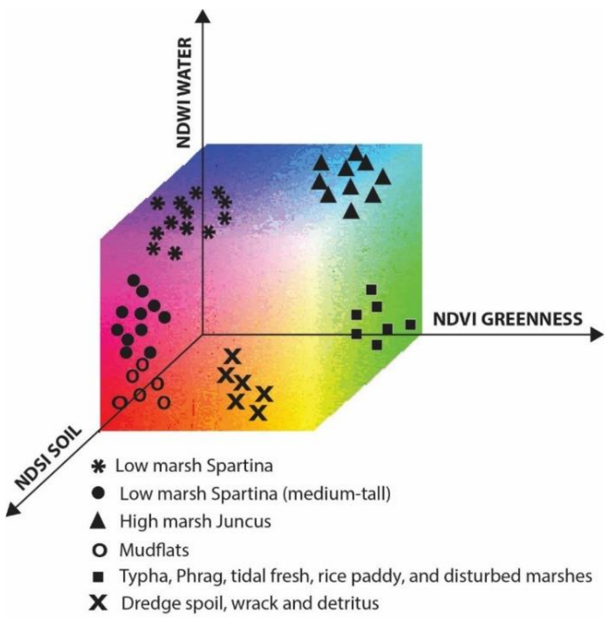

Figure 10 Conceptual model of marsh and related intertidal cover types segregating in NDX composite spectral space and RGB color cube (NDSI, NDVI, and NDWI as RGB.)

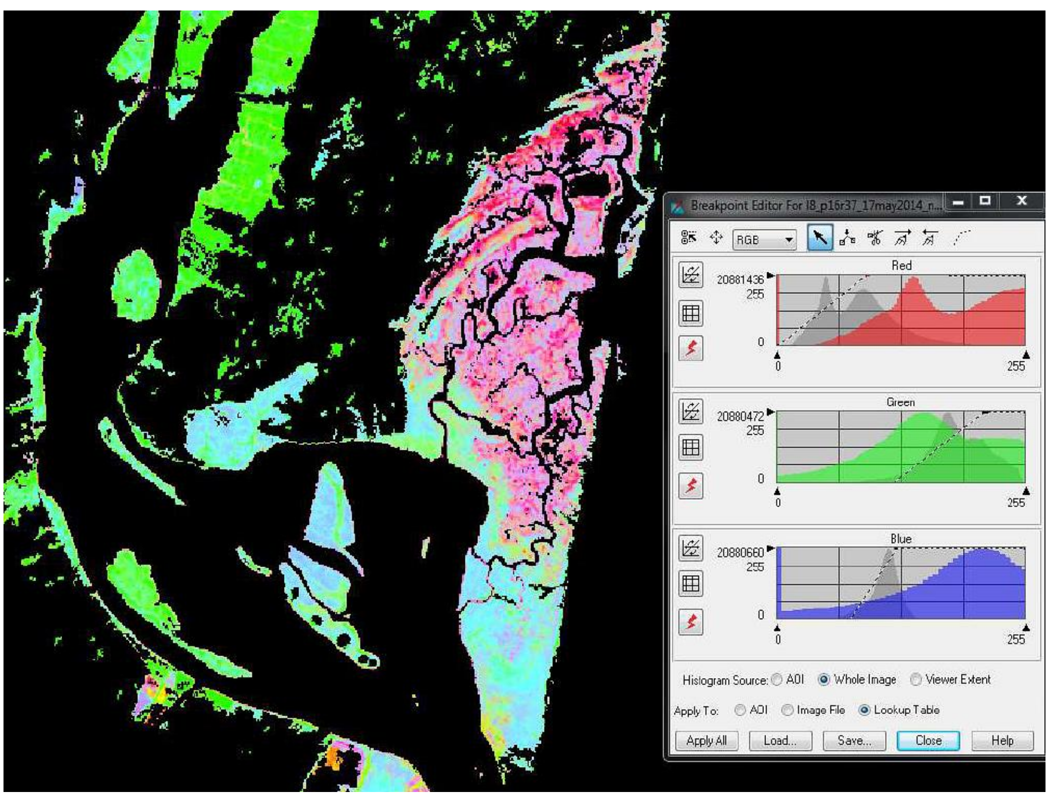

Figure 11 NDX composite for North Inlet-Winyah Bay, SC, where the NDX method was previously implemented for SALCC (NDX bands NDWI, NDVI, and NDSI as RGB, respectively) with histograms illustrating custom break point stretches to highlight NDX contrast.

Figure 15 Comparison of Landsat 8 OLI (a) false-color RGB Middle-IR composite (bands 6,5,4 RGB) and (b) NDX composite (NDWI, NDVI, NDSI as RGB). Both masked composites exclude upland and water, with the background image providing context from a true-color orthoimage basemap. This example from North Inlet, Winyah Bay NERR, South Carolina shows typical spectral variation reflecting marsh zonation also found in northeast Florida estuaries and lagoons.

2.4.3 Field Work and Training in Intensive Study Areas

The approach used Intensive Study Areas (ISAs) as a focus of training site selection and field visitation for accuracy assessment of separate sample areas later in the study. ISAs were selected based on for several factors, including known existence of a variety of marshes, public accessibility, availability of a local site expertise, and sufficient area so as to offer multiple training sites. The purpose of training sites was to identify representative examples of the patches of marsh classes in the classification process. Through existing contacts and field experience, we selected a range of sites most typically at wildlife refuges, preserves, wildlife management or hunter reserves with public access, and a set of National Estuarine Research Reserves and other publicly accessible locations.

After selecting candidate ISAs, we contacted staff to obtain permission and local knowledge and assistance. Oftentimes, these contacts provided an expert crowdsource of information on marshes, noting historical dynamics and disturbances, or relevant conservation management activities.

For northeast Florida, 153 field sites were visited in March 2018, descriptively characterized, and photographed for creation of a composite training sites and later accuracy assessment dataset. The dataset was stored as a GIS shapefile and included with training site and webmap publication. Hyperlinks to field photographs (also published online) and descriptive text about marsh species, cover, and other site information are included. Training sites were created in ArcGIS Pro using a supervised classification wizard in order to develop training signatures for classes. Several candidate sites for each class were identified, then iteratively edited and winnowed to a smaller set to produce the most homogeneous possible training signatures. The training sites were based on image segments, polygon features of homogeneous spectral values, described in the classification phase.

Field photographs and notes were made for each site, including a classification code and saving these annotations and photos to an online GeoForm using Esri ArcGIS Online. Several candidate sites for each class were identified, then iteratively edited and winnowed to a smaller set to produce the most pure spectral signatures. The training sites were based on image segments, polygon features of homogeneous spectral values, described in the classification phase. The same process was used for Gulf Coast sites and the Panhandle, requiring two trips in March and June 2019 to cover St. Pete north to the Big Bend and Big Best west to Alabama, respectively, with 332 sites visited. In total 485 field sites were visited. Detailed notes and photographs including annotations for typical examples of each class are provided in the appendices. All sites are also provided digitally in feature layers on the webmaps and available for download.

2.5 Image Classification

Next, the core of the image classification was run using ***ArcGIS Pro 2.3x Image Analyst*** which includes the image segmentation and SVM classifier. The software used vector segmentation to create homogeneous polygons of a minimum of 9 pixels. Most scenes were run with an 11-pixel minimum to develop a spatial representation that matched the visual interpretation of the NDX composites. This parameter become a functional minimum mapping unit as well as a factor in the number of polygons that the classifier would analyze and ultimate product would store. Training sites were selected within ISAs by a visual interpreter using NIR orthoimagery, field GPS and photographs, and annotated maps provided by volunteer experts from the NERRs or research stations in the ISAs. Thirty to forty training polygons were sought per class, per ISA and mosaic scene. In a few instances, ISAs were deemed not to have adequate coverage of particular classes, so training sites were visited outside of these locations. This was a particular issue for the great geographic extent of North Carolina, where sites were sought in the Pamlico and Neuse Estuary, Albemarle and Currituck Sounds.

2.5.1 OBIA Machine Learning Classification

Features of classification include the following for spectral measures (mean, variance, skewness, and kurtosis of each spectral index), and patch shape measurements (elongation, physical area, and Flusser moments of shape geometry (Flusser and Suk 1993.)

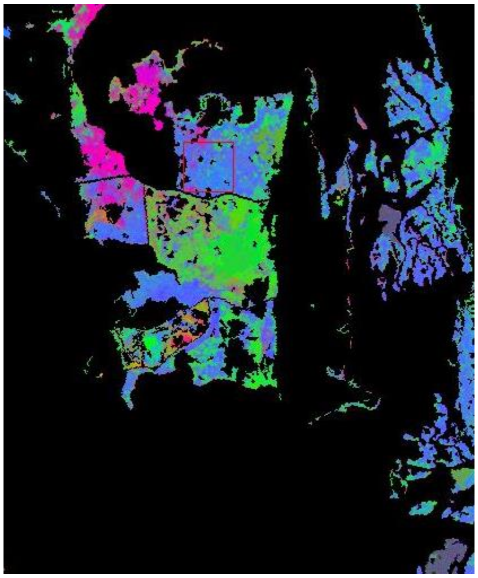

Figure 12 Screenshot of the SVM training site feature objects. Before classification, OBIA techniques first segment images into polygons of homogeneous spectral-spatial characteristics. These polygons are classified rather than per-pixel classification. The result yields maps that feature reduced speckle or "salt and pepper" patterns that would requiring post-classification smoothing, and/or suffer from excessive mixed pixels.

2.5.2 Segmentation, Training and Classification

Image segmentation, the statistical process of creating homogenous and representative vector objects, was applied to create image segments for later classification. Creating these objects moves the subsequent analyses into object-based spectral-statistical domains. A region-growing algorithm seeded by pixels at training sites in ISAs was used to initialize wider neighborhood segmentation. The resulting segments would fully cover the extent of all marshes and related classes in the input image, dividing them into vector objects. Subsequently, mean shift clustering would use the spectral statistics and spatial characteristics to classify each object. This algorithm was implemented in the ***ArcGIS Pro Imagery Analysis*** toolset.

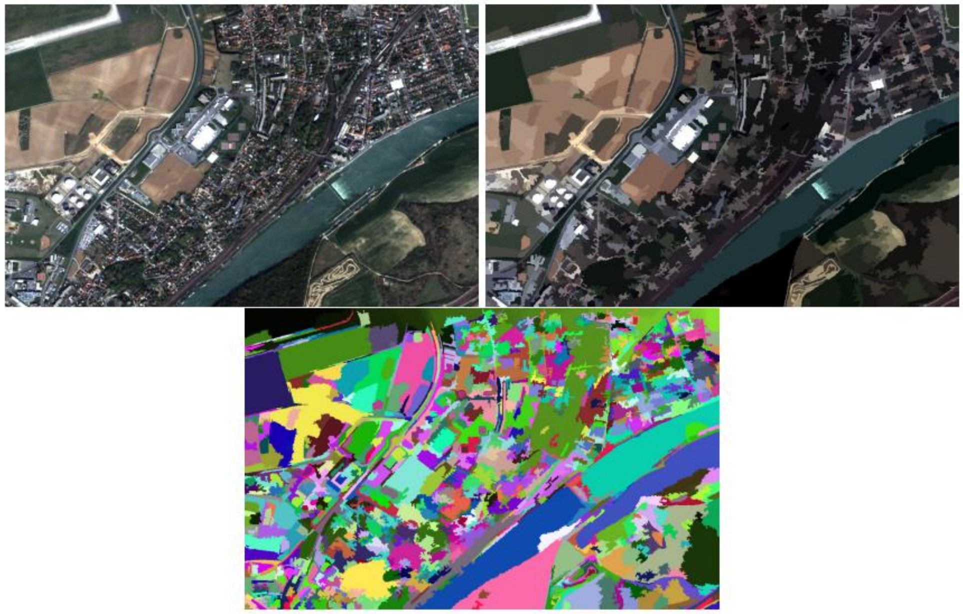

Figure 13 Original image (top left) and image filtered and mean shift clustered to objects (top right) and labeled for classification (bottom) (source: Orfeo Toolbox Software Guide 6.4.0, December 2017.)

In general, 30-40 training objects were created per class for each satellite scene. Spectral features from NDX values were retained, while some spatial variables were removed or retained, depending on training site classification accuracy, in an iterative fashion. Table 2. Summarizes the classes used for the training sites. Image interpretation training keys for identifying sites included color/tone, shape, size, pattern, and texture.

Training site classification accuracy aimed for near 100% accuracy, with adjustments made to sites if any class fell below 95%. For each scene mosaic, after images were segmented and training sites and final classification criteria chosen, we applied SVM classification to cluster the spectral-spatial objects and create classified maps. These maps were visually inspected, and in a few instances, spatial patterns of the marsh classification suggested returning to the training step to adjust classes, typically removing uncertain sites and emphasizing the purity of training sites. Then, the SVM classification was reapplied. Following classification, resulting classified objects were again

Table 2 Training classification scheme. (Note: These classes are comparable and interoperable with the SALCC marsh classification conducted previously for North and South Carolina and Georgia. After adopting and implementing this scheme, the Class code or Value, is subsequently used in any vector-raster conversions as well as the final products, i.e., values 1-8 correspond to the thematic classes presented.)

Class code	Class Name	Representative species cover
0	Unclassified or NODATA	N/A reserved for open water and upland mask and non-marsh cover types
1	Low Marsh- Spartina type	Dominated by short growth form cordgrass *Spartina alterniflora;*
2	Low Marsh- Spartina medium-tall growth form	Predominant medium-tall growth form *Spartina alterniflora*, often creekbank levees or fringing mudbanks of Phragmites patches. Isolated *S. patens* may also be found in fringes in tall growth form.
3	High Marsh- Juncus	Black needle rush *Juncus roemarianus* occurring in expansive patches (e.g., NC sounds, SC lagoons, or fringes in the upper intertidal to supratidal elevation range)
4	Salt Pan and Intertidal Flats	Salt flats or pannes with sparse or isolated short-growth *Spartina alterniflora* (<5% cover), *Salicornia virginica*, saltwort *Batis maritima* or saltgrass (*Distichlis spicata*) <10% cover
5	Mudflats and Dredge Spoil	Where not obscured by tide or water level, mudflats and dredge spoils that were not masked were classified.
6	Tidal Fresh and Brackish	Oligohaline transitional dominant marshes (salt marsh species < 5%) with predomintant common reed *Phragmites australis*, cattails (*Typha domiguensis*), sawgrass (Cladium jamaicense), bulrush (*Scirpus robustus*). Big cordgrass *Spartina cynosuroides*, sawgrass *Cladium mariscoides*, *Salicornia*, and *S. patens* (short growth form), *Schoenoplectus americanus*,
7	Mangroves	Mangrove forest and scrub features were mapped where found.
8	Swamp and Riparian Coastal Forests	Palustrine wetland forests along riverine/riparian corridors or immediately adjacent high marsh and brackish tidal marshes were included in the classification.

merged across the original Landsat path/rows to create a seamless vector map of marshes. A raster version was also created for this for ease of use to disseminate and publish online as a tiled webmap service (WMS) layer. Both raster and vector data were coded and named with corresponding fields.

2.5.3 Accuracy Assessment

The overall approach to accuracy assessment required a methodology that was robust yet efficient, spatial extensive so as not to introduce bias or mask error within the region, and statistically parsimonious. We adopted a stratified random sampling approach focusing on a combination of aerial and ancillary data sources and field sites (n=479). In addition, prior to sampling we shared preliminary maps for NE Florida with ACJV and interested parties on a conference webinar, resulting in approximately 30 polygon corrections. Later, we repeated this step including a scan of all maps at fine-scale for gross errors. In addition, Dr. Chirstine Hladik from Georgia Southern University provided qualitative comments that led to some editing. Hladik's prior work at the Georgia Marine Ecosystems L-TER and Sapelo Island, Georgia, using high resolution and hyperspectral imagery provided helpful insight to address isolated errors as well as affirming the general pattern of low-, high-, and brackish tidal marsh progression from ocean to river settings. This step resulted in our decision to manually correct and remove isolated mixed pixel effects primarily inland. Approximately 100 small polygons were corrected in this manner, spanning the full extent of the region and typically noting gaps where marshes were now established (but had been masked as water, or vice-versa). In a few instances, we did correct some confusion in the classification among *Spartina* classes, which we addressed by generalizing.

After the sampling generated accuracy assessment points, we overlaid these sites on Landsat and orthoimagery for assigning the reference class value by image interpretation. The classified category was held blind to the interpreter, so as to not bias the assignment. Where confidence in the imagery was low, additional field data was sought for sites, other imagery, and ground views (including Google Street View for areas with access and viewshed of marshes.) It should also be emphasized that there are inherent limitations on the sampling of rare or sparse classes, notably mudflats (which were masked out by water for the most part), salt pans and flats (which are rare and very fine scale in spatial extent), and mangroves (also rare excepting the far central to southwest.) Despite these very low prevalence and extents, they were included a priori in case of detecting any gross errors in the classification. They are retained for the purpose of completeness in the resulting error matrix.

After all assessment sites were labeled, we derived an error matrix, individual class and overall accuracy percentages.

3 RESULTS

3.1 Map Results and Comparison

This section summarizes classification results in map and comparisons between alternative ancillary sources. The section following this reviews the accuracy assessment tabular and statistical results, followed by an integrated discussion. Appendices showcase the individual map products by path mosaic. Rather than present and discuss individual geographic products, this section summarizes the overall results and explains them versus traditional pixel-based classification or ultra-fine resolution classifications that can be accomplished on more limited geographic areas of study.

Figure 18 depicts a comparison of pixel-based classification (a) NDX composite bands (b) and resulting classification of spatial objects. Although some patterns are apparent as compared to the NDX pattern, such as high marsh along the marsh interfluve and upland-marsh boundary, it is much more difficult to discern zonal patterns with pixel-based classification. Resulting classification 18(b) depicts generalized, zonal patterns are evident in the low and high marsh zones, leading upstream to tidal brackish marshes and riparian swamp forests. Timucuan Preserve is an example where object-based classification can overcome the noise inherent at a pixel scale, where individual cells contain mixtures of marsh condition, cover types, that propagate spectrally into the classification, adding noisy, speckled maps. While this can be reduced by filtering imagery or generalization of the post-classification method, the example OBIA product provides a superior user-oriented map (not unlike the convenience of NWI vector data.)

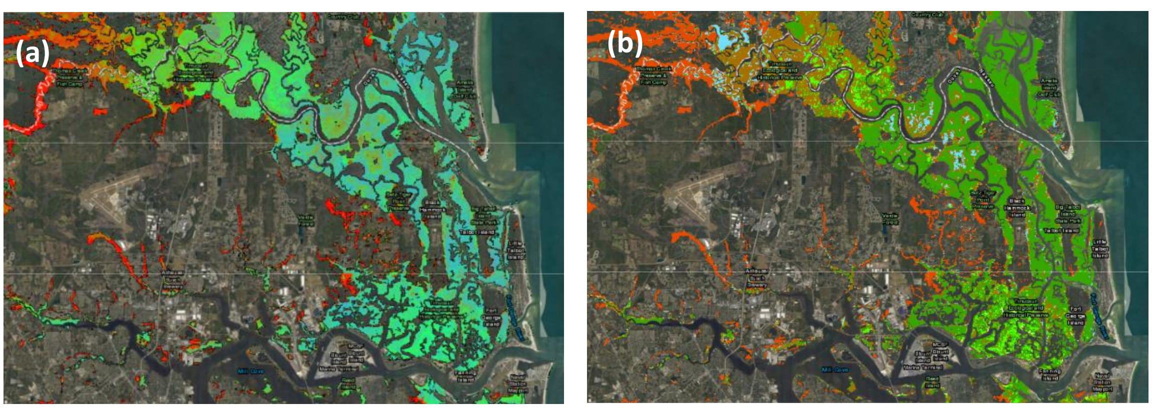

Figure 14 Comparison of pixel-based classification (a) with the NDX composite image (NDWI, NDVI, NDSI as RGB) and (b) object-based classification product.

To compare and contrast alternative spatial resolution and thematic detail, Figure 24 overlays the Georgia Coastal Ecosystems LTER vegetation classification onto the background of the OBIA classification of this project. Sapelo Island can be seen to have very fine spatial patterns in the map produced by ultra high-resolution aerial imagery and satellite data. Nonetheless, the classification thematic detail is quite similar with respect to the more extensive marsh zone classes. The comparison also underscores the fact that even ultra-fine resolution imagery may encounter the same difficulties of pixel-based classification. Further, such spatial resolution, while certainly ideal for scientific and site-scale analysis and management, remains largely infeasible for regional mapping. At the north end of Sapelo, along the edge of the images, it is evident that the classifications share strong agreement on the extent of *Spartina alterniflora* salt marshes and that the differentiation of short vs.

medium-tall growth form zones in the Landsat data is corroborated by the patterns mapped at finer scale.

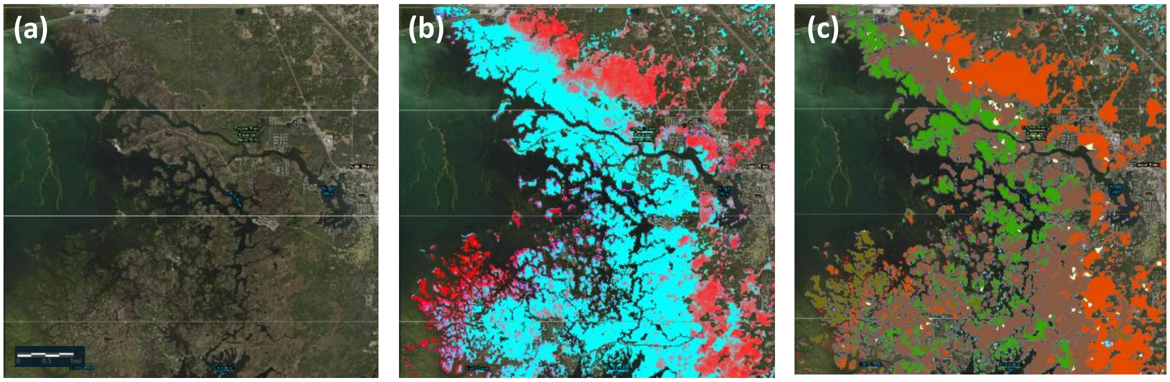

Figure 15 Comparison of OBIA classification versus ultra-fine scale image classification of Crystal River Preserve State Park. A productive and biodiverse landscape, Crystal River Preserve exhibits mosaic of salt marshes, mangroves, and upland pinewood and scrub vegetation shown here in aerial imagery (a), NDX composite (b), and classified marshes.

3.2 Accuracy Assessment Results

The stratified random sampling (n=479) results were analyzed with ArcGIS Accuracy Assessment tools to generate an error matrix (Table 3) and associated accuracy statistics. Table 2 provides this error matrix, cross-tabulating the classified OBIA class versus the reference "true" validation. Cells in the diagonal represent agreement between the classification and reference. Importantly, it must be noted that the unit of observation are spatial patches, not pixels. The stratified random sample resulted in stronger sampling of the more spatial extensive and numerous patches of marshes, while rare classes were far lower in the sample representation. Mudflats, salt pans, and other fresh-emergent classes, for instance, were nearly purposively sampled since they exist in limited extent given the approach. It should be noted that water masking may have eliminated mudflats that are extensive below the meant tide level. Salt pans also are exceedingly rare from northern Georgia northward. These classes may suffer residual bias given their limited extent and low sampling, so precaution is warranted in their management using these maps. This is reflected in the lower user accuracy of Table 3.

Producer's accuracy summarizes from the point of view of the map maker (producer) and how real features on the map appear in the classification (i.e., probability that a cover type on the ground is classified as such in the map.) *User's accuracy*, on the other hand, takes the viewpoint of the user of the map. Accuracy here is a measure of reliability of the map, how often the class on the map is actually that class on the ground. [For a cogent summary of Producer and User accuracy, see http://gsp.humboldt.edu/olm_2016/Courses/GSP_216_Online/lesson6-2/metrics.html]

Further interpretation of the error matrix yields valuable qualitative assessment of the two types of error present. Omission error tallies the reference sites that were left out (or omitted) from the correct class. Conversely, commission errors are instances when the reference sites are misclassified as other sites. Rows in the error matrix reveal counts of sites misclassified. From the perspective of the user, this is important to note the reliability of a class. Individual class accuracies are tabulated, reflecting combined user and producer accuracy. Further, these are integrated into a single total or overall accuracy percentage.

Results of these accuracy metrics reveal and an overall high accuracy of the classification, with a high reliability for marsh classes. Lower reliability is evident for the unvegetated or sparser intertidal and supratidal brackish/tidal fresh water classes, which are rare and of less priority in the overall project. There is also limitation reflected in the gradational aspects of *Spartina alterniflora* physiognomic classes. Some confusion is evident in the low vs. medium-tall growth forms of this class, yielding user accuracies that are would be improved if these classes were aggregated. However, managers using the data may still find the marginal thematic class differences useful. Estimates were calculated on this possible improvement, wherein if one, generalized low marsh Spartina class were to be created, the accuracy could be improved to mid-90%. Since sampling was not sub-stratified within each region owing to accessibility and cost constraints, caution is worth noting there could be local scale idiosyncrasies and reliability of the presented classes could have some increased error where the two classes interdigitate extensively in the outer estuarine or back barrier and tidal inlet areas.

Table 3 Error matrix

	REFERENCE								
CLASSIFIED	**Low Marsh (Sp. alterniflora)**	**Low marsh (Sp. Med-tall)**	**High Marsh (Juncus)**	**Salt Pan**	**Mudflats and Dredge Spoil**	**Tidal Fresh Brackish**	**Mangrove**	**Swamp and Riparian Forest**	**Users Accuracy**
Low Marsh (Sp. alterniflora)	6	1	2	0	0	0	0	0	0.667
Low marsh (Sp. Med-tall)	4	36	6	2	0	4	2	3	0.632
High Marsh (Juncus)	1	1	68	1	0	2	0	3	0.895
Salt Pan	0	0	0	2	0	3	0	1	0.333
Mudflats and Dredge Spoil	0	0	2	1	5	1	0	0	0.556
Tidal Fresh Brackish	1	1	1	0	2	31	0	1	0.837
Mangrove	0	0	0	0	0	0	10	0	1
Swamp and Riparian Forest	2	3	15	1	0	13	0	225	0.818
Producer Accuracy	0.428	0.857	0.723	0.285	0.714	0.574	0.833	0.965	**Overall 79.99%**

The overall accuracy of the classification is near 80%, and satisfactory and par with many classification products of Landsat image classification. If the low marsh *Spartina* classes (short and medium-tall growth forms) are merged, then the overall classification accuracy rises to approximately 90%. Noteworthy in this project is that most land cover classifications achieve such accuracy, but not with the thematic specificity of salt marshes in this project. The Kappa statistic *K-hat* = 0.701 also corroborates the overall percentage accuracy. Conventional practice in remote sensing with Kappa in this range could be deemed "substantial agreement," yet deeper interpretation or affirmation of this statistic is not advised. The Kappa coefficient is prone to dependence on the prevalence of observations. With our project's inclusion of rare or sparse classes (e.g., mangroves and mudflats) as well as limited extent and gradational variation among low marsh *Spartina alterniflora* growth forms, we recommend against inferences using Kappa statistics.

The above covers the overall or summative accuracy of the marsh classification. The next section discusses some implications for map users and future mapping and classification.

3.3 Mapping Limitations

This section discusses the results and issues concerning the methodology and future applications of the resulting maps as well as monitoring or change detection. The discussion is organized around three key topics: 1) Utility of Landsat 8 and image acquisition, preprocessing and classification; 2) Accuracy and its limitations concerning specific marsh zones and regions; and 3) Considerations for future monitoring, change detection, or updating of the marsh classification.

The selection of Landsat 8 OLI sensor for this project was both opportunistic and a feasibility constraint. The opportunity presented with the timely occurrence of Landsat 8 launch and its accelerated release schedule by USGS in radiometrically-calibrated data readily available. The improved radiometric resolution of OLI and calibration stood to support finer thematic detail as compared to Landsat 5 or 7 Enhanced Thematic Mapper (ETM+).

The relatively modest number of Landsat orbital paths/rows allowed an efficient analysis, and a limited timespan between paths (also cloud-free) reduced potential errors in classification or "edge-matching" effects. Nonetheless, the regional distribution of marshes was a constraint on the application of these images, particularly for the Panhandle, where multiple path of Landsat required individual satellite scene analysis (rather than creation of a mosaic along-track.) In fact, the westernmost scene available for path 20 was a full year later and 3+ months seasonally (August) versus our other imagery. In addition, the tidal conditions and solar illumination (or even growing season) were not identical and the 2-week offset for path 17-20 did induce some spectral variation. These factors caused some additional preprocessing burden in the classification (by path and date), rather than mosaicking a single NDX image and classifying the full region. Although a full mosaic was produced *post-classification*, the tidal and phenological variations may present residual variation. In almost all cases, however, no edge matching issues are evident, which supports the approach taken. Further preprocessing could reduce this variation, but would have required substantial normalization image to image and ground measurement data. Several weeks' efforts at radiometric and spectral normalization did not yield satisfactory results. Accordingly, individual scenes were trained, classified, and assessed as a final map mosaic for the Panhandle and Gulf Coast Peninsula.

Accuracy of the resulting classification presented in webinar, conference call, and discussed with local resource manager and researchers (e.g., USF, UCF, UFL) determined the results satisfactory for regional landscape ecological management. The differentiation of high and low marshes, for instance, provides for floristic and hydrogeomorphic zonation that is relevant to habitat conservation for other species, ecosystem goods and services. It may also provide for a baseline for further monitoring and wetland studies (e.g., sea level rise, storm impacts, and other threats.) Specific concerns for individual classes are noted here:

Low and High Marsh Classification Reliability

- Multiple *Spartina* classes and mixed brackish/tidal fresh marshes. Accuracy of low marsh *Spartina* is limited by our differentiation of the expansive class and a second medium-tall growth form typical of levee and creekbanks and some backbarrier fringe patches. Aggregating these classes would improve the low marsh *Spartina* accuracy at the cost of losing this thematic detail, particularly in SC and GA where it is more prevalent.
- Regional floristic and physiognomic gradients exist as a response to climate and particularly the variable tidal gradient and sedimentary regimes across the SALCC. Rather than aggregate or generalize, we retained the *Spartina* classes as well as the tidal-fresh mixed and mud flat and salt pan classes, even though these have subregional clustering in SC and GA.
- The fine spatial resolution of Landsat (30m) is still insufficient to delineate certain fine-scale features that managers and scientists may desire to map. Extensive high marsh *Juncus* marshes in eastern NC will interdigitate with other marshes at fine scales that Landsat cannot delimit, particularly upland fringes.
- Some areas of extensive platform marsh *Juncus* appeared exposed to storm erosion, wrack deposition, or in the upland transition…prescribed burning.
- *Spartina bakeri* (sand cordgrass, bunch cordgrass, or Baker's cordgrass) may also be found in Georgia and northeast Florida, in particular, and this could present very isolated classification errors with the low marsh *Spartina* classes. However, *Sp. bakeri* is less tolerate to saline soils, is more often planted as an ornamental in its site expression, tends to prefer brackish to fresh zones, lake margins and even non-wetland sites.

Old Fields, Rice and Polders

- Rice fields, other old fields containing a secessional mix of emergent wetlands were a challenge to the classification, necessitating the approach to include them for their spectral and floristic distinctiveness.
- Prevalent in pockets of the Cape Fear River, NC, and more in SC along the lower Waccamaw and other basins originating along the coastal plain, these areas are oftentimes difficult to access.
- Some of these fresh to brackish emergent marshes could have been excluded from the mapping owing to predominance of fresh water, their close proximity to salt marshes and tidal influence led the project to include but attempt to isolate them spectrally and spatially. In addition, these areas could also be of significant interest to future marsh transgression and salinization, so this potential mapping value supported including them.

Mangroves

- Mangroves were encountered in the field in sparse locations on the central Space Coast and more extensively on the Gulf Coast, particularly north of Clearwater to Big Bend. Many of these areas were very limited in accessibility and required interpretation from aerial imagery to train and assess their accuracy.
- *Juncus* and other marsh species can co-occur with mangroves, yet when observed tended to be at very fine spatial scale, not allowing Landsat image classification.

Dynamic Shorelines and Human Alteration

- Particularly dynamic shorelines and areas adjoining inlets or channels merit mention. These areas are apt to show shifting states among classes in the maps or trends reflecting continual disturbance from storms or sea level rise over longer time spans.
- Where extensive ditching and dredging occur, many salt marshes exhibit fine-scale patterns interdigitated with dredge spoil islands (trees and shrubs) or water. This was observed extensively on the developed east coast between St. Augustine Beach and Cape Canaveral.
- As sea level rises and/or dredging activities shift, the pattern of these features are apt to change.

4 CONCLUSIONS

This study has accomplished its primary goal of synthesizing the typology and mapping of salt marshes across the extensive geography the Florida Peninsula and Panhandle. The project completed this inventory and delivered products that can provide for improved conservation management and monitoring. In addition to raster and vector geospatial classifications of marshes, the project provides a seamless continuous dataset in the form of Landsat-derived Normalized Difference Indices (NDX) that can provide a basis for future change analysis. During the project, several hurdles were overcome, such as limited cloud-free Landsat 8 availability and handling variable date and phenology, particularly along the west-east satellite paths. Periodic communications via conference calls, and engagement of experts and staff proved to be feedback on the mapping process.

Our findings conclude that low and high salt marshes follow expected trends in relation to the tidal frame, salinity gradients, and intertidal accommodation space across Florida's Atlantic and Gulf Coasts. Nonetheless, the results indicate local variation, such as human use disturbance or purposeful alterations, coastal erosion, and transgressive coastal processes related to sea-level. These patterns merit careful consideration to site-specific studies using the map products as well as suggesting potential scientific investigations to further understand marsh responses to sea level rise.

The classification scheme adopted provides a seamless, mutually exclusive categorization inclusive of inundation, salinity, and substrate and autochthonous processes in marshes. The scheme will also prove operable with the prior salt marsh mapping of the South Atlantic region. The range of classes provides for the inclusion of tidal fresh and brackish marshes that are extensive in the tidal riverine zones, mudflats in the lower intertidal zone, salt flats and pans in the upper tidal frame and mangroves to the south. These classes were originally tangential to the study, yet their inclusion represents additional value. Such sites in proximity and ecologically adjoining salt marshes are liable to exhibit dynamic transitions or transgressions in the future. Hence, including them at some additional cost to the project timeline and effort was prioritized.

Future research may capitalize upon more abundant water level monitoring and tidal gages and the aforementioned satellite sensors to produce marsh-corrected LiDAR DEMs for wetland monitoring and sea level response modeling. Although DEMs were considered a possible helpful input to marsh classification, their variable quality and gaps in the study rendered this approach infeasible at the time.

Cloud-based and Application-Ready Datasets

To mitigate the substantial scene-by-scene analysis necessary for this study, future work should consider adopting a cloud-based analysis, such as Google Earth Engine, which includes access to a wealth of data. While this system was rapidly developing during the project, the machine learning classification, iterative analyses with field training data, and limited cloud-free available data would likely have prevented adequate results. Also since the inception of the study, NASA and USGS initiated creation of "Application-ready" datasets for research. During the first year of this project, these data were also consulted, and as of 2019, no adequate cloud-free seamless imagery datasets were available for this study area.

Spectral Vegetation Changes

Another avenue of future work would be pursuing a stronger integration of field biophysical measurements and remotely sensed conditions. State changes or continuous biophysical indices such as biomass, carbon, species cover, or leaf area could be analyzed with satellite based NDX data and techniques such as change vector analysis (CVA) to track and predict marsh conditions or class changes. Such continuous metrics could be used as diagnostic or predictive indicators of change. Rogers and Kearney (2004), for instance, have developed "marsh condition indices" using NDX, and over a time series, conditions and states changes could be tracked.

Other Satellite Imagery and Synthetic Aperture Radar (SAR)

In addition, integrating ancillary and increasingly ubiquitous raster GIS or other Earth Observation imagery could improve the classifications. For instance, LiDAR point clouds and bare earth or surface models could differentiate high and low marsh as future LiDAR datasets improve and "marsh correction" techniques are implemented by producer agencies. The European Space Agency (ESA) also has several emerging Copernicus satellites capable of finer resolution multispectral imaging versus Landsat, as well as continued plans to sustain a satellite Synthetic Aperture Radar (SAR.) SAR is an active sensor, and C-, X-, and L-band microwave SAR has potential to see-thru clouds and characterize vegetation surfaces, water surface roughness and soil moisture. These backscatter features could be included with spectral imagery to differentiate marshes by canopy surface roughness or texture as well as water and mudflats or salt pans.

Since the inception of the project, other machine learning techniques and cloud computing have also rapidly advanced. Future studies could utilizing computational cloud processing (e.g., Google Earth

Engine) or additional artificial intelligence (AI) classifiers in conjunction with Landsat 8 or other satellite sensors. These approaches could speed the classification process and reduce the cost of inventorying and monitoring.

Sentinel Sites and Field Data

Another recommended resource for future updates or inventories of marshes is the use of crowdsourcing methods and technologies. This project used Google Earth extensively with shared KML place marks and annotations to solicit input from resource managers and local experts. This process allowed for more efficient field work for training site selection. In addition, the project used Esri ArcGIS Online extensively to share preliminary maps widely among interested parties. The webinars showcased and shared these intermediate results, allowing for strong feedback and some corrections to the classification at various sites. Future efforts at regional remote sensing might further invest in crowdsourcing and volunteered geospatial information for efficient mapping, review, and sharing.

Finally, all data and supporting metadata have previously been provided to staff at the Atlantic . These data may be accessed online data directly from the Atlantic Coast Joint Venture (ACJV) or by contacting the lead author of this report, Dr. Thomas Allen (tallen@odu.edu) In addition, the report authors will be glad to assist with metadata and data transfer to support publication and dissemination of the data to repositories, such as https://salcc.databasin.org/. The ACJV is encouraged to share these data with Data Basin and other federal partners and conservation planners and managers.

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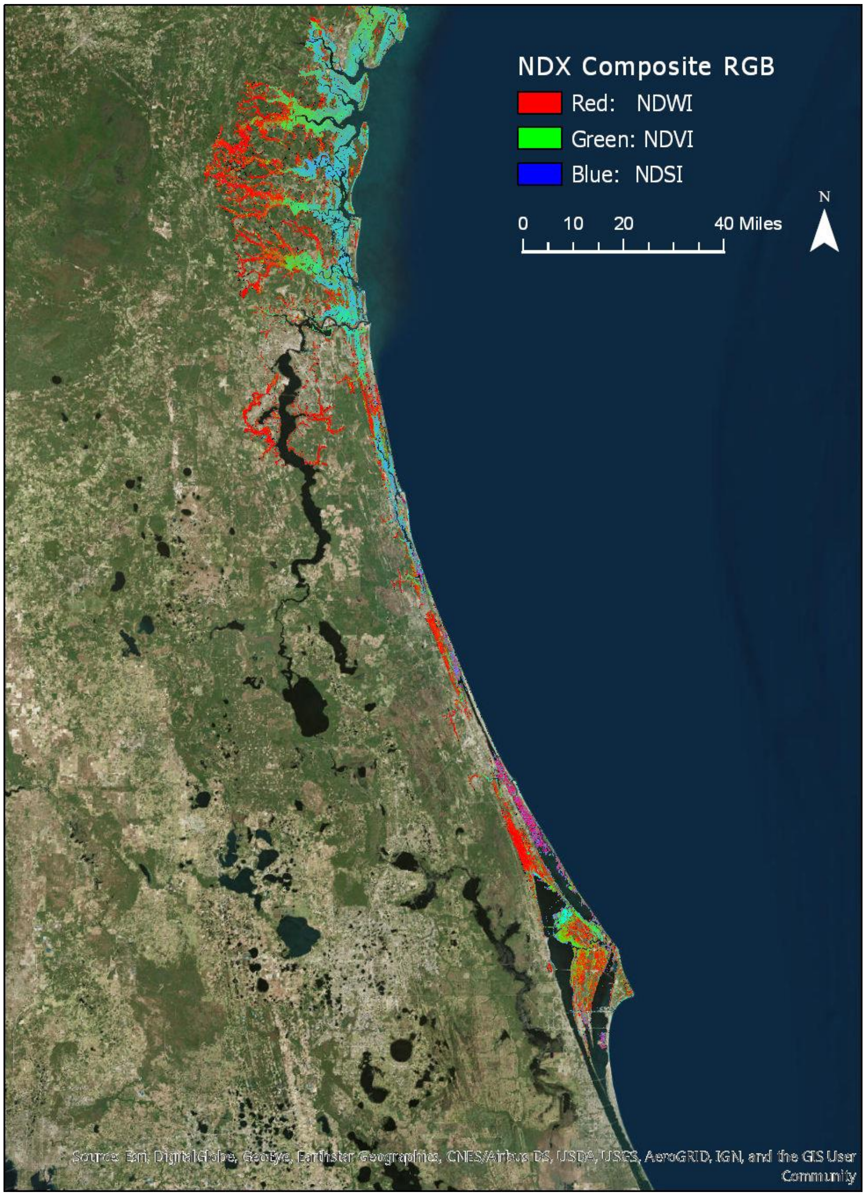
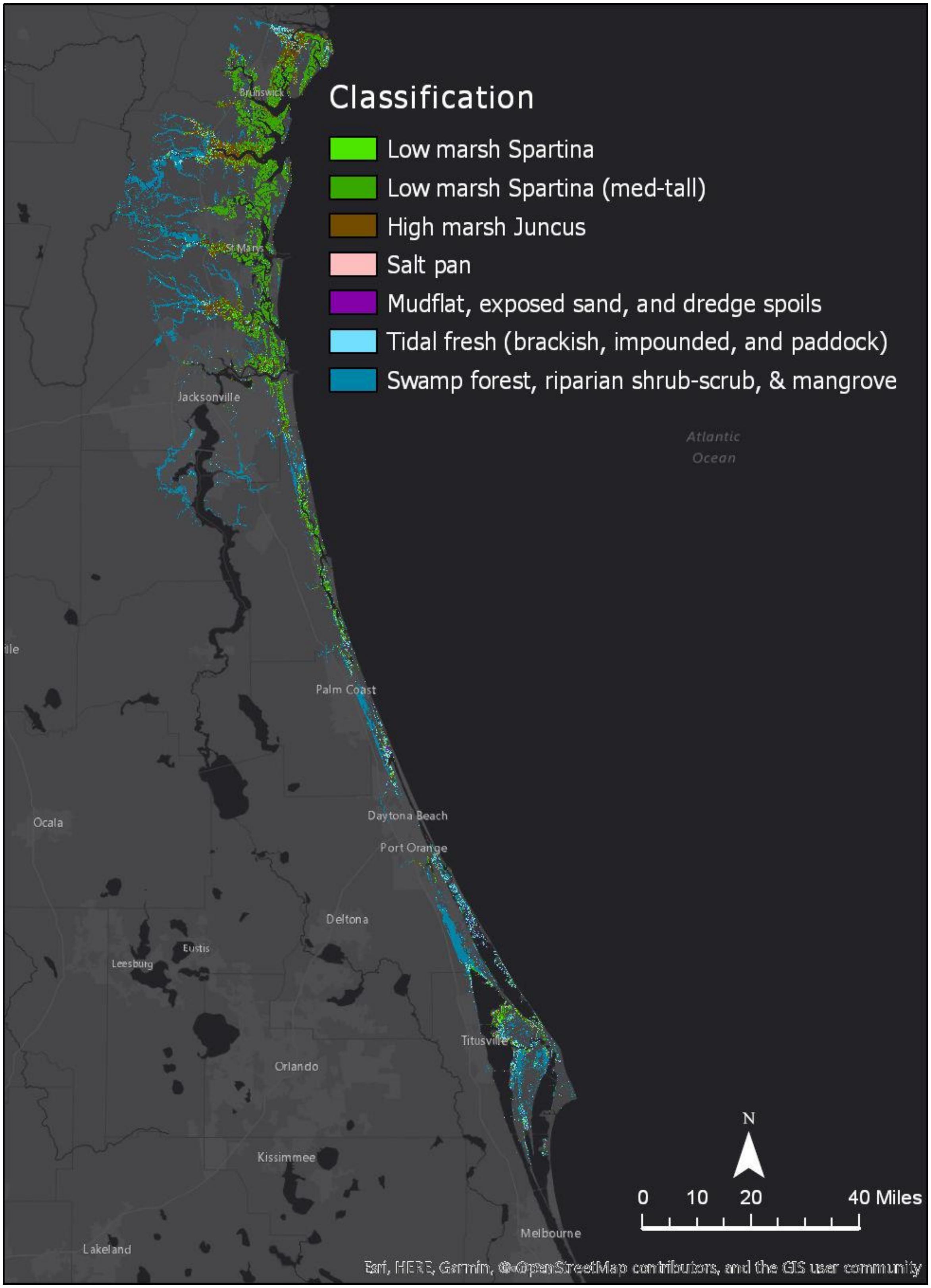
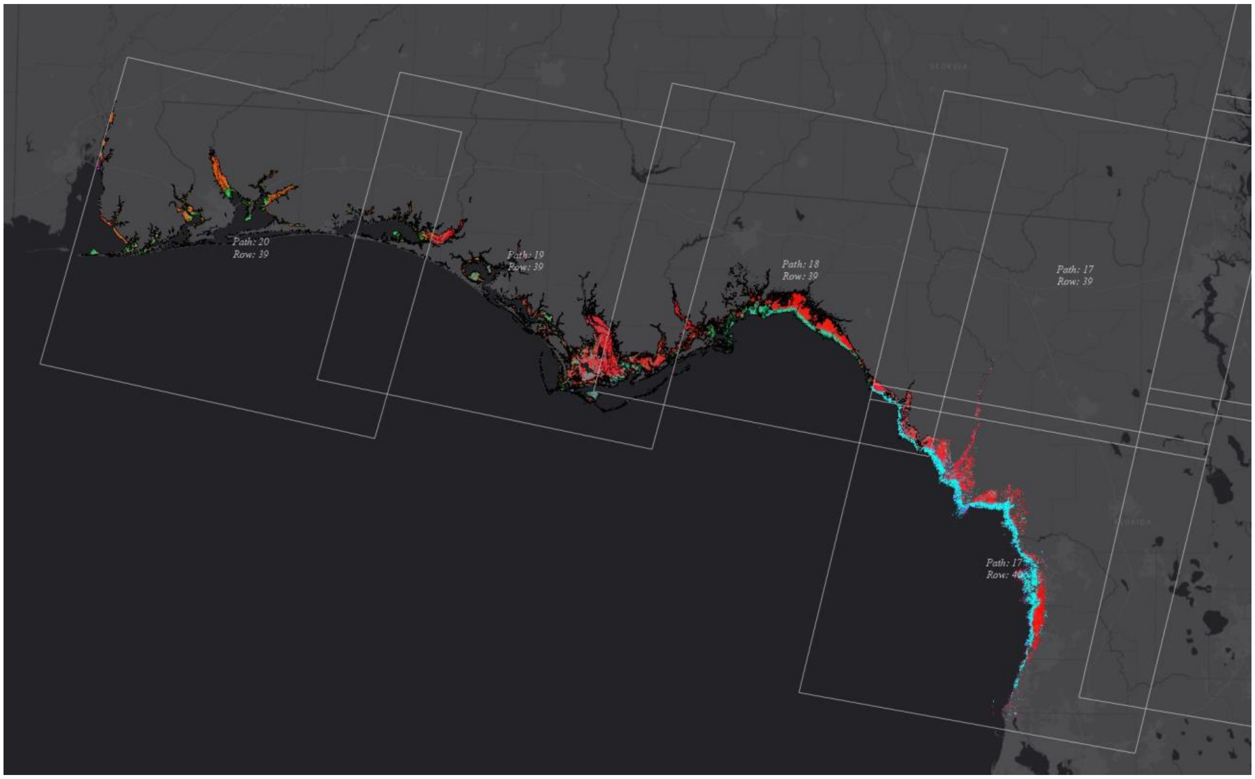
Appendices

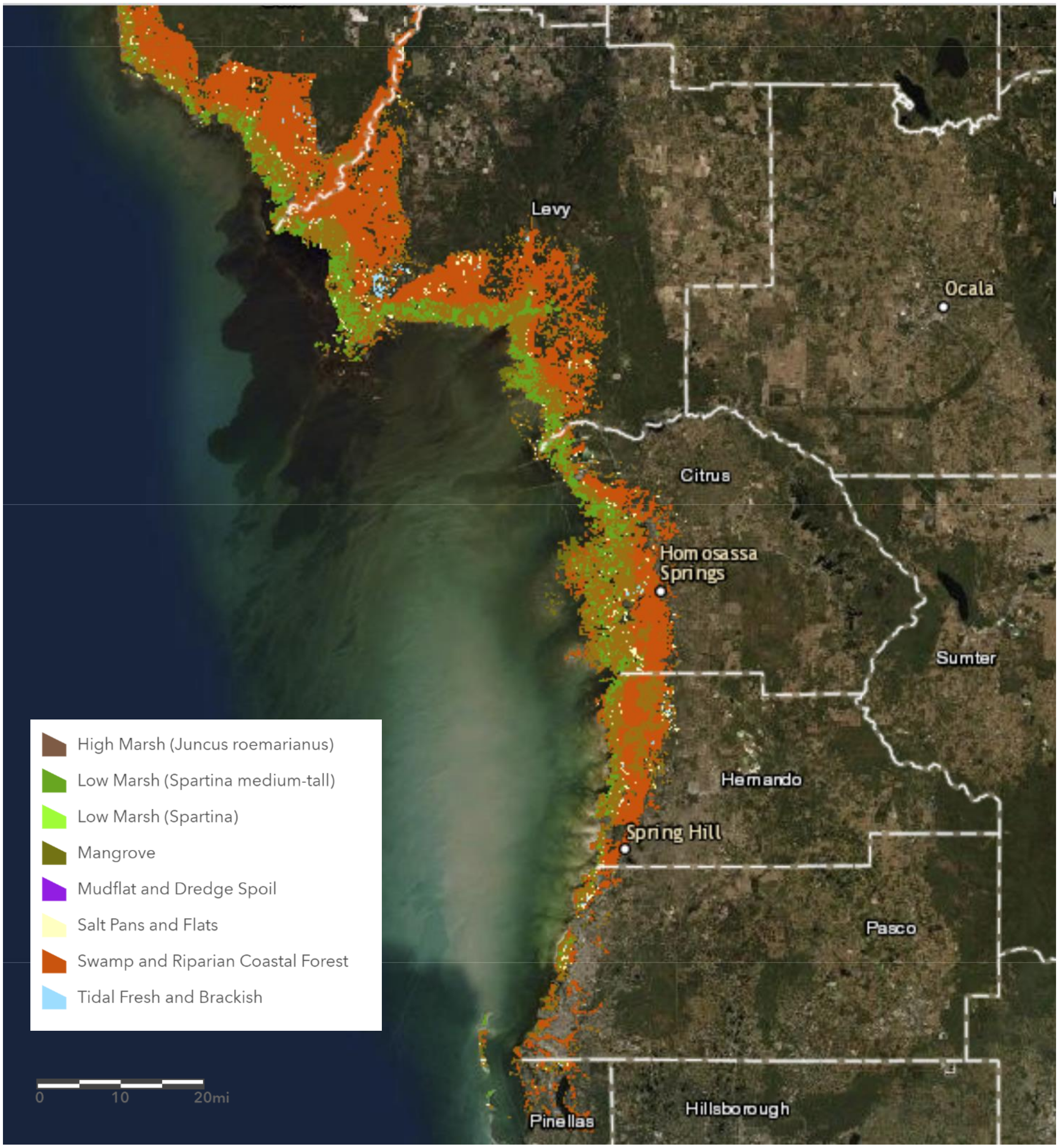
Appendix A. Northeast FL and Georgia NDX Composite and Classification Maps



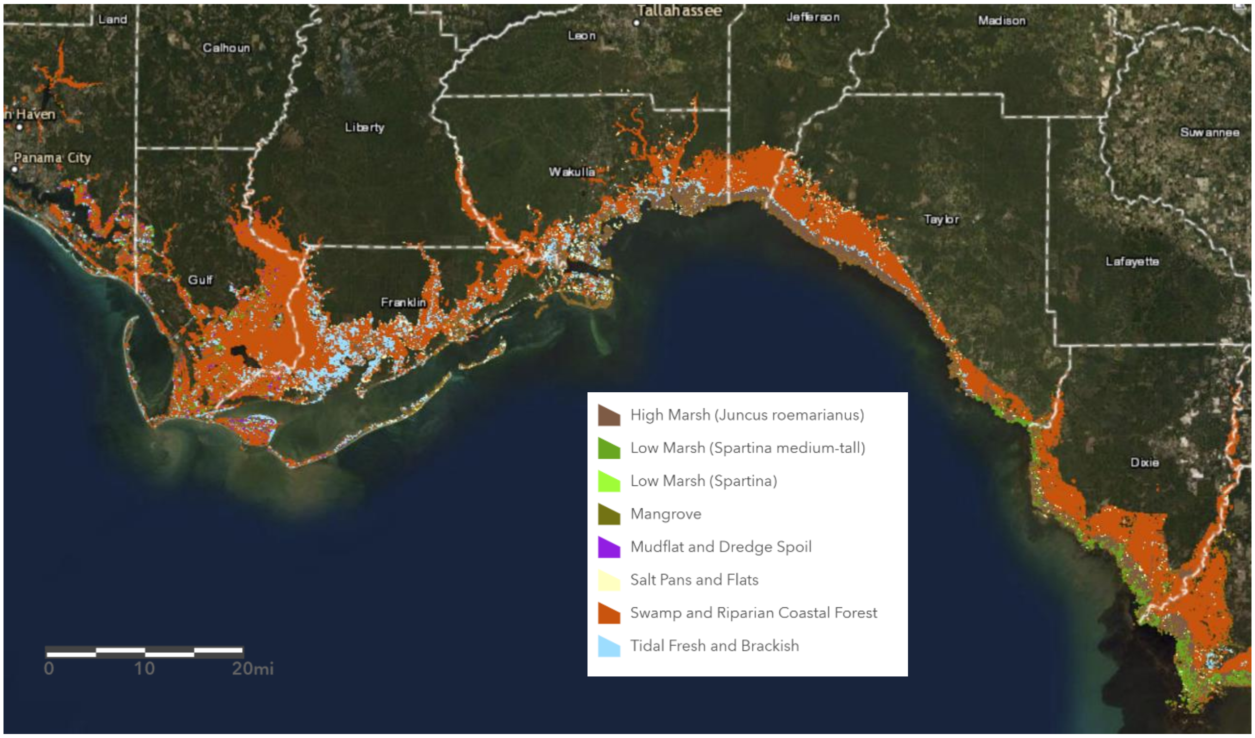

Classification
Low marsh Spartina
Low marsh Spartina (med-tall)
High marsh Juncus
Salt pan
Mudflat, exposed sand, and dredge spoils
Tidal fresh (brackish, impounded, and paddock)
Swamp forest, riparian shrub-scrub, & mangrove
Atlantic Ocean
Brunswick
St Marys
Jacksonville
Palm Coast
Daytona Beach
Port Orange
Deltona
Eustis
Leesburg
Ocala
Titusville
Orlando
Kissimmee
Melbourne
Lakeland
N
0 10 20 40 Miles
Esri, HERE, Garmin, © OpenStreetMap contributors, and the GIS user community

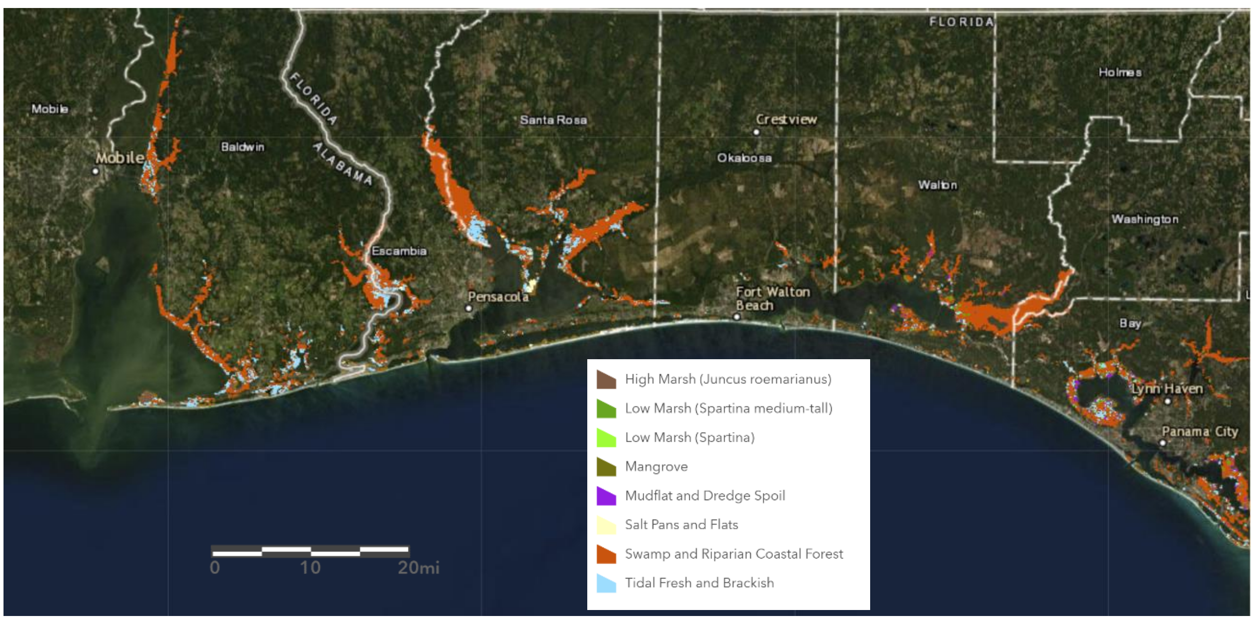
Appendix B. Gulf Coast Peninsula and Panhandle Extent NDX Composite and Classified Maps





Levy
Ocala
Citrus
Homosassa Springs
Sumter
Hernando
Spring Hill
Pasco
Pinellas
Hillsborough
High Marsh (Juncus roemarianus)
Low Marsh (Spartina medium-tall)
Low Marsh (Spartina)
Mangrove
Mudflat and Dredge Spoil
Salt Pans and Flats
Swamp and Riparian Coastal Forest
Tidal Fresh and Brackish
0 10 20mi


Tallahassee
Jefferson
Madison
Leon
Land
Calhoun
Haven
Liberty
Suwannee
Panama City
Wakulla
Taylor
Lafayette
Gulf
Franklin
Dixie
High Marsh (Juncus roemarianus)
Low Marsh (Spartina medium-tall)
Low Marsh (Spartina)
Mangrove
Mudflat and Dredge Spoil
Salt Pans and Flats
Swamp and Riparian Coastal Forest
Tidal Fresh and Brackish
0
10
20mi


FLORIDA
Holmes
Mobile
Mobile
FLORIDA
ALABAMA
Santa Rosa
Crestview
Baldwin
Okaloosa
Walton
Washington
Escambia
Pensacola
Fort Walton Beach
Bay
Lynn Haven
Panama City
High Marsh (Juncus roemarianus)
Low Marsh (Spartina medium-tall)
Low Marsh (Spartina)
Mangrove
Mudflat and Dredge Spoil
Salt Pans and Flats
Swamp and Riparian Coastal Forest
Tidal Fresh and Brackish
0
10
20mi

Appendix C.

Florida marsh field mapping classification scheme notes for all three survey regions, per Nicole Knudson (9/29/2019):

Class code	Class Name	Representative species cover	Comments
0	Unclassified	N/A	N/A reserved for NODATA
1	Low Marsh Spartina (short)	Dominated by short (approx. 0.5 meter or under) growth form cordgrass *Spartina alterniflora.*	Short form was generally seen in high marsh/salt pans, not low marsh. Thus, it was often seen with other high marsh and salt pan vegetation or unvegetated surface. A notable exception seemed to be a Wakulla Beach, where the short Spartina was located in the low marsh zone (emergent at the interface of Goose Creek Bay, see Tampa and Panhandle Data Points layer, OID 211).
2	Low Marsh Spartina (medium-tall)	Predominant medium-tall (generally over 0.5 meter) growth form *Spartina alterniflora*, generally seen in marsh systems with extensive creek networks, with tall form often along creekbank levees or fringing mudbanks.	Mudflats/unconsolidated bottom or shore and oyster beds may also be present.
3	High Marsh Juncus	*Juncus roemerianus* (black needle rush) occurring in expansive patches.	Different growth forms were seen on Tampa and Panhandle surveys. The short form often appeared paler in color (approaching straw color versus the darker green often seen in the tall form). The (north) east coast of Florida did not seem to have different growth forms (at least this was not apparent during my March 2018 survey). It appears that *Juncus roemerianus* forms on the west coast are equivalent to the *Spartina alterniflora* growth forms on the Florida east coast (i.e., short forms present at a higher landscape

			position/topography where soil salinity is higher due to reduced tidal influence).
4	Salt Pan	Salt flats or pannes with short-growth *Spartina alterniflora*, *Salicornia* spp. (glassworts), *Batis maritima* (saltwort) or *Distichlis spicata* (saltgrass), *Borrichia frutescens* (sea oxeye), *Juncus roemerianus* (especially short form on west coast).	Salt pans included barrens within high marsh zone/higher topography as well as vegetated areas. Vegetation coverage ranged from sparse to complete across the area.
5	Mudflat and Dredge Spoils	Exposed mudflats with no or limited vegetation. Limited coverage of *Spartina alterniflora* (med-tall) and mangrove trees is possible. Oyster beds may be present during low tide.	Generally unconsolidated bottom (muck) located in low marsh zone but may be stream bottom. SAV present in some creeks, which may not be visible or may be readily apparent depending on tidal and rainfall conditions. Some features classified as Mudflat should probably be classified as Salt Pan (e.g., FIDs 116 and 140 in East Coast Data Points (collected March 2018) layer.
6	Tidal Fresh (brackish, impounded, and rice)	Fresh water to oligohaline transitional dominant marshes with predominant *Cladium jamaicense* (sawgrass), *Typha* spp., *Zizaniopsis miliacea* (southern wild rice), *Juncus effusus* (soft rush), *Bolboschoenus robustus* (saltmarsh bulrush), *Arundo donax (giant reed), Spartina bakeri (sand cordgrass)* or *S. spartinae*, (gulf cordgrass).	*Eleocharis* sp. (spikerush) was present at St. Marks – a very short plant which will be visible above the waterline at low tide or completely submerged at high tide.
7	Swamp Forest and Riparian Scrub-shrub	*Non-herbaceous vegetation dominant, including Sabal spp. (palms), Pinus spp. (pines), Juniperus virginiana (red cedar), Quercus spp. (oaks), Iva frutescens (marsh-elder), Borrichia frutescens* (sea oxeye). M*angrove trees/shrubs* and *Juncus roemerianus* (black	Vast expanses of dead trees were also seen at Lower Suwannee National Wildlife Refuge and Crystal River Preserve State Park (potential ghost forests?)

		needle rush) may be present but infrequent/limited in coverage.	
8	Mangrove	Mangroves dominant (did not identify to species level), but *Salicornia* spp., *Batis, and Juncus roemerianus* may be present in limited coverage. Mudflats may be present, as well as oyster beds during low tide.	FID 33 in East Coast Data Points (collected March 2018) layer should probably be classified as Mangrove.
9	Other	Used for sites that didn't fall under a defined classification, for sites with multiple species but none that could be considered dominant, or where I was otherwise unable to make a class determination.	Perhaps many of these features could be placed into a class following the image classification.
Additional classes used for March 2018 Florida east coast and GA survey:			
	High Marsh not *Juncus* dominated	May include *Juncus roemerianus* but was not the dominant species. *Borrichia frutescens, Distichlis spicata, Spartina patens, Salicornia* spp., *Batis maritima.*	
	Spartina alter. Undetermined form	*Spartina alterniflora* – unable to determine if short or med-tall form.	
	Multiple classes or undetermined	Generally one of two conditions: 1) a dominant species present but landscape position/marsh zonation not able to be determined (e.g., *Distichlis spicata* in FID 76 in East Coast Data Points (collected March 2018) layer, 2) multiple species or classes in a patchy or mosaic pattern preventing classification of a predominant species or class (e.g., *Spartina alterniflora*, exposed oyster beds, and patchy mangrove trees in FID 82 in East Coast Data Points (collected March 2018) layer.	

Appendix D.

Florida Marsh Photos for Classification Training Sites. (These points are also stored in training point feature layers with provided webmaps.)

Class code	Class Name	Webmap layer name	FID/OID (features used in red)	Webmap layer name	FID/OID	Reference photos	Notes
0	Unclassified					N/A	
1	Low Marsh Spartina (short)	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	211			1_211a; 1_211b	Lack of photos represents few occurrences, limited areal coverage, or lack of confidence in classification.
2	Low Marsh Spartina (medium-tall)	East Coast (supplemental photos only)	21, 25, 37	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	50, 71, 79, 89	2_25; 2_71; 2_89;	
3	High Marsh Juncus	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	20, 23, 30, 41, 47, 66, 69, 105, 106, 107, 213, 216, 221, 224, 232, 233, 245, 262, 336, 338,			3_23; 3_213; 3_221; 3_233	
4	Salt Pan	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	203, 212, 215, 218,			4_203; 4_212; 4_215; 4_218;	

5	Mudflat and Dredge Spoils	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	78			5_78	
6	Tidal Fresh (brackish, impounded, and rice)	East Coast Data Points (collected March 2018)	10, 12	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	101, 102, 197, 200, 207, 210, 249, 252, 255, 333, 347	6_10; 6_101; 6_197; 6_210; 6_255; 6_333;	
7	Swamp Forest and Riparian Scrub-shrub	East Coast Data Points (collected March 2018)	17	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	264	7_17; 7_264;	Several of the features in Tampa and Panhandle layer "Other" class could probably be reclassified as SFRSS.
8	Mangrove	Tampa and Panhandle Data Points (collected Dec. 2018 and May/June 2019)	14, 15, 16,			8_14; 8_15; 8_16	
9	Other						I assume you don't want any photos for this "class." Several of these features can probably now be classified. I didn't do this as I didn't

							want to negatively impact image classification results.
Additional classes used for March 2018 Florida east coast and GA survey:							
	High Marsh not Juncus dominant						I assume you don't want any photos for this "class."
	Spartina alter. Undetermined form						I assume you don't want any photos for this "class." Looking back at these photos, I think most are medium or tall (not short form, at any rate).
	Multiple classes or undetermined	East Coast Data Points (collected March 2018)	82 (site with mangroves and Spartina alterniflora as exclusive veg, mudflats, and extensive oyster reefs on creek bottom)				This feature should perhaps be reclassified as Mangrove or Mudflat. FID 82 includes three photos of the site. Did not include in any photos for this "class."

1_211a: Low Marsh Spartina (short): End of Wakulla Beach Rd. at Goose Creek Bay. About 25 to 30 meters of very short (around a foot or less tall) *Spartina alterniflora* fringing water's edge before meeting *Juncus roemerianus* (short form) interior of shoreline (seen in background).

1_211b: Low Marsh Spartina (short): End of Wakulla Beach Rd. at Goose Creek Bay. About 25 to 30 meters of very short (around a foot or less tall) *Spartina alterniflora* fringing water's edge.

2_25: Low Marsh Spartina (medium-tall): Rt 1 at Moultrie Creek.

2_71: Low Marsh Spartina (medium-tall): Shell Mound County Park boat launch (part of Lower Suwannee National Wildlife Refuge?). *Spartina* expanse near launch transitioning to *Juncus roemerianus*.

2_89: Low Marsh Spartina (medium-tall): Shired Island. Predominantly *Spartina alterniflora* but with some small patches or clumps of *Juncus roemerianus*. *Juncus roemerianus* in foreground at transitional zone.

3_23: High Marsh Juncus: Bay Blvd. at Wilmslow Park. Enormous monotypic expanse of *Juncus roemerianus*, not even a shrub visible mixed in. *Juncus* bordered by 30+ foot tall pines (unsure if cedar also), border of mangroves (plus maybe other shrubs?) at tree/*Juncus* edge.

3_213: High Marsh Juncus: Past south terminus of Wakulla Beach Road. Vast *Juncus roemerianus* high marsh. Short form *Spartina alterniflora* very narrowly fringing path and in occasional rivulets in *Juncus*.

3_221: High Marsh Juncus: Terminus of Kornegay Way at Oyster Bay.

3_233: High Marsh Juncus: East side of Bottoms Road, Saint Marks National Wildlife Refuge. At this exact spot right across from ditch short form *Juncus roemerianus* looks more like *Spartina alterniflora* on Google Maps because the short *Juncus* doesn't collapse into lumps or form cowlicks and doesn't collect wrack either. In the field it looks more like neat and perky *Spartina alterniflora*.

4_203: Salt Pan: Terminus of Lighthouse Road at St Marks River/Gulf of Mexico, Saint Marks National Wildlife Refuge. Taken from observation deck behind Saint Marks Lighthouse. Extensive salt pan with salt/glasswort and patchy *Juncus roemerianus* in foreground. *Juncus roemerianus* extensive in background.

4_212: Salt Pan: Southern terminus of Wakulla Beach Road just beyond boat launch, Saint Marks National Wildlife Refuge. Lush salt/glasswort. Small pond and extensive *Juncus roemerianus* short form seen in background.

4_215: Salt Pan: East side of Wakulla Beach Road, Saint Marks National Wildlife Refuge. Barrens, salt/glasswort with sparse short *Spartina alterniflora*, and *Juncus roemerianus* short to medium form.

4_218: Salt Pan: Wakulla Beach Road, Saint Marks National Wildlife Refuge. Various species of succulents.

5_78: Mudflat and Dredge Spoils: Shell Mound (part of Lower Suwannee National Wildlife Refuge?). Unvegetated intertidal flats along with oyster reefs and rubble/rock.

6_10: Tidal Fresh (brackish, impounded, and rice): East side of Rt 17, about one half mile south of Altamaha River, in GA. *Zizaniopsis miliacea* (straw colored with broad blades) dominant but also with large region of *Juncus* sp. (probably *J. effusus*) running mostly parallel to road. Minor occurrence of *Typha* sp. along road edge.

6_101: Tidal Fresh (brackish, impounded, and rice): Shoal Line Blvd. at Jenkins Creek. Vast monotypic stand of *Cladium jamaicense*.

6_197: Tidal Fresh (brackish, impounded, and rice): Impounded area along Lighthouse Road, Saint Marks National Wildlife Refuge. *Bolboschoenus robustus* (Saltmarsh Bulrush) dominant but with some *Typha* sp. near bridge.

6_210: Tidal Fresh (brackish, impounded, and rice): Lighthouse Road, Saint Marks National Wildlife Refuge. Various species of freshwater to oligohaline species, including *Typha* sp. and *Cladium jamaicense*.

6_255: Tidal Fresh (brackish, impounded, and rice): Seafood Landing Park, Apalachicola. *Bolboschoenus robustus* (Saltmarsh Bulrush) taking on various appearances- upright, washed/blown on side, swirls/cowlicks.

6_333: Tidal Fresh (brackish, impounded, and rice): Southern terminus of Rake Creek Road, near Cash Bayou of East Bay. Photo shows what appears to be *Juncus effusus* taking on golden color due to apparent recent (controlled?) burn. Note burn line on pines.

7_17: Swamp Forest and Riparian Scrub-shrub: South side of Walter Boardman Lane at Bulow Creek and Bulow Creek State Park. Facing south. Various woody species, along with *Juncus roemerianus* and *Borrichia frutescens* and sparse *S. bakeri or S. spartinae* at road edge/levee and high marsh/shrub margins. Mangroves were not present.

7_264: Swamp Forest and Riparian Scrub-shrub: Route 87 bridge over Yellow River, near Yellow River Water Management Area. Species rich. Photo taken from kayak launch under bridge. Much of this may be so well drained as to consider it upland forest.

8_14: Mangrove: Eagle Point Park, at Fillmans Creek and Trouble Creek. Mangroves dominant and dense. Some scattered patches of salt/glasswort with young mangrove shoots.

8_15: Mangrove: Sand Bay, end of Straub Memorial Drive, near Seven Springs. Mangroves surrounding sandy silty channel.

8_16: Mangrove: Northwest side of Bailey's Bluff Road, near Seven Springs, FL.