MOBILE BAY NATIONAL ESTUARY PROGRAM

Project Title:
2016 Uplands/Wetlands Habitat Mapping Project

Submitted to:
Roberta Arena Swann, Director
Mobile Bay National Estuary Program
118 N. Royal St.
Mobile, AL 36602

Kelley Barfoot
Community Outreach Coordinator
Mobile Bay National Estuary Program
118 N. Royal St.
Mobile, AL 36602

Submitted by:
Radiance Technologies, Inc.

Date: 31 July 2017

Uplands/Wetlands Habitat Mapping Project

ACKNOWLEDGEMENTS

This project was supported by the Mobile Bay National Estuary Program (MBNEP), a division of the Dauphin Island Sea Lab. The geospatial data analyzed in this report conformed with Federal Geospatial Data Center (FGDC) Standards developed under Executive Order 12906, “Coordinating Geographic Data Acquisition and Access: The National Spatial Data Infrastructure.”

TABLE OF CONTENTS

Mobile Bay National Estuary Program

UPLANDS/WETLANDS HABITAT MAPPING PROJECT

INTRODUCTION

Alabama's coastal landscape and the natural resources, habitats, and species that inhabit the area are important components of an interconnected system that make up local, regional, and Gulf-wide ecosystems. The Mobile Bay watershed encompasses an incredible diversity of habitats such as marine and estuarine ecosystems, terrestrial wetlands, and uplands that have a significant influence on the water quality of the bay and surrounding waters. Alabama's coastal habitats have undergone significant changes over time due to a multitude of factors, including population growth, the spread of urban development, land conversion, pollution, invasive species colonization, hydrological modifications, and repeated natural and anthropogenic disasters. The resulting patterns and stressors have produced a substantial impact on coastal ecosystems in both the terrestrial and marine environments. In addition to stresses imposed by local impacts, coastal habitats that are located on the downstream portion of drainages have been subjected to the cumulative impacts of degenerative landuse practices that occur in entire watersheds[1]. In order to assess changes and the impacts incurred, habitat data is needed to allow resource managers and decision makers to better plan for restoration and conservation activities that will uplift and protect our coastal resources.

The Mobile Bay National Estuary Program (MBNEP) is a federally authorized National Program responsible for promoting wise stewardship in the Mobile Bay estuarine system and developing a comprehensive conservation and management plan (CCMP). The 2013-2018 CCMP included two restoration goals 1) improve trends in water quality of priority fishery nursery areas; and 2) improve ecosystem function and resilience through protection, restoration, and conservation of habitats. In order to implement CCMP goals, MBNEP needed an updated inventory of wetlands and upland coastal habitats in Mobile and Baldwin counties in Alabama to help assess water quality trends, identify degraded habitats, and recommend corrective actions. The goal of the project was to generate an updated habitat classification map covering wetland and upland coastal habitats throughout Mobile and Baldwin counties (approximately 3,671 square miles).

IMAGE ACQUISITION

The Radiance Team coordinated the acquisition of new 4-band imagery over Baldwin and Mobile Counties. Quantum Spatial (QSI) used a Leica ADS 100, which has a 4 channel (RGB & IR) multi-spectral capability. Project specific flights were conducted over a two-month period (January 17, 2016-February 10, 2016). Nine aircraft lifts were completed.

---

[1] Shirley, L. J., & Battaglia, L. L. (2006). Assessing vegetation change in coastal landscapes of the northern Gulf of Mexico. *Wetlands*, *26*(4), 1057-1070

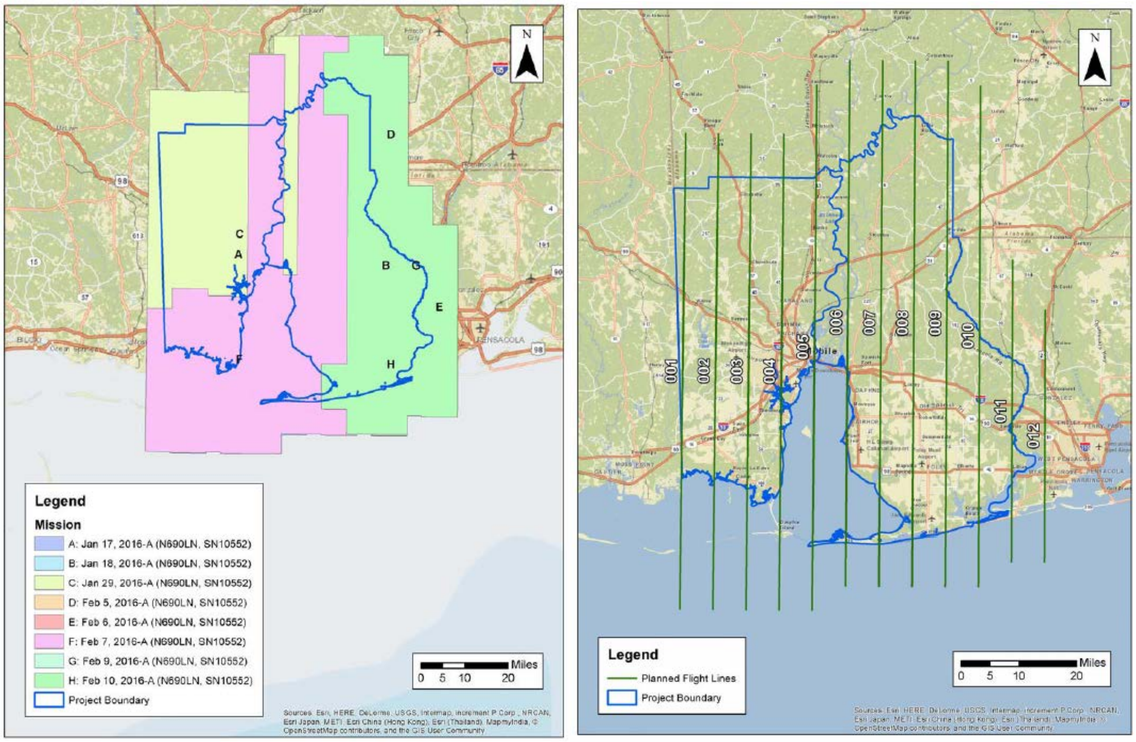


Figure 1. QSI Flight Frame Coverage and Flight Lines.

ORTHORECTIFICATION

Following flight acquisition, QSI processed and verified the data for proper project area coverage and data accuracy and post-processed the raw imagery in two steps. First, the radiometric correction was applied to compensate for temperature, aperture effects, etc. Second, geometric corrections were applied to correct for lens distortion and tilt. Stereo models validated horizontal and vertical accuracy before the raw data was archived. Hardcopy and digital format recordings delineated the nadir point on each exposure for validating that project accuracy standards are met. A full description of image processing procedures is included in Appendix A.

Aerotriangulation (AT) was performed using Z/I Systems Image Station Automatic Triangulation (ISAT) software to minimize dependence on ground control by extending and supplementing the airborne and base station control. An aero triangulation report outlines all the relevant information pertaining to the accuracy of the control data (Appendix A). The report includes summary of aerial triangulation results; descriptions of equipment, procedures, and computer software used; Summary Remote Monitoring System errors for bundle adjustment, photographic measurement residuals, or strip tie point residuals and misclosures at control/check points; significant misfits encountered at control points and procedures taken to analyze and rectify such misfits; a listing of all misclosures at ground control points with and without use of checkpoints; computer printout of the final adjusted analytical triangulation solution to horizontal and vertical ground control. The report also contains the final coordinates for all ground control points, pass points, and checkpoints, and identification of all points that were included in the initial solution and subsequently discarded, with an explanation of the reasons for being discarded.

A complete differential rectification removed any image displacement due to topographic relief and camera tip/tilt. This ensured that that each pixel in the image was positioned into its correct horizontal ground location (X-Y coordinate value). QSI used OrthoPro software for radiometric tone matching, cropping, and feathering, to create a seamless image mosaic with invisible joint lines. *The final outputs from the post processing were high resolution, orthro-ready, panchromatic, color, and color infrared images covering Baldwin and Mobile counties.* QSI delivered the imagery within 45 working days. A final digital orthoimage was provided on an external hard drive in the following coordinate system UTM Zone 16 NAD 83, GRS 1980 Spheriod. In accordance with FGCD Wetlands Mapping Standard, the imagery acquired was color infrared, 1m resolution (1:12,000 scale), cloud-free and leaf off, with a winter tasking acquisition window. The final product delivered was in UTM Zone 16 NAD83, and was delivered to MBNEP Program Manager at the time (Ms. Amy Newbold) via portable hard drive in April 2016.

Figure 2. Leaf-Off Mosaic Collected by Quantum Spatial (Flown Jan-Feb 2016).

FIELD SAMPLING

Field personnel visited field sites during the leaf-off imagery acquisition window and used a vegetation inventory protocol to ensure consistency across all sampling locations. Apple iPad tablets were preloaded with ESRI's Collector App, a mobile application used to capture field data and log site information matching the Cowardin wetland classification scheme[2] and a modified Anderson scheme for uplands[3] in custom-made data forms that integrate directly with ESRI ArcGIS.

[2] Cowardin, L. M., Carter, V., Golet, F. C., & LaRoe, E. T. (1979). Classification of wetlands and deepwater habitats of the United States. US Department of the Interior, US Fish and Wildlife Service.

[3] Anderson, J. R. (1976). A land use and land cover classification system for use with remote sensor data (Vol. 964). US Government Printing Office.

To ensure location accuracy, high-performance GPS receiver Bad Elf GPS Pro Plus units were tethered to the tablets to increase geographic positioning to 2.5 meters. Collector for ArcGIS has the capability to provide ancillary map data such as existing habitat maps, soil data, topographic maps, DEM data, recent imagery, and cadastral maps as the backdrop to aid field personnel in the decision-making process. Photos were taken at each site with the iPad and linked with the site location through Collector. A total of 300 sample sites were visited, each with a consensual observation. The observations were roughly half in each county, and about half of each county was sampled in the north and about half in the south to ensure wide coverage of the samples. We employed a stratified random sampling approach to ensure an unbiased data collection and provide a good distribution of sampling sites across all class categories. This method assigned a specific number of locations to each class in proportion to the size or significance of the class. Although the stratified random approach was the primary site selection method, a systematic component was required to realistically meet goals. Large amounts of private land exist in both counties, which hindered the ability of field personnel to visit each randomly selected site. An additional selection process identify points that were within 200 meters of an accessible roadway.

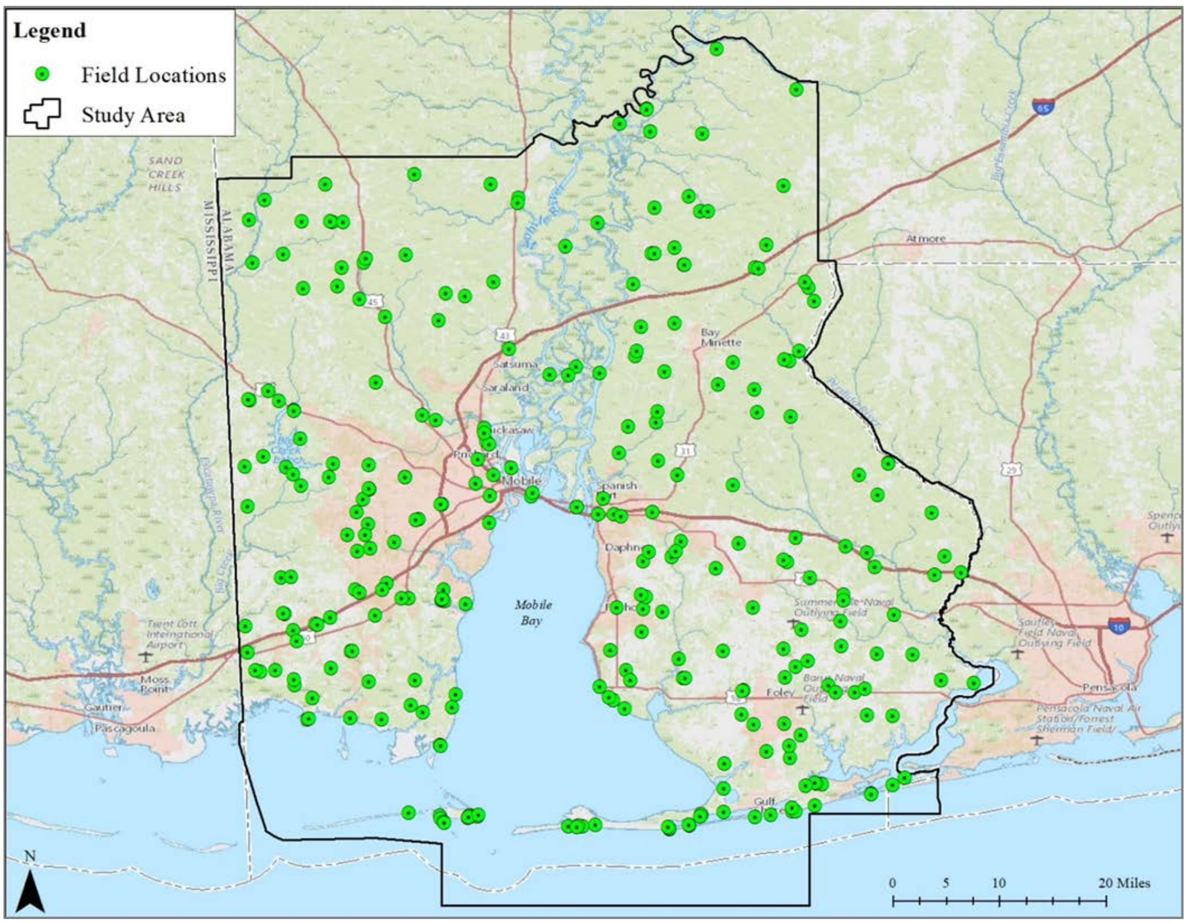


Figure 3. Field Locations in the Project Study Area.

Figure 4. Field personnel visiting field sites and collecting training samples at all sampling locations.

METHODOLOGY: IMAGE CLASSIFICATION AND FEATURE EXTRACTION

The Radiance Team established an image classification workflow using the latest version of ERDAS IMAGINE. Traditional pixel-based land cover classifications are unsupervised, supervised, or a combination of both and these classifications do not often incorporate spatial context in the classification. In contrast, object based image analysis (OBIA) groups the pixels with similar data value properties (*i.e.*, radiance/reflectance, texture, *etc.*) into clumps known as objects. Classifications then can be done by object, instead of pixel by pixel, and can potentially provide higher mapping accuracy.

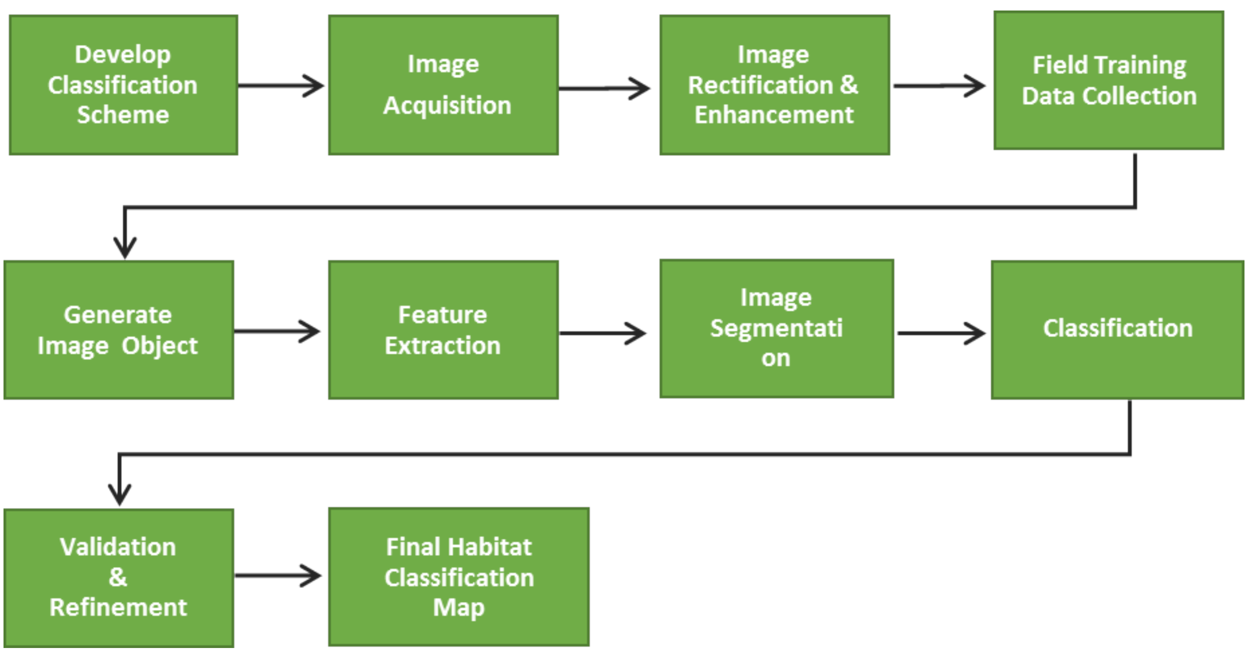


Figure 5. Classification Workflow.

OBJECT ORIENTED FEATURE EXTRACTION: ERDAS IMAGINE OBJECTIVE

We used Hexagon Geospatial's ERDAS Imagine Objective to develop an object-based image analysis model for classification and feature extraction. The IMAGINE Objective extension provides a step-wise modelling environment for object-oriented classification. The object-oriented approach emulates human visual processing by analyzing the data, not just on a pixel-by-pixel basis, but also by looking at contiguous object-based measures such as shape, size, and texture. The modelling environment also includes vector processing operators that produce polygon data, which allowed us to directly export results to ESRI ArcGIS with minimal processing.

Feature Models formed the basis for the extraction with the following series of "Process nodes." It is worth noting that the Objective extension has additional and alternative process nodes, however, our feature extraction methodology only included the following steps:

1) Raster Pixel Processor (RPP):

We used Single Feature Probability (SFP) to perform pixel based classification. SFP is a pixel cue that computes a probability metric (a number between 0 and 1) for each pixel of the input image based on its likeness to the training samples. The features to be extracted (e.g. forest) were selected by the user as training samples; and based on the pixel values of the training samples, the SFP cue assigned probability values to each pixel. Higher probability values were assigned to those pixels whose values were similar to ones of pixels in the training samples. Lower probability values were assigned to pixels whose values were significantly different from the values of pixels in the training samples.

The training samples were carefully selected and care was taken to not include any background pixels (i.e. pixels other than the pixels that are similar to the training pixels are considered background pixels). Our image analysts used their interpretation skills to select sample areas for training. Sample size was limited to 512 x 512 pixels each. In all, we collected over 1,500 training samples for each major classification group - all the way to the sub-class level of the classification scheme.

During the training phase, candidate samples for the subject class were submitted to IMAGINE Objective for statistical analysis. Then, based on the pixel cue, each pixel was evaluated to measure how closely they resembled the training pixels. The output of this step was a pixel probability layer in which each pixel value represented the probability that it was the in the class of interest. The values were represented as a normalized percentage from 0 - 1.

Figure 6 on the next page is a snapshot of the raster pixel probability for agriculture habitat class in Baldwin County. In this greyscale image, brighter pixels have higher probability values (i.e., there is greater certainty that the pixel belongs to the target Agriculture land class) while darker pixels have lower probability values.

Figure 6. Snapshot of the raster pixel probability (RPP) for agriculture lands in Baldwin County.

2) Raster Object Creators (ROC):

The Raster Object Creator is used to identify and group contiguous segments of pixels with similar characteristics. Radiance selected the Lambda Schedule Segmentation process. With Lambda Schedule Segmentation, the Pixel Probability Layer input is used to compute the pixel probability zonal mean of each segment. Then, the zonal mean is used as the value of the segment's Pixel Probability attribute. Lambda Schedule is valuable because it is a bottom-up merging algorithm. It also considers spectral content, as well as the segment's texture, size, and shape for merging decisions. Furthermore, it provides some control over the pixel-segment ratio, as well as minimum and maximum segment size constraints.

Pixels that are spatially connected and have similar probability values are grouped in a single segment. This step performs segmentation on the raster image specified and outputs a Raster Object Layer. Output from the Raster Objects Operator contains pixels that are grouped as raster objects and have the associated pixel probability zonal mean as a single common attribute. The user can govern some characteristics of the raster objects such as minimum, maximum, and average size as well as the influence that size, shape, and texture of the objects plays in the merging pixel decisions. For each segmentation process, experimentation was evaluated to determine ideal characteristics for the land cover type.

Image segmentation classification employs properties of both spectral value classification and photo-interpretation elements such as texture, size, and shape for merging decisions. The object-oriented approach, or OBIA, partitions raster images into segments based on similarity in pixel spectral values and location clustering. Pixels that are spatially connected and have similar values are grouped in a single segment. Image segmentation performs segmentations on the image using edge detection. This method segments the image pixels into objects and utilizes the texture information of the object rather than using only spectral information relied upon by pixel-based methods.

3) Raster Object Operators (ROO):

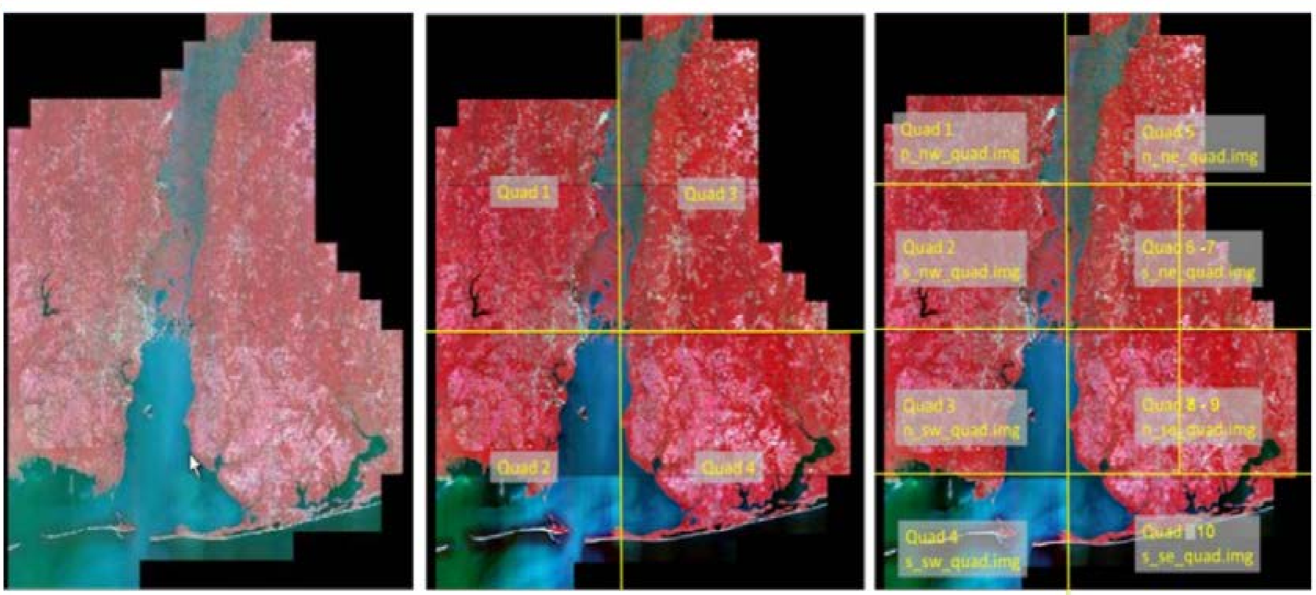
We utilized raster object operators such as "Probability Filter" to create thresholds that segments must meet to be considered part of the class being evaluated. Size Filters also helped to minimize segments that were not large enough to be considered relevant for final classification. In general, we only accepted candidate segments that met a .85 probability per target class. Figure 7 shows the raster objects (colored purple) that have been filtered based on probability thresholding. The objects overlay the same RPP image from step 1.

Figure 7. Snapshot of raster objects (purple) overlaying the RPP

4) Raster to Vector Conversion (RVC):

The primary challenge with the use of IMAGINE Objective is the inability of the software extension to utilize system resources beyond that of a typical desktop computer. Objective only runs in a single thread so adding CPUs to a machine running an Objective model does not increase performance. Moreover, most Objective algorithms are implemented in such a way that their memory usage is not optimized to use more available RAM on the computer and instead in a way that they can be run successfully on a computer which meets the minimum computer specification requirement, so more memory does not improve Objective performance either.

Hexagon Erdas software engineers had not conducted extensive testing with Objective models running on image files of the size that were collected for this project prior to releasing the software for public purchase. Our team found that the optimum image file size for Objective processes (specifically the segmentation step) is between 5 – 10 GBs. The MBNEP study area was greater than 100GB in total and crashed the software each time a process was executed on the entire image file. Therefore, we were forced to divide the imagery into 10 regions to accommodate the software's processing deficiencies (Figure 8A-C). While this was handled easily enough, it required 10 different model executions to capture a single class across the entire study area. Statistical characteristics for the training data are computed for all the samples, regardless of input image, so there were not issues with regional differences but the schedule impact was significant. This, however, resulted in longer processing times and a more complicated workflow, resulting in the project getting behind schedule (i.e. The classification process had to run 10 times across 10 quads, instead of running it once across one entire image).



A. Original Image (~65GB) (Too large to process)

B. Subset into 4 quads (~17 GB) (Still too large to process)`

C. Subset into 10 quads (~6 GB) (Sufficient size to process)

Figure 8. Imagery subset to an acceptable processing size for ERDAS objective classification.

While there are parameters whose relative weights can be adjusted in the Lambda Schedule Segmentation process, the segment borders cannot be directly influenced. Those decisions are driven exclusively by the algorithms. The Segmentation routine will occasionally create segments that overlap an obvious boundary between unique land classes. Where obvious and practical, we have manually edited the output polygons and changed the classification to appropriately attribute a distinct area. However, this is one area of inaccuracy that is inherent in an object-oriented classification. On the positive side, the non-spectral characteristics often led to precise segment boundary decisions.

Many of the same uncertainties that exist with traditional supervised classification methodologies apply to object-oriented classifications, as well. Namely, there will always be some degree of confusion between spectrally similar land classes. For example, we noticed initial confusion between Evergreen Forest and Evergreen Scrub/Shrub classes and between Range-Pasture and Agriculture classes.

WETLANDS DEFINITION AND WATER REGIME MODIFIERS

Spectral and object-based cues existed for delineating the wetland areas and segregating them from uplands. However, initial trials to perform this routine as an exclusive function for wetland definition had a poor overall performance. Therefore, we used a set of geoprocessing functions to define the wetland areas. These models provided the additional benefit of informing the classification water regime modifiers.

Without current soils data which may have contributed to the wetland definition model (note: the concurrent soil assessment project data was not available during habitat classification), wetness indices were viewed as a valuable alternative. We generated a number of band-ratio and elevation derived products to assist in the definition of wetland areas. Normalized Difference Vegetation Index (NDVI) and Normalized Difference Wetness Index (NDWI) were computed across the study area and served to inform areas where water may be present yet not visible through vegetative canopy. NDWI, especially, provides insight into the water content of vegetation indicating areas of more abundant soil moisture.
We also used elevation-derived products to identify low-lying areas and hydrologic drainage patterns. Most notably, we generated a Topographic Wetness Index (TWI), which can be a good indicator of soil conditions. It is derived by calculating a slope raster, the upslope contributing area, and other geometric functions. Flow accumulation numbers in flat areas, such as the Mobile Bay region, are known to be quite large, and therefore, TWI is not as useful in these environments. Out team found TWI to be informative but it did not have the utility that we had hoped for several reasons. First, the most readily available elevation data that covers the entire study area were USGS 10m Digital Elevation Model (DEM) raster scenes. The scenes over Mobile Bay had defects that made some areas incalculable. In addition, the spatial resolution of these products was much coarser than the 1m imagery collected for the project. Therefore, the precision these elevation derived datasets provided did not adequately meet the standard of this effort. Our project team also focused on National Hydrography Datasets (NHD) published by USGS. These datasets are the most up-to-date and detailed hydrography dataset for the nation. Proximity to the stream network was considered as part of the overall wetland definition model.

Once we had defined potential wetland areas through band-ratios, elevation-derived wetness products, and proximity to known hydrologic features, we used an object-oriented segmentation approach to detecting differences in the land cover. This approach worked quite well in delineating landscape changes indicative of seasonally flooded, semi-permanently flooded, and saturated areas. However, in some areas, there was too much ambiguity or land cover changes were too subtle to discern the boundary between wetland and upland areas. This was especially true for discriminating upland forested areas from temporarily flooded forested wetlands. Where the model had difficulty with delineating a wetland extent, we consulted ancillary sources such as the National Wetlands Inventory boundaries.

Once our wetland areas were defined, we again computed NDVI and NDWI zonal means to make determinations of water regime modifiers. This method worked well in areas with evergreen vegetation cover (Forested or Scrub/Shrub) or wetland classes without vegetative canopy (Emergent or Aquatic Bed). In areas of dense deciduous cover, more traditional image interpretation methods were used to apply a water regime modifier. Special modifiers were added based solely on image interpretation methods.

PIXEL BASED CLASSIFICATION

In addition to conducting an object-oriented classification, we also conducted a “traditional” pixel-based classification approach. The intent was to use the pixel-based classification in areas where confusion existed with the object-based approach and reduce uncertainty.

Pixel-based classification relies on the spectral reflectance values of individual pixels in an image to discriminate different classes. This frequently used technique has the capability to detect fine-level differences in reflectance values and is a commonly used technique. Although the acquired image data for this project has a high spatial resolution (1 m/pixel), the spectral limitations (4 bands) were anticipated to diminish the effectiveness of pixel-based classification. More importantly, many of the classes mapped are based on the context in which a pixel is found, such as pixels, representing trees found in the various urban and forest classes. Context is an important element of object-oriented classification; but is completely omitted from pixel-based classifications.

Various supervised pixel-based classifications were performed, with once class always dominating a resulting classification. Two improvements to the classification approach were made by including multiple related classes for each desired end class (such as urban-concrete, urban-asphalt, etc.) and by adding an NDVI as a layer in the classification. However, the spectral similarity of some features, such as sand and concrete, and the large measured spectral range of other features, such as water, precluded obtaining a desirable result from the pixel-based classification approach (Figure 9).

On the other hand, the object-oriented approach involved the segmentation of image data into objects at multiple scale levels. Objects were assigned class rules using spectral signatures, shape and contextual relationships. The rules were then used as a basis for the classification of the imagery. The supervised pixel-based classification involved the selection of training areas and a classification using maximum likelihood algorithm. Accuracy assessments of both classifications were undertaken, and a comparison of the results showed better overall accuracy of the object-oriented classification over the pixel-based classification. Because the object-based classification showed better results for classifying high resolution imagery than the pixel-based methods, we chose not to incorporate the results of the pixel-based classification.

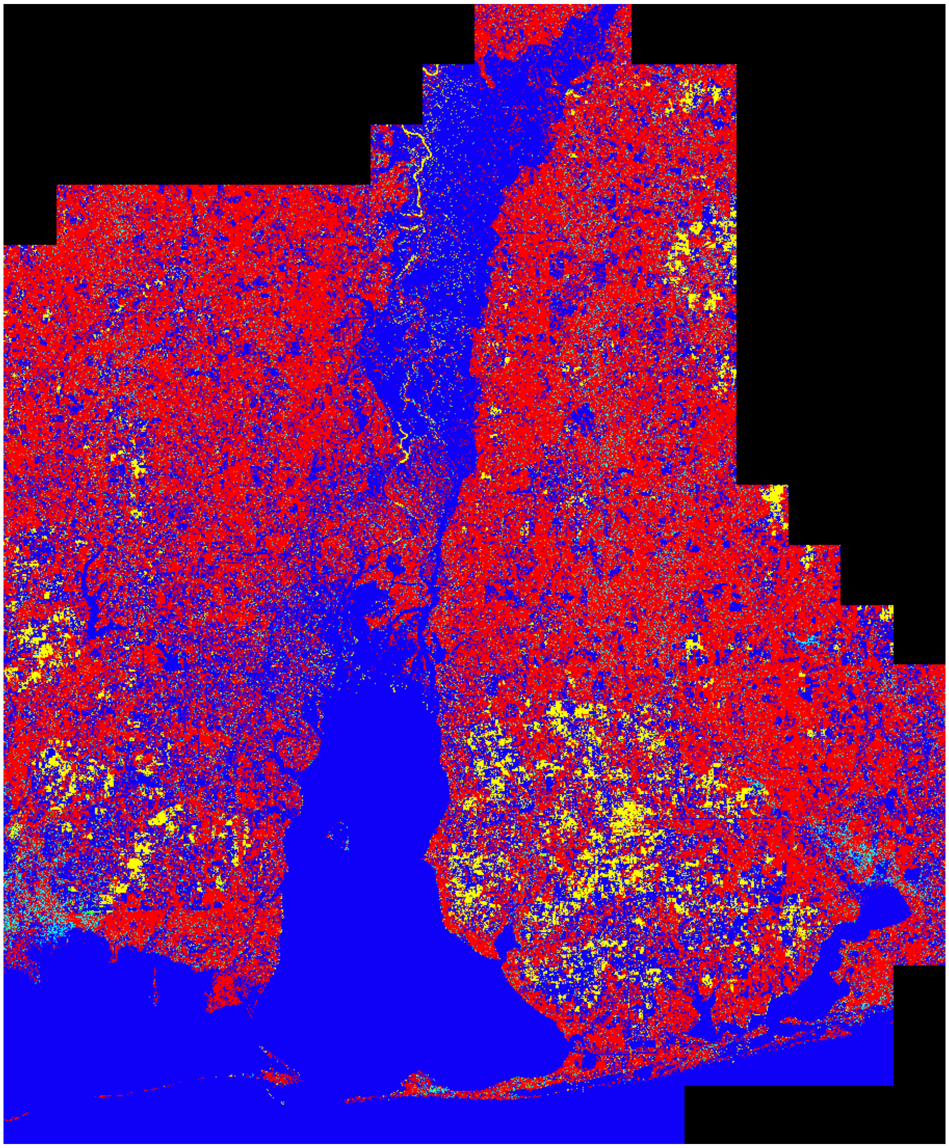


Figure 8. Example of pixel-based classification results.

NORMALIZED DIFFERENCE VEGETATIVE INDEX (NDVI)

When using ERDAS Imagine Objective's object-oriented feature extraction models (outlined previously), our team recognized a limitation when classifying open water. Segmentation is intended to group similar pixels and the size of these segments are influenced by user defined minimums, maximums and averages. However, the tidally influenced estuarine areas, such as those shown in Figure 7, as well as shallow inland water bodies presented challenges to the segmentation routines. With intricate channels and meandering water, the segmentation tended to "over group," leading to segments with dissimilar classes. If we reduced the segment size, the number of overall segments ballooned and became unmanageable from a processing perspective. These issues were compounded in shallow water areas where the bottom is visible or suspended sediment can confuse the classifier. Therefore, we also used a Normalized Difference Vegetative Index (NDVI) across the study area to define areas of where water exists.

NDVI is a commonly used remote sending technique often applied to enhance the detection of live/healthy vegetation. NDVI is calculated by deriving a ratio between the red and near infrared spectral bands:

$$\mathrm{NDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{red}}}{R_{\mathrm{NIR}} + R_{\mathrm{red}}}$$

Where red and NIR stand for the spectral reflectance measurements acquired in the red (visible) and near-infrared regions, respectively. Free standing water will have a rather low reflectance in both spectral bands and thus result in very low positive or even slightly negative NDVI values. These low values help to discriminate freestanding water from other classes and therefore presented a finer resolution water class than the segmentation process used for land classes (Figure 9).

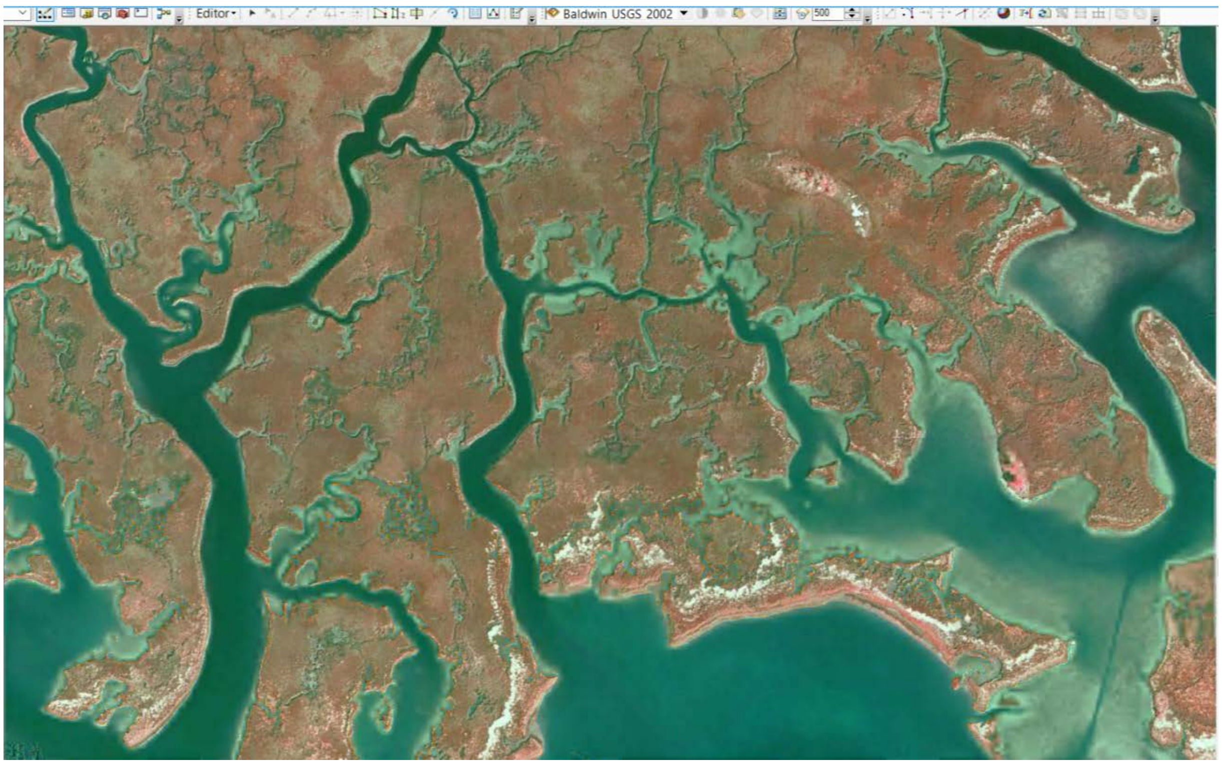


Figure 9. Estuarine environment with tidal creeks and embankments.

Figure 10. NDVI for comprehensive water classification.

HABITAT CLASSIFICATION TOOL

Classification of objects to the modifier level required manual interpretation with the assistance of ancillary data such as DEM derivatives and soils data, where available. Additionally, each habitat object needed to be attributed across the entire classification hierarchy and end up with a final classification code that represents each level in the hierarchy. To streamline the process of attribute entry, the Radiance Team developed the Habitat Classification Script (HCS) to populate polygon attributes in an automated fashion (Figure 12). Attribute selections developed to mirror the Cowardin and upland classification schemes and enforce logic rules specific to the scheme. The primary requirement of the HCS was to ensure the highest level of accuracy attainable for polygon classification within the ArcMap environment. Second to accuracy, the script was likewise intended to optimize specialist workflow wherever possible.

1) Accuracy Standard

To ensure classification accuracy, the HCS served as a medium between the specialist and the database, which held the final classification data. The HCS allowed the specialist to construct the classification for an individual polygon or groups of polygons incrementally, beginning with the System level classification and proceeding hierarchically to the bottommost Modifier level. At each stage of classification construction, HCS allowed the specialist to append more nuanced classification levels with the restriction that all additions must strictly adhere to the Cowardin *et al.*, 1979 Wetlands Classification and Deepwater Habitats of the United States schema. These standards were re-enforced recursively upon every change to a classification that was being constructed, providing a cascading safeguard that staved errors, which may have been made with manual, human entry.

In addition to cascading standard reinforcement, HCS was programmed to automatically populate the habitat code corresponding to each classification level for every possible valid classification. This allowed for significant time reduction on part of the specialist and ensured both consistency and accuracy in the final dataset, going so far as to ensure that the ordering of habitat codes at the modifier level would remain consistent for any third party wishing to manipulate this data in the future.

The preceding accuracy assurance features were implemented by default and could not be disabled or circumvented. In addition to these features, HCS implemented auxiliary, user-controlled features that contributed to the overall accuracy standard. These features included safeguards against writing empty fields, or “None” values to the database, an option to ensure classifications were completed to the modifier level, options which guarded the capability to classify all polygons in a shapefile with a single command, and a descriptive system that managed error logging and warnings.

2) Work-flow Optimization

HCS directly integrated with the ArcMap environment using Esri’s ArcPy library. Through this interface, HCS was able to directly acquire data from ArcMap, responding to real-time shapefile and feature class manipulations made by the ArcMap user. This data was queried, analyzed, and verified by the HCS to ensure Cowardin *et al* 1979 conformance and to employ the configuration system, neither of which could be achieved with ArcMap alone. After the proper manipulations had taken place, HCS was then able to re-integrate with ArcMap to write the classification information to the final database and expose the changes to the ArcMap session. In this way, the user was able to seamlessly use the facilities of ArcMap, with project-specific features tailored for this project.

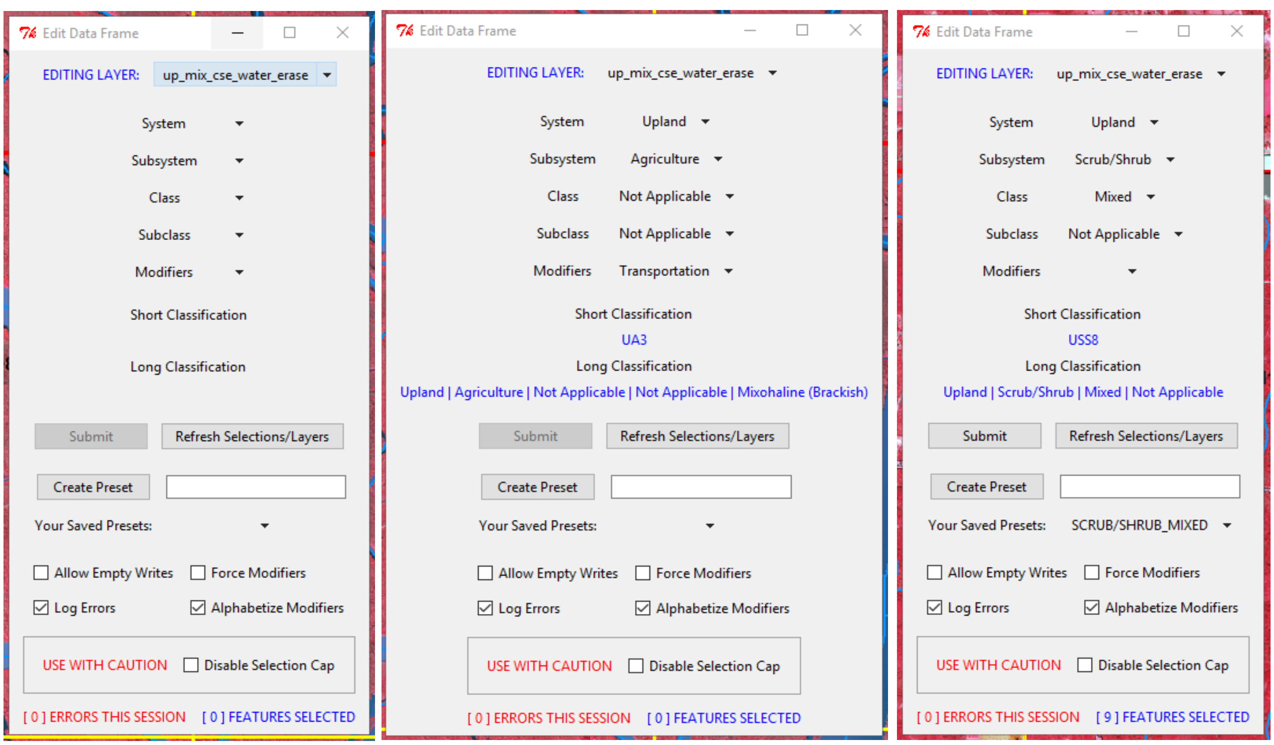


FIGURE 11. Habitat classification script GUI.

HCS was designed with a per-user configuration system, which could store popular classifications that the user chose to save for future implementation with a single click, as well as the capability to recall which auxiliary accuracy assurance features and layers a user had enabled the last time the script was used. Other workflow enhancements included window layering with ArcMap that made the script available to the user during simultaneous ArcMap sessions, the ability to share window focus with ArcMap in order to switch between applications without the need to restart the script after every classification, and auto-population of short and long-name habitat classification.

Two classification schemes were used in this study: (a) A simple wetland versus upland discrimination, (b) Wetlands classified to the Cowardin class level (Cowardin et al., 1974). ***The habitat classes were to be labeled according to a hierarchical classification scheme using a combination of Anderson (1976) and Cowardin (1979) classification systems.*** The Cowardin scheme was used for all wetland features and included classifications for System, Class, Subclass, and water regime modifiers. All wetland features were identified at the feature level to 98% accuracy and a minimum of 85% accuracy at the attribute level with a Targeted Mapping Unit of 0.5 acres, as stated by the FGDC Wetland Mapping Standard. The feature level refers to the broad identification of wetland vs upland. Attribute accuracy refers to thematic information associated with each mapped feature. A map of the final habitat classifications is shown on the following page in Figure 13.

ACCURACY ASSESSMENT

Once the final compiled geodatabase of vector-based features began to take shape, we conducted an accuracy assessment of the classification. We performed this assessment with ESRI's ArcGIS platform. ArcGIS has a set of tools for performing accuracy assessments of feature data whereas other software systems such as ERDAS IMAGINE only allow for classification of thematic raster data.

We utilized an ArcGIS tool suite (Spatial Analyst > Classification and Segmentation) that created a random set of points across the study area, allowed us to 'ground truth' those points, and compared them to the classification at each area. We chose a stratified random sampling strategy that generates a set of points that is randomly distributed throughout each class, where each class has a number of points proportional to its relative areas. We began by generating 700 random points. We also appended an additional 300 points that validated by the field surveys conducted in 2016. This field survey data was not used as training samples for the classifiers so it served well as confirmed control data for the accuracy assessment. That yielded 1000 points of ground truth to compare to the classification. Upon review, we decided to remove approximately 100 points for various reasons such as, the feature where the field data was collected or control point or was placed was so small that it did not meet the one-half acre precision requirement, or the feature was ambiguous and could not be appropriately ground validated. We also eliminated 50 points within the Mobile Bay because the accuracy assessment was weighted too heavily on the water (due to relative area). The water classes such as Unconsolidated Bottom performed extremely well so the removal of so many points over open water was completely appropriate.

Classification errors occur when a feature belonging to one class is assigned to another class. *Errors of omission* (Producer's Accuracy) occur when a feature is left out of the class being evaluated; *errors of commission* (User's Accuracy) occur when a feature is incorrectly included in the category being evaluated. An error of omission in one category will be counted as an error in commission in another category.

After running the initial accuracy assessment, we identified a number of areas where the classifiers had trouble discriminating between classes. We used this information to go back and revise the classifiers by providing additional training data or running separate classification models. Each time, we would generate new random accuracy assessment points. Ultimately, the classification improved to point that it met the accuracy tolerance set out for this project of 85% at the class level. The final accuracy assessment report is included as Figure 14. It should not be surprising that the greatest difficulty was discriminating between spectrally and textually similar classes. For example, Upland Range (only **47.62**% Producer's Accuracy) is often confused for Agriculture, and Scrub/Shrub (only **57.58**%

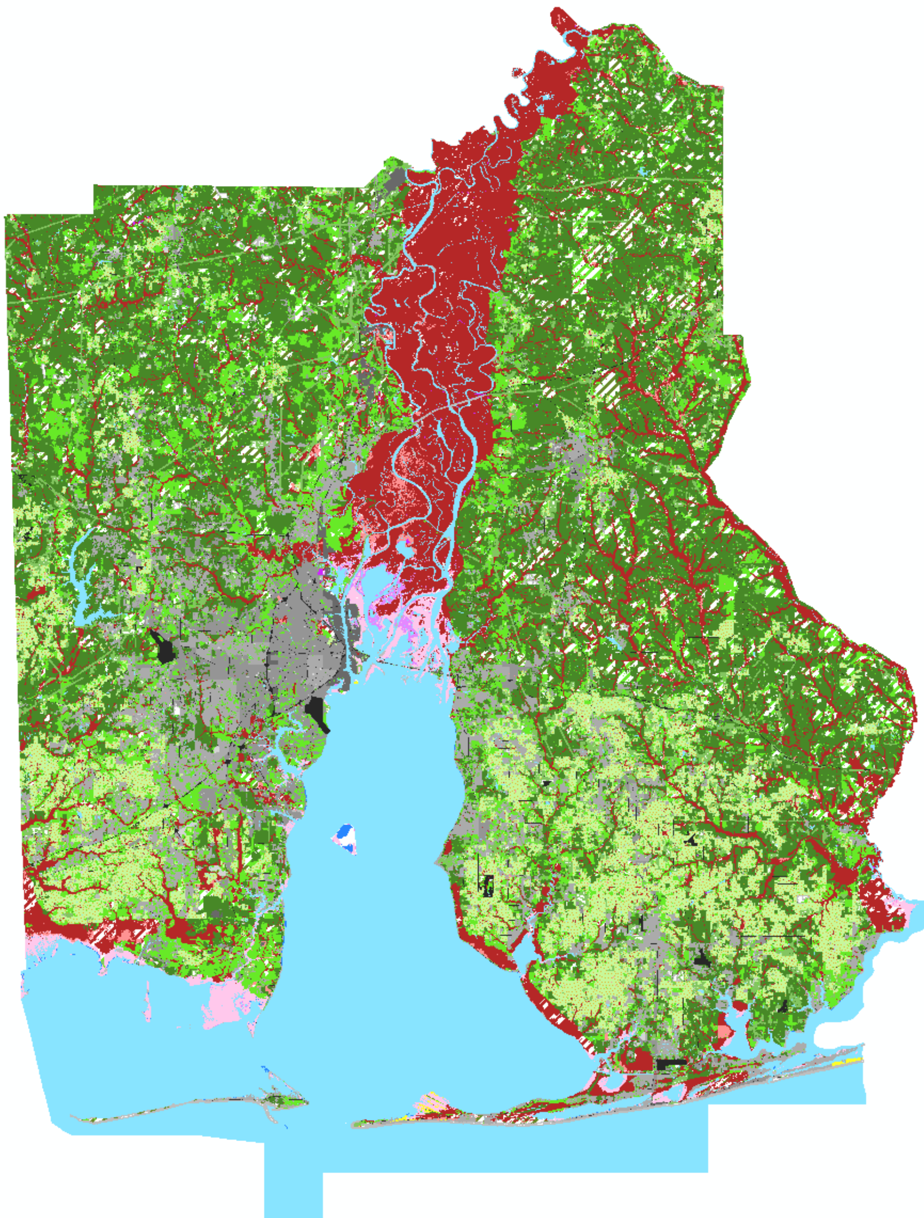


Figure 12. Final Habitat Classification Results for Baldwin and Mobile Counties, Al.

Producer's Accuracy) is often confused for Forest. These were the most error prone classes. Of notable success were exceptionally high accuracy rates of open water classes (Unconsolidated Bottom) and low rates of confusion between Wetland Forest and Upland Forest classes, which was anticipated beforehand. The final accuracy report generated an observed accuracy **89.86%.** The Kappa Coefficient was **88.55%.** The Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification. For example, the Kappa statistic cited here implies that the classification process is avoiding 88.55% of the errors that a completely random classification would generate.

DATA ORGANIZATION

The final upland/wetland habitat dataset was stored in an ESRI file geodatabase and included one integrated feature class. Upon project completion, the final geodatabase and associated reports were delivered to MBNEP Outreach Coordinator, Ms. Kelley Barfoot, on an external drive.

The final deliverables included following:

1. Digital copy of Final Report (.pdf)
2. Quantum Spatial's (QSI) Image Acquisition Final Report (.pdf)
3. Quantum Spatial's (QSI) Appendices (Flight Logs) (.pdf)
4. ESRI Geodatabase and associated metadata (.gdb)
5. Accuracy assessment points (feature class)
6. Accuracy assessment table (ESRI table)
7. 4-band imagery (original TIF images and MrSID mosaic)

KEYWORDS: wetlands; uplands; topographic; object based image analysis; segmentation, habitat classification, Cowardin; coastal restoration

Class	Estuarine | Subtidal | Unconsolidated Bottom	Estuarine | Intertidal | Aquatic Bed	Estuarine | Intertidal | Emergent	Estuarine | Intertidal | Scrub-Shrub	Estuarine | Intertidal | Unconsolidated Shore	Lacustrine | Limnetic | Aquatic Bed	Lacustrine | Limnetic | Unconsolidated Bottom	Lacustrine | Littoral| Aquatic Bed	Lacustrine | Littoral| Unconsolidated Bottom	Marine | Subtidal | Unconsolidated Bottom	Marine | Subtidal | Unconsolidated Shore	Palustrine | Aquatic Bed	Palustrine | Emergent	Palustrine | Forest	Palustrine | Scrub-Shrub	Palustrine | Unconsolidated Bottom	Palustrine | Unconsolidated Shore	Riverine | Tidal | Unconsolidated Bottom	Riverine | Lower Perennial | Unconsolidated Bottom	Riverine | Lower Perennial | Unconsolidated Shore	Upland | Agriculture	Upland | Barren	Upland | Forest	Upland | Range	Upland | Scrub-Shrub	Upland | Urban	Total	User's Accuracy	Kappa
Estuarine | Subtidal | Unconsolidated Bottom	73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	2	78	93.59%	0
Estuarine | Intertidal | Aquatic Bed	0	5	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	62.50%	0
Estuarine | Intertidal | Emergent	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	100.00%	0
Estuarine | Intertidal | Scrub-Shrub	0	0	1	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	90.91%	0
Estuarine | Intertidal | Unconsolidated Shore	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	100.00%	0
Lacustrine | Limnetic | Aquatic Bed	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	100.00%	0
Lacustrine | Limnetic | Unconsolidated Bottom	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	100.00%	0
Lacustrine | Littoral| Aquatic Bed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%	0
Lacustrine | Littoral| Unconsolidated Bottom	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	100.00%	0
Marine | Subtidal | Unconsolidated Bottom	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	100.00%	0
Marine | Subtidal | Unconsolidated Shore	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	100.00%	0
Palustrine | Aquatic Bed	0	0	0	0	0	0	0	1	0	0	0	16	2	0	0	0	0	0	0	0	0	0	0	0	0	0	19	84.21%	0
Palustrine | Emergent	1	0	0	0	0	0	0	0	0	0	0	1	21	1	0	0	0	0	0	0	0	0	0	0	0	0	24	87.50%	0
Palustrine | Forest	0	0	0	0	0	0	0	0	0	0	0	2	1	81	1	1	0	0	1	0	0	0	3	0	0	0	90	90.00%	0
Palustrine | Scrub-Shrub	0	0	0	0	0	0	0	1	0	0	0	0	0	1	8	0	0	0	0	0	0	0	0	0	0	0	10	80.00%	0
Palustrine | Unconsolidated Bottom	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0	0	0	35	97.14%	0
Palustrine | Unconsolidated Shore	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	100.00%	0
Riverine | Tidal | Unconsolidated Bottom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	15	100.00%	0
Riverine | Lower Perennial | Unconsolidated Bottom	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	15	100.00%	0
Riverine | Lower Perennial | Unconsolidated Shore	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2	100.00%	0
Riverine | Intermittent | Stream Bed	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	0	0	10	4	3	72	76.39%	0
Upland | Agriculture	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	27	0	0	0	0	29	93.10%	0
Upland | Barren	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	1	1	227	5	8	4	252	90.08%	0
Upland | Forest	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	20	1	1	24	83.33%	0
Upland | Scrub-Shrub	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	19	0	22	86.36%	0
Upland | Urban	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	2	1	5	1	78	90	86.67%	0
Total	75	5	27	10	10	7	16	2	14	23	8	19	25	90	10	36	2	15	19	2	57	31	231	42	33	88	897	0.00%	0
Producer's Accuracy	97.33%	100.00%	85.19%	100.00%	90.00%	100.00%	100.00%	0.00%	100.00%	100.00%	87.50%	84.21%	84.00%	90.00%	80.00%	94.44%	50.00%	100.00%	78.95%	100.00%	96.49%	87.10%	98.27%	47.62%	57.58%	88.64%		89.86%	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88.55%

FIGURE 13. ACCURACY ASSESSSMENT CONFUSION MATRIX