Remote Sensing and Mapping of Plant Communities for the Preservation of Natural Systems

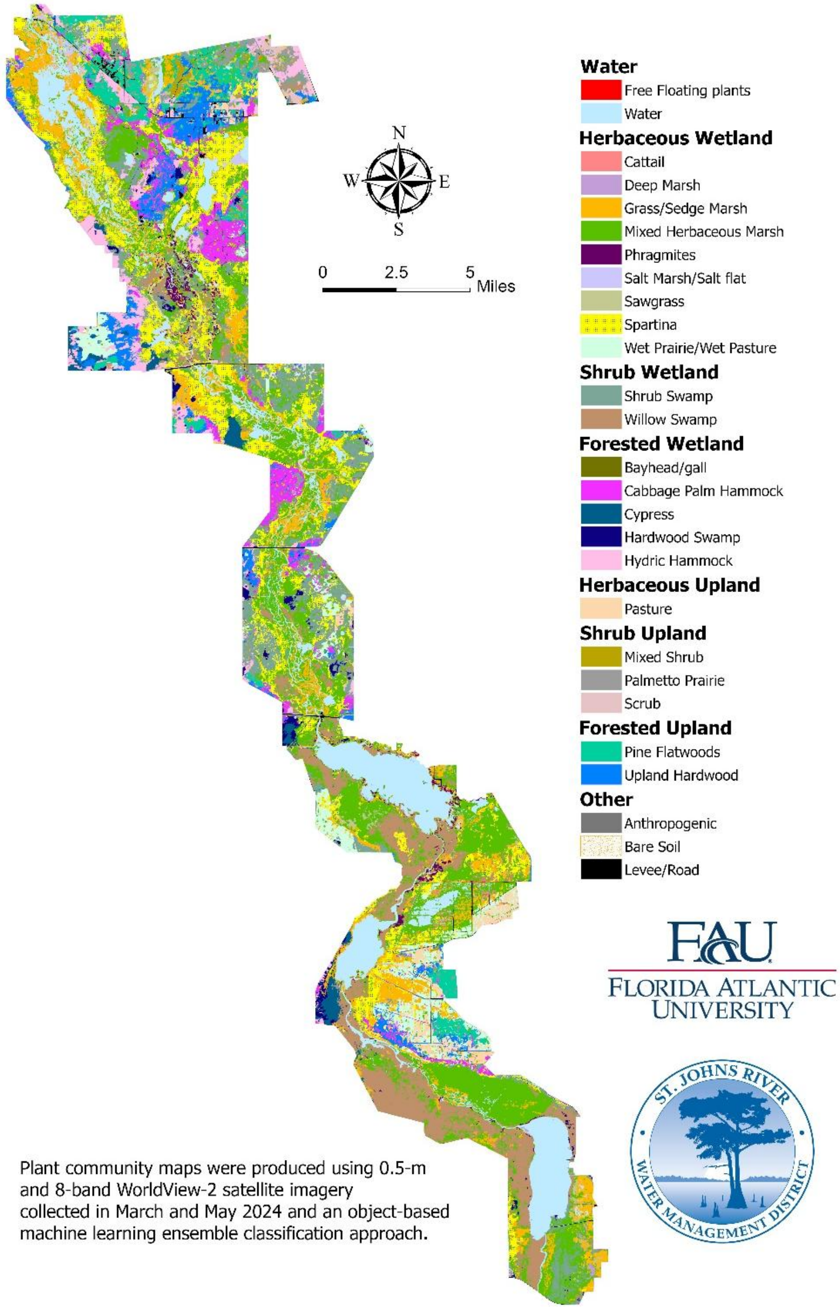
Year 3 (2024-2025) Report (Contract 38076)

Submitted to: St. Johns River Water Management District

Caiyun Zhang, PhD, Professor

Department of Geosciences, Florida Atlantic University

777 Glades Road, Boca Raton, FL 33431, Tel: 561-297-2648; czhang3@fau.edu



Map of wetland communities in 2024 with a coverage of 130,966 acres generated from an ensemble of machine learning classifications and WorldView-2 satellite imagery.

Contents

1. Project background

The St. Johns River Water Management District (District) manages more than 315,000 acres of wetlands which are mapped on a regular basis to monitor the response of natural systems to environmental changes and management activities. In the past, the District collected digital aerial imagery with four spectral bands (Red, Green, Blue, and Near-Infrared (NIR)) to generate maps through a manual interpretation procedure. It takes months to collect aerial imagery, including time spent on flight planning, sensor selection, and final aerial imagery generation and rectification. After the acquisition of aerial imagery, it takes several months to generate a map product through the manual interpretation procedure. This conventional vegetation mapping procedure is time-consuming and labor-intensive and can result in vegetation maps that are inaccurate due to the length of time between imagery acquisition and ground truthing of the mapped environments. Updating the map inventories is challenging due to the high cost and lengthy time of the mapping procedure over such a large area. The previous maps for the current project areas were generated approximately seven years ago.

Satellite remote sensing has been frequently cited as a cost-effective and labor-saving technique for monitoring and mapping wetlands. The operational WorldView-2/3 (WV-2/3) satellites are the most technologically advanced high-resolution optical sensors, collecting 46-centimeter (cm) panchromatic and 1.85-meter (m) multispectral imagery. WV-2/3 sensors have a comparable spatial resolution to aerial imagery, but they add four extra spectral bands: coastal, yellow, red edge and an additional NIR band to the traditional four (Red, Green, Blue, NIR) bands. The revisitation frequency of WV-2/3 (~2 days), in conjunction with their large spatial coverage, make spaceborne sensors more appealing for monitoring wetland response to changing environments than using airborne platforms, especially over large areas.

Contemporary machine learning-based digital imagery classification techniques have been widely used as an alternative to manual interpretation, which is more challenging when delineating natural landscapes because human-generated plant community boundaries are subjectively drawn. In contrast, computer-based digital classification methods are more objective in delineating boundaries based on imagery-based spectral signatures. Integrating the computer-based semi-automated/automated machine learning techniques with WV-2/3 satellite imagery can largely accelerate the wetland mapping process, making it more effective for informing decision making in wetland management than the traditional manual interpretation of aerial imagery.

The project Principal Investigator (PI), Dr. Caiyun Zhang, at Florida Atlantic University (FAU), has over 15 years of experience in satellite remote sensing and digital image analysis. We (Dr. Zhang's team at FAU) previously successfully completed a similar project for the District during 2020-2022 entitled "Development of Automated Methods for Using Satellite Imagery to Monitor Changes in Vegetative Communities" (Contract 35547-1) mapping plant communities over 55,955 acres including the Lake Apopka North Shore, Ocklawaha Prairie Restoration Area, Emerald Marsh Conservation Area, Moccasin Island Restoration Area, and Buck Lake Conservation Area. The developed methods were effective and efficient across these wetland areas. In this project year 3 (2024-2025) annual report, we include information on the data we received from the District, data we collected in the field, methods we used in generating year 3 map products, map products we created, new image interpretation keys, issues we encountered and how they were solved, and suggestions to the District to improve the mapping process.

2. Project areas and data

2.1 Project areas

In project year 3, we mapped five areas: Buck Lake Conservation Area (BLCA - 10,651 acres), Seminole Ranch Conservation Area (SRCA – 37,832 acres), Canaveral Marshes Conservation Area

(CMCA – 35,543 acres), River Lakes Conservation Area– RLCA-28,917 acres), and Moccasin Island Marsh Restoration Area (MIMRA – 14,023 acres). The location of these areas is displayed in Figure 1.

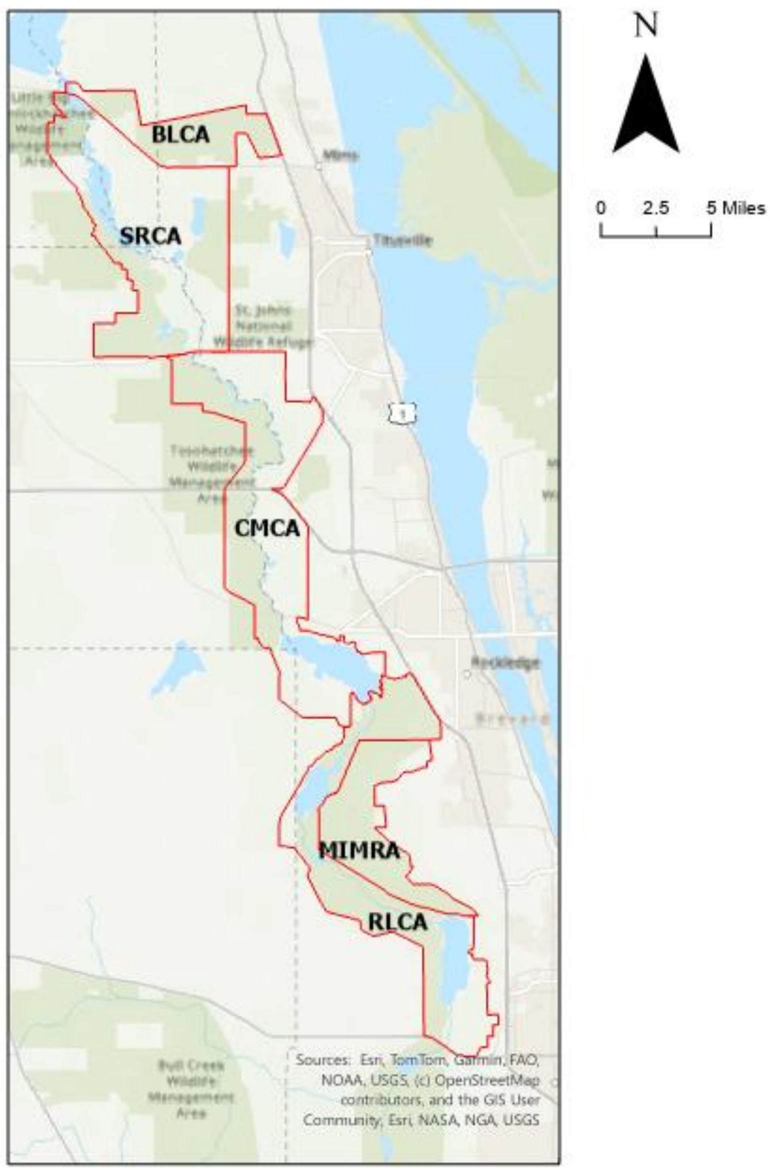


Figure 1 Location of project year 3.

2.2 Data provided by the District

The District delivered a hard drive with satellite imagery collected in March 2024 and May 2024 due to cloud patches on single scene. Other datasets used in this project year were delivered in 2022 including historical aerial photography collected in 2017, lidar Digital Elevation Models (DEMs), historical vegetation maps created in 2017 by manual interpretation of the aerial photography, road map data, project boundary, elevation contour maps, and a plant community cross walk file to document the modification of plant community names used in the historical maps and the current plant community classification system. These data were provided in different formats including ArcGIS vector Shapefile, raster data (TIF), ArcGIS lpk (map package format), MS Word and Excel. In total, over 200 GB of satellite imagery data were received from the District during this period including 16-bit, 8-band, 0.5-m WV-2/3 imagery product and mosaic of 8-bit, 4-band, 0.5-m imagery product. Images collected on March 24, 29 and May 16, 2024, were merged for mapping the entire project area to patch cloud cover.

2.3 Newly collected data

To teach a machine learning model to classify different plant communities, training samples from each community are required. This process in remote sensing is known as supervised learning. Training samples can be collected from visual interpretation of high-resolution imagery, as well as from field visits. We combined both methods for training sample collection in this project. These samples are used to develop spectral signature keys in the classification. The samples can be split into training samples and testing samples to calibrate and then validate the mapping models in the project. The plant communities, corresponding community type, and abbreviations that we mapped for are listed in Table 1. Their definitions are provided in Appendix 1.

We made a detailed field plan, and collected training samples during 23-25 July 2024 with District personnel, including Dr. Dianne Hall (Dr. Hall, Project Manager), Jodi Slater, Christy Akers, and Kimberli Ponzio. The group considered site accessibility by the District and FAU's truck, vegetation communities, and the logistics of planned field time schedule (time and cost budget). The District provided a 3-seat airboat with Environmental Scientists Christy Akers, Jodi Slater and Kimberli Ponzio as the driver each day. We did not collect drone data this year due to constraints from FAU and the State of Florida.

In total, we collected 2228 field points and took 378 pictures during the visit to document the signatures of each vegetation community appearing in project areas (Figure 2). Figures 3-7 show some of the field pictures, and Figures 8-12 are the pictures of the crew in the field.

Table 1 Plant community mapped in this project.

Plant Community	Abbreviation	Community Type	Abbreviation
Free Floating plants	FF	Water	W
Submerged Aquatic Beds	SAB	Water	W
Water	OW	Water	W
Cattail	CT	Herbaceous Wetland	HW
Deep Marsh	DM	Herbaceous Wetland	HW
Grass/Sedge Marsh	GS	Herbaceous Wetland	HW
Mixed Herbaceous Marsh	HM	Herbaceous Wetland	HW
Wet Prairie/Wet Pasture	WP	Herbaceous Wetland	HW
Spartina	SP	Herbaceous Wetland	HW
Sawgrass	SG	Herbaceous Wetland	HW
Salt Marsh/Salt flat	SM	Herbaceous Wetland	HW
Phragmites	PH	Herbaceous Wetland	HW
Shrub Swamp	SS	Shrub Wetland	SW
Willow Swamp	WS	Shrub Wetland	SW
Bayhead/gall	BG	Forested Wetland	FW
Cabbage Palm Hammock	CP	Forested Wetland	FW
Cypress	CY	Forested Wetland	FW
Forested Flatwood Depressions	FD	Forested Wetland	FW
Hydric Hammock	HH	Forested Wetland	FW
Hardwood Swamp	HS	Forested Wetland	FW
Dry Prairie	DP	Herbaceous Upland	HU
Pasture	PA	Herbaceous Upland	HU
Mixed Shrub	MS	Shrub Upland	SU
Scrub	SC	Shrub Upland	SU
Palmetto Prairie	PP	Shrub Upland	SU
Upland Hardwood	UH	Forested Upland	FU
Pine Flatwoods	PF	Forested Upland	FU
Pine Plantation	PI	Forested Upland	FU
Sandhill	SH	Forested Upland	FU
Anthropogenic	AN	Other	O
Bare Soil	BS	Other	O
Levee/Road	LR	Other	O

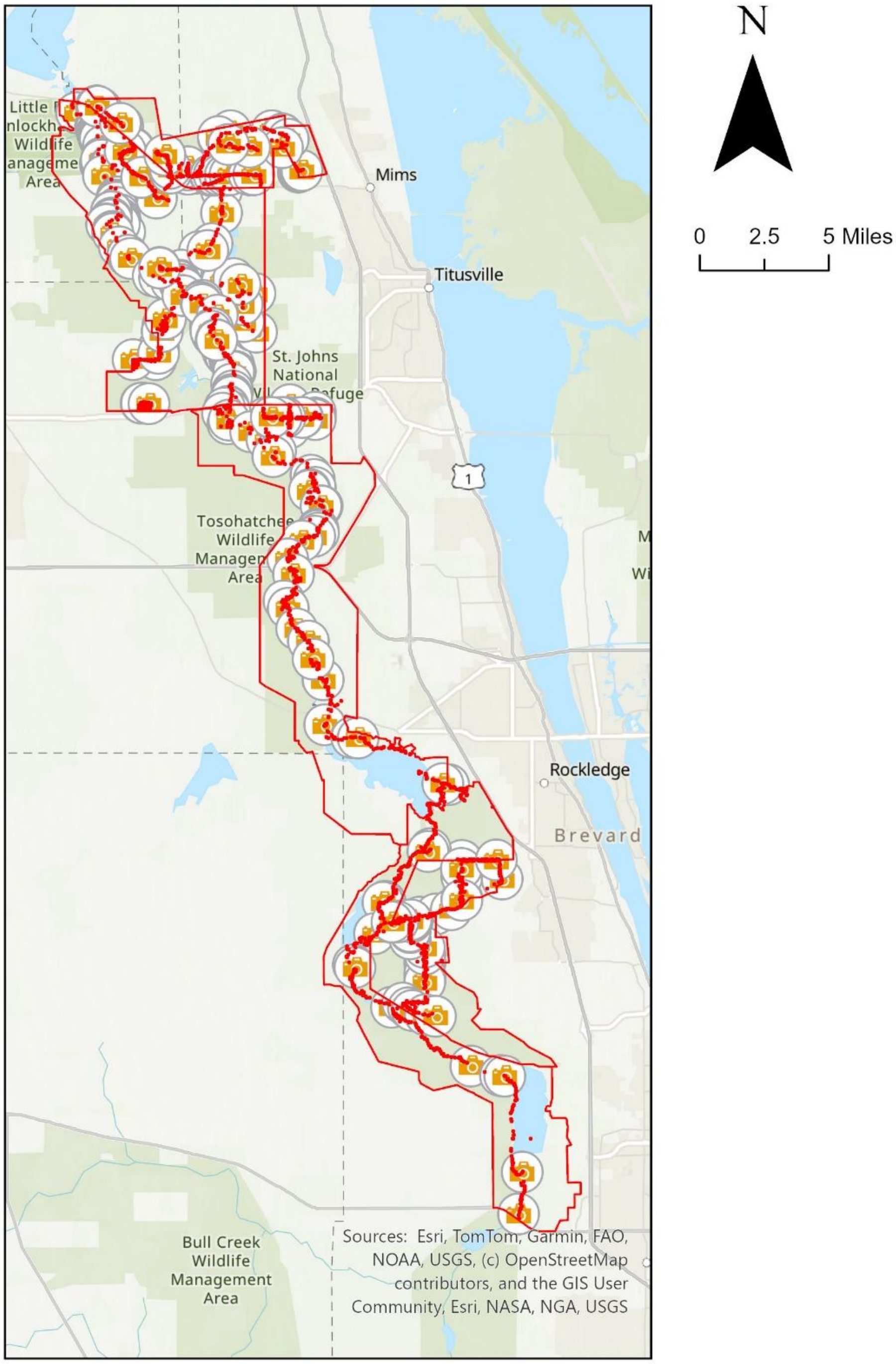


Figure 2 Field point data and pictures collected in project year 3 during July 23-25, 2024.

Figure 3 Mixed Herbaceous Marsh at BLCA.

Figure 4 Grass/sedge Marsh in front, and Upland Hardwood mixed with pines in the back at SRCA.

Figure 5 Mixed Herbaceous Marsh, Cattail, Willow, and Hydric Hammock at SRCA.


Figure 6 Spartina, Shrub Swamp, and Cabbage Palm at CMCA.


Figure 7 Wet Prairie/Pasture with Cabbage Palm in distance at MIMRA.

Figure 8 FAU students, Dr. Dianne Hall (Right) discussing safety on the airboat. Photo was taken by PI Zhang on 7/22/2024.

Figure 9 FAU student crew, Dr. Dianne Hall (left 2) and Environmental Scientist and airboat driver Jodi Slater (right 1) from the District in the field. Photo was taken by PI Zhang on 7/22/2024.

Figure 10 FAU students Fiona Benzi and Sandip Rijal, and Environmental Scientist and airboat driver Christy Akers (seated top) from the District in the field. Photo was taken by PI Zhang on 7/23/2024.

Figure 11 FAU crew with Environmental Scientist and airboat driver Kimberli Ponzio (standing top) from the District in the field. Photo was taken on 7/24/2024.

Figure 12 FAU crew and District manager Dr. Dianne Hall (left 3) in the Buck Lake Conservation Area. Photo was taken on 7/25/2024.

3. Methodology

3.1 Object-based machine learning ensemble classification

We have developed an object-based machine learning ensemble protocol to map wetland communities using satellite imagery and lidar Digital Elevation Models (DEMs) provided by the District. This approach proved effective and achieved high accuracy in mapping many diverse wetland vegetation communities in our first contract with the District. It combines modern machine learning, object-based image analysis (OBIA), and ensemble analysis techniques in the mapping procedure. Our previous studies have proven that object-based vegetation mapping is more effective and accurate than traditional pixel-based mapping methods in wetland environments, especially when high resolution imagery like WV-2 data is used, and application of an ensemble analysis which combines the outputs of multiple classifiers makes the final classification more robust (Zhang et al., 2016, 2018; Zhang and Xie, 2014; Zhang, 2014).

Multiple steps are required in the methodology. To conduct OBIA mapping, we first applied the multiresolution segmentation algorithm to the pansharpened WV-2 imagery products in eCognition 10 with the scale set to 150. After segmentation, we fused lidar DEM features including mean and standard deviation of elevation with image features to be used for classification. We spatially matched the ground-truth/reference data with the fused dataset, leading to a matched dataset for classification model development. Contemporary machine learning classifiers including Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) were selected and used to classify the matched dataset, and the classification results were assessed using error matrix techniques and the *k*-fold cross validation approach. SVM is a supervised classifier that aims to find a hyperplane that can separate the input dataset into a discrete predefined number of classes in a fashion consistent with the training samples. RF is a decision-tree-based ensemble classifier, and is a sophisticated machine learning model. ANN is an important technique in image classification that functions by simulating the method by which human brains recognize patterns. All of these classifiers have been widely applied in remote sensing classification with great success. However, each classifier has its pros and cons, and thus ensemble analysis is more valuable than the application of a single classifier to make the plant community classification more robust. We applied an ensemble approach to integrate the outputs of SVM, RF, and ANN for the final classification map generation. In the ensemble procedure, if a majority of the three classifiers determine the segment is the same plant community, then the segment will be assigned to that plant community. If none of the classifiers agree on the plant community for a segment, the segment will be assigned the plant community that has the highest individual accuracy among the three classifiers. We collected both field-based and imagery-based reference samples to train and test the classification models.

3.2 Split of project boundary

In year 3, the mapping area was much larger, and each project area needed to be split into multiple pieces to map. In addition, there were cloud patches within the images, which required the collection of images from different dates. To facilitate the mapping of such a large area, the entire project area was split into ten pieces, taking into consideration the original size of each individual project area and the location of cloud patches with the aim to constrain the total number of segments for each piece to less than 50,000.

3.3 Mapping anthropogenic areas and levees/roads

Both anthropogenic areas and levees/roads are challenging to classify using automated digital image analysis. Anthropogenic areas can include boat ramps, buildings, crops, cars, etc., while levees/roads can be dirt roads, paved roads, or grassed levees. This causes computer confusion due to the diversity of spectral signatures within these two classes and between these classes and the other plant community classes. For this year, we aligned the LR/AN polygons from the 2017 map and manually edited it on WV imagery. The wetland community map was erased for areas covered by levee/road or anthropogenic classes first and then merged with the levee/road and anthropogenic layers to generate the final map product. Therefore, the error matrix of each project area did not include these two classes.

3.4 Automation of map product generation

For this year, we implemented the entire machine learning and classification process using *R* script. In this way, the inputs and outputs are consistent in data format, and product attributes, making the process more efficient.

3.5 Post-classification refinement

The automated digital procedure generated encouraging results for delineating communities for each project area. However, misidentifications could appear for classes within a community type, which is the upper level of the plant community used by the District's classification system (Appendix 1). For example, within the Forest Wetland community type, Cypress (CY) can be confused with Hardwood

Swamp (HS), and within the Shrub Wetland community type, Shrub Swamp (SS) can be confused with Willow Swamp (WS) because their definitions are not mutually exclusive. Cypress trees occur in HS and willows occur in SS. The definition of the communities is dependent on the percent cover of cypress or willow, respectively, which is open to interpretation by the personnel selecting the training samples. To reduce the small, misclassified segments and by considering the Minimum Mapping Unit (MMU) for a project area, polygons with a size less than the the MMU were relabeled and merged with the neighboring polygon with the longest adjacent boundary. However, small water bodies were kept per District request.

The imagery collected in March or May often shows all vegetation as green, which made the classification of trees and shrubs difficult. To better refine the classification, the ArcGIS Pro base imagery or NAIP collected in winter can be helpful because the winter and summer imagery shows the phenology of trees and shrubs. Cypress, Hardwood Swamp, and Willow are deciduous and look grey in winter imagery on a natural color composite. Pairing a winter image with the collected WV can better identify these communities. The following keys are summarized if winter and summer high resolution images are paired:

- Upland Hardwood (UH) is at the highest elevation and has some Cabbage Palm (CP) but very few deciduous trees. Therefore, we shouldn't see many trees without leaves on both images. However, areas that are dominated by cabbage palms should be labeled CP.
- Hydric Hammock (HH) has some CP and lots of deciduous trees, so the winter imagery will have a grey cast. Also, we can see the tops of some of the deciduous trees in the canopy shown against the darker subcanopy.
- Cypress is dominated by cypress that look white, grey or brown and have fuzzy tops on the winter imagery. The fuzzy tops come from the cypress needles turning brown but remaining attached to the tree branches throughout the winter.
- Willows show up on the WV imagery taken at the end of March but don't show up on the winter imagery because they are deciduous and do not have their leaves on yet.

Another issue is the misclassification of shadows which often appear beside tall shrubs or forests. Because we did not include shadow in the classification system and it appears in fine resolution imagery such as WV-2 products used in the project, we need to correct these misclassifications. Shadows are often misclassified as water because they both appear dark on an image in a natural color composite. We manually assigned the shadows to shrubs or forests adjacent to them. Small patches such as shrubs that appeared in a big patch such as Upland Hardwood (UH) were suspected of being misclassified. By examining the historical map to gain the domain knowledge and the current imagery, these suspicious misclassifications were manually revised. ***The manual post-classification procedure is time consuming but necessary to improve the integrity of the map products. However, this refinement is not captured in the accuracy assessment error matrices. Consequently, the accuracy of the maps is greater than the error matrices indicate.***

4. Results

4.1 Three testing plots

As required in this project, the developed procedures need to be tested over selected plots to meet the accuracy requirement before going further to map the entire project area. The selected three 500-acre plots were within BLCA, CMCA, and one covering MIMRA and RLCA with a diverse plant community (in total of 19 communities). The mapping results are provided in Figure 13. In general, the mapping products, and accuracy was acceptable after discussions with Dr. Hall, but also raised concerns for some communities such as mixed herbaceous marsh (HM), CY, and grass/sedge (GS) for each individual testing area. This was mainly caused by the limited training samples in the selected areas, but the low accuracy of mixed herbaceous marsh in these test areas was mainly caused by the difficulties of the training sample selection on the imagery because of the overlap of species between different plant communities. The testing results also suggested the necessity of post-classification manual refinement. After refinement of each test plot, the maps were considered very accurate and were used to guide us during selection of additional training samples across the entire project area.

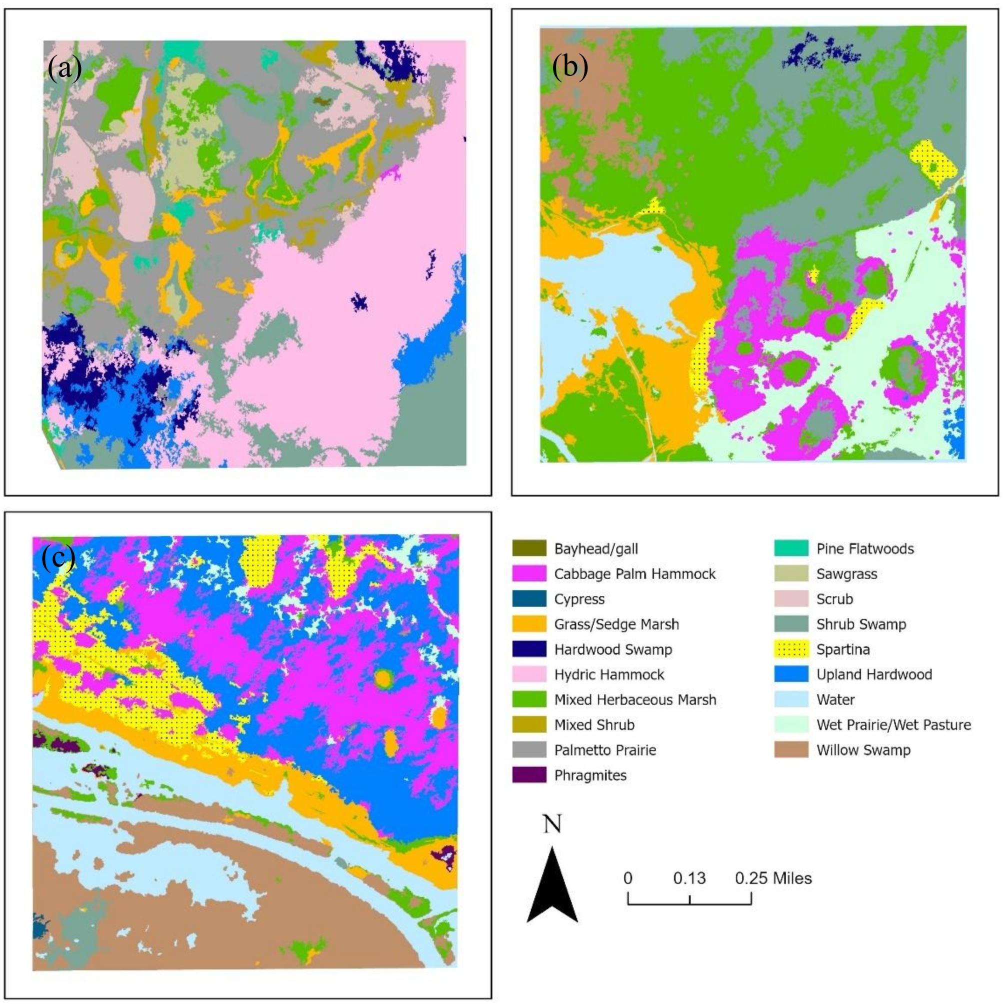


Figure 13 Maps of three 500-acre testing plots within (a) BLCA, (b) CMCA, and (c) between MIMRA and RLCA.

4.2 Machine classification accuracy

The project was split into 10 pieces labeled as BLCA1, BLCA2, SRCA1, SRCA2, SRCA3, CMCA1, CMCA2, CMCA3, South RLCA, and North RLCA_MIMRA. The error matrix for each piece from the machine learning model is displayed in Tables 2-11, and corresponding location is displayed as a screenshot in Figures 14-23. UA represents User's Accuracy, and PA represents Producer's Accuracy. The Overall Accuracy (OA) represents the total correctly classified segments, while Kappa measures how much better a classification is compared to pure chance and it adjusts OA by accounting for the probability of correct classification happening randomly.

An OA of over 80% was achieved for each piece except for BLCA1 which was mainly pulled down by a lower accuracy for HS because HS was confused with HH, as expected. With the keys developed for manual labeling HH and HS by switching the NAIP and WV imagery, the classification of two classes was improved after post-classification refinement. Similarly, WS was confused with SS, leading to a low accuracy because WS can be part of SS, and this was manually fixed by using the keys developed for identification of WS on WV imagery. CP was confused with UH in BLCA2, again which was fixed by using the new keys developed this year. In all the tables, individual accuracies lower than 0.7 were caused either by few training samples due to being scarce communities, similarities between short trees and tall shrubs, or the heterogeneity of an herbaceous community (e.g., grasses being a part of both Grass/Sedge Marsh and Mixed Herbaceous Marsh communities [Appendix 1]). These errors are discussed in detail in Section 5.

Table 2 Error matrix for BLCA1.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1		HM	GS	SP	SG	SM	HH	HS	CP	PP	WS	UH	PF	SS	OW	Column Total	UA
2	HM	65	12	4	2	1	0	0	1	9	1	0	0	0	0	95	0.684
3	GS	18	41	3	9	0	0	0	0	3	0	0	2	0	0	76	0.539
4	SP	3	6	56	2	0	0	0	0	0	0	0	0	0	0	67	0.836
5	SG	6	6	2	36	0	0	0	0	0	0	0	0	0	0	50	0.72
6	SM	0	0	0	0	33	0	0	0	0	0	0	0	0	0	33	1
7	HH	0	0	0	0	0	75	11	0	1	0	6	10	7	0	110	0.682
8	HS	1	0	0	0	0	32	14	1	0	1	6	1	3	0	59	0.237
9	CP	2	0	0	0	0	1	0	24	1	0	0	5	0	0	33	0.727
10	PP	0	1	0	0	0	1	0	0	145	0	0	0	0	0	147	0.986
11	WS	0	0	0	0	1	0	0	0	1	4	1	0	11	0	18	0.222
12	UH	0	0	0	0	0	14	6	0	1	0	51	14	1	0	87	0.586
13	PF	0	0	0	0	0	2	0	6	2	1	8	82	0	1	102	0.804
14	SS	1	0	0	0	0	4	4	1	3	2	1	0	38	0	54	0.704
15	OW	0	0	0	0	0	0	0	0	0	0	0	0	0	15	15	1
16	Row Total	96	66	65	49	35	129	35	33	166	9	73	114	60	16	946	
17	PA	0.677	0.621	0.862	0.735	0.943	0.581	0.4	0.727	0.873	0.444	0.699	0.719	0.633	0.938		
18	Overall Accuracy	0.718															
19	Kappa	0.688															

Figure 14 Location of BLCA1.

Table 3 Error matrix for BLCA2.

	HM	GS	CP	UH	PF	SS	PA	OW	Column Total	UA
HM	46	2	1	0	0	0	3	0	52	0.885
GS	2	19	1	0	0	0	4	0	26	0.731
CP	1	0	2	4	0	0	0	0	7	0.286
UH	1	1	0	56	1	0	0	0	59	0.949
PF	0	0	0	10	12	2	0	0	24	0.5
SS	0	0	0	5	3	4	0	0	12	0.333
PA	3	4	0	0	0	0	84	0	91	0.923
OW	0	0	0	0	0	0	1	8	9	0.889
Row Total	53	26	4	75	16	6	92	8	280	0
PA	0.868	0.731	0.5	0.747	0.75	0.667	0.913	1	0	0
Overall Accuracy	0.825	0	0	0	0	0	0	0	0	0
Kappa	0.777	0	0	0	0	0	0	0	0	0

Figure 15 Location of BLCA2.

Table 4 Error matrix for CMCA1.

	A	B	C	D	E	F	G	H	I	J	K	L
1		HM	GS	SP	HS	CP	UH	SS	WP	OW	Column Total	UA
2	HM	215	7	25	0	3	0	4	0	0	254	0.846
3	GS	27	158	23	0	0	0	0	5	0	213	0.742
4	SP	17	8	313	0	2	1	0	1	0	342	0.915
5	HS	0	0	0	54	12	6	8	0	0	80	0.675
6	CP	1	0	0	0	237	10	5	0	0	253	0.937
7	UH	1	0	0	1	35	120	10	0	0	167	0.719
8	SS	5	1	2	3	10	5	155	0	0	181	0.856
9	WP	5	8	2	0	0	0	0	46	0	61	0.754
10	OW	0	0	0	0	0	0	0	0	21	21	1
11	Row Total	271	182	365	58	299	142	182	52	21	1572	0
12	PA	0.793	0.868	0.858	0.931	0.793	0.845	0.852	0.885	1	0	0
13	Overall Accuracy	0.839	0	0	0	0	0	0	0	0	0	0
14	Kappa	0.81	0	0	0	0	0	0	0	0	0	0

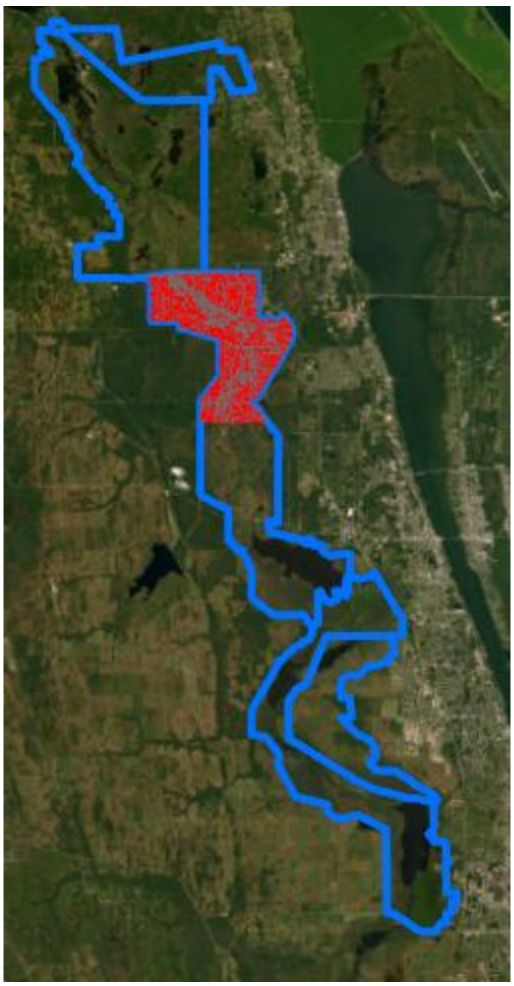


Figure 16 Location of CMCA1.

Table 5 Error matrix for CMCA2.

	HM	GS	SP	HS	UH	CP	SS	WS	WP	OW	Column Total	UA
HM	135	8	20	0	0	0	2	1	0	0	166	0.813
GS	8	104	2	0	0	0	0	0	0	0	114	0.912
SP	21	2	87	0	0	0	0	0	0	0	110	0.791
HS	0	0	0	80	1	0	6	1	0	0	88	0.909
UH	0	0	0	6	42	13	2	0	0	0	63	0.667
CP	2	0	0	2	10	64	6	0	0	0	84	0.762
SS	2	0	0	6	3	1	96	4	0	0	112	0.857
WS	0	0	0	1	0	0	2	39	0	0	42	0.929
WP	0	1	0	0	0	0	0	0	60	0	61	0.984
OW	0	0	0	0	0	0	0	0	0	11	11	1
Row Total	168	115	109	95	56	78	114	45	60	11	851	0
PA	0.804	0.904	0.798	0.842	0.75	0.821	0.842	0.867	1	1	0	0
Overall Accuracy	0.844	0	0	0	0	0	0	0	0	0	0	0
Kappa	0.822	0	0	0	0	0	0	0	0	0	0	0

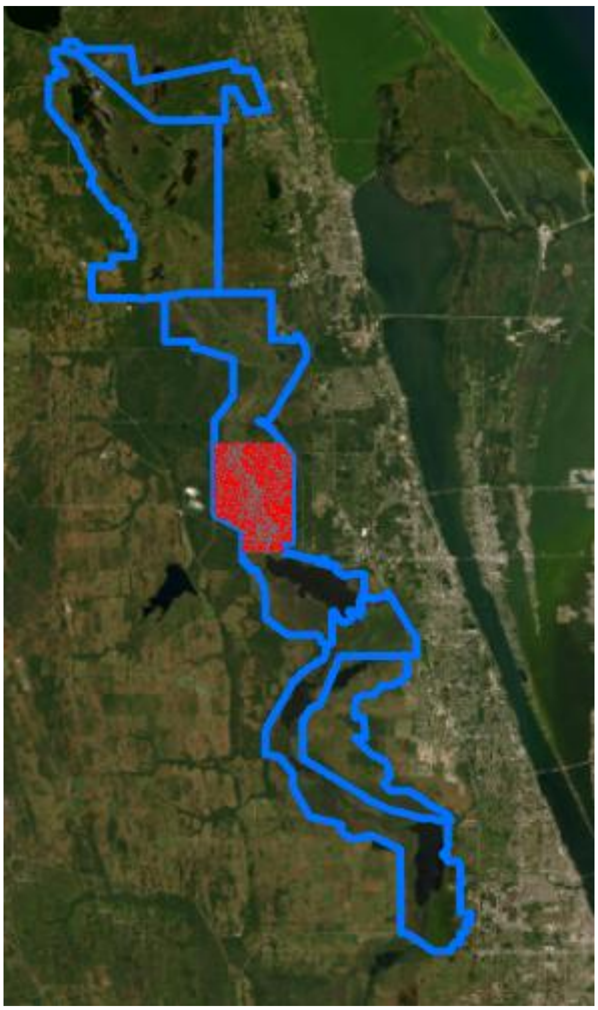


Figure 17 Location of CMCA2.

Table 6 Error matrix for CMCA3.

	A	B	C	D	E	F	G	H	I	J	K	L
1		HM	GS	SP	SG	WP	SS	WS	OW	PH	Column Total	UA
2	HM	235	1	5	12	1	1	0	0	1	256	0.918
3	GS	4	41	0	3	3	0	0	0	6	57	0.719
4	SP	4	0	71	0	1	0	0	0	1	77	0.922
5	SG	13	1	0	151	2	0	3	0	0	170	0.888
6	WP	2	1	1	0	127	0	0	0	1	132	0.962
7	SS	1	0	0	0	0	52	1	0	0	54	0.963
8	WS	1	0	0	0	0	0	157	0	0	158	0.994
9	OW	0	0	0	0	0	0	0	31	0	31	1
10	PH	4	8	2	1	0	0	1	0	45	61	0.738
11	Row Total	264	52	79	167	134	53	162	31	54	996	0
12	PA	0.89	0.788	0.899	0.904	0.948	0.981	0.969	1	0.833	0	0
13	Overall Accuracy	0.914	0	0	0	0	0	0	0	0	0	0
14	Kappa	0.898	0	0	0	0	0	0	0	0	0	0

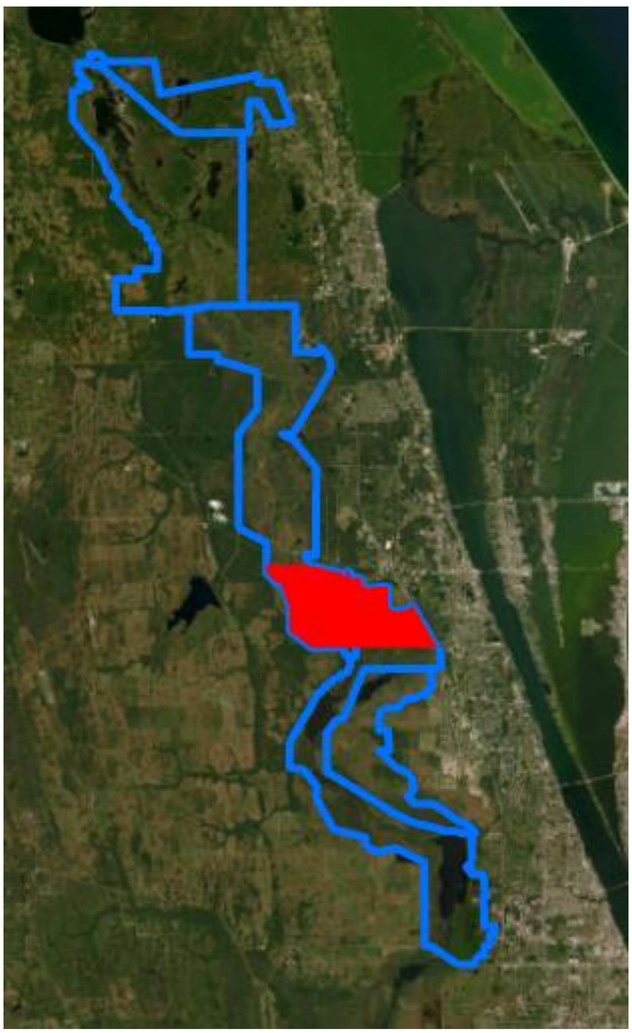


Figure 18 Location of CMCA3.

Table 7 Error matrix for SRCA1.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1		HM	GS	SP	SM	HS	CP	PP	UH	PF	OW	Column Total	UA
2	HM	174	0	12	0	0	0	0	0	0	1	187	0.93
3	GS	8	7	9	0	0	5	2	1	0	0	32	0.219
4	SP	6	1	190	0	0	0	0	0	0	0	197	0.964
5	SM	0	1	0	15	0	0	0	0	0	0	16	0.938
6	HS	0	0	0	0	27	2	0	23	0	0	52	0.519
7	CP	2	0	0	0	0	194	0	9	1	0	206	0.942
8	PP	0	0	0	0	0	1	17	0	0	0	18	0.944
9	UH	1	0	0	0	8	16	0	109	3	0	137	0.796
10	PF	0	0	0	0	1	2	1	3	62	0	69	0.899
11	OW	0	0	0	0	0	0	0	0	0	47	47	1
12	Row Total	191	9	211	15	36	220	20	145	66	48	961	0
13	PA	0.911	0.778	0.9	1	0.75	0.882	0.85	0.752	0.939	0.979	0	0
14	Overall Accuracy	0.876	0	0	0	0	0	0	0	0	0	0	0
15	Kappa	0.852	0	0	0	0	0	0	0	0	0	0	0

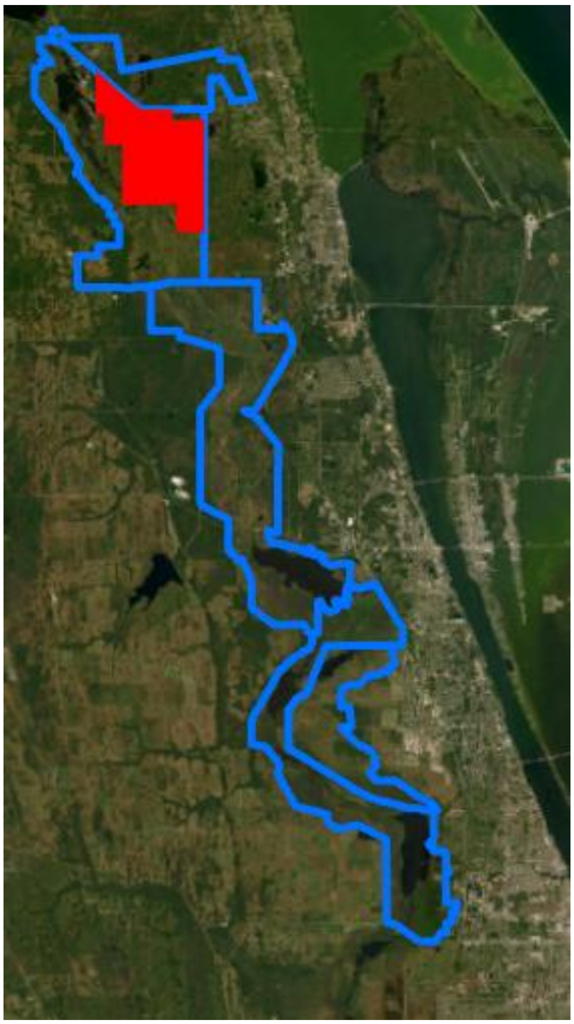


Figure 19 Location of SRCA1.

Table 8 Error matrix for SRCA2.

	HM	GS	SP	SM	HS	CP	UH	PF	SS	WS	OW	Column Total	UA
HM	67	8	5	0	0	0	0	0	0	0	0	80	0.838
GS	11	150	2	1	1	1	0	2	0	0	0	168	0.893
SP	3	1	307	0	0	0	0	0	0	0	0	311	0.987
SM	0	0	2	94	0	0	0	0	0	0	0	96	0.979
HS	0	0	0	1	46	1	1	1	0	1	0	51	0.902
CP	0	5	0	0	1	22	2	0	3	0	0	33	0.667
UH	0	0	0	0	4	1	19	0	0	0	0	24	0.792
PF	0	0	0	0	2	1	1	38	0	0	0	42	0.905
SS	0	1	0	0	1	2	0	1	42	0	0	47	0.894
WS	0	0	0	0	0	0	0	0	0	20	0	20	1
OW	0	0	0	0	0	0	0	0	0	0	27	27	1
Row Total	81	165	316	96	55	28	23	42	45	21	27	899	0
PA	0.827	0.909	0.972	0.979	0.836	0.786	0.826	0.905	0.933	0.952	1	0	0
Overall Accuracy	0.925	0	0	0	0	0	0	0	0	0	0	0	0
Kappa	0.908	0	0	0	0	0	0	0	0	0	0	0	0

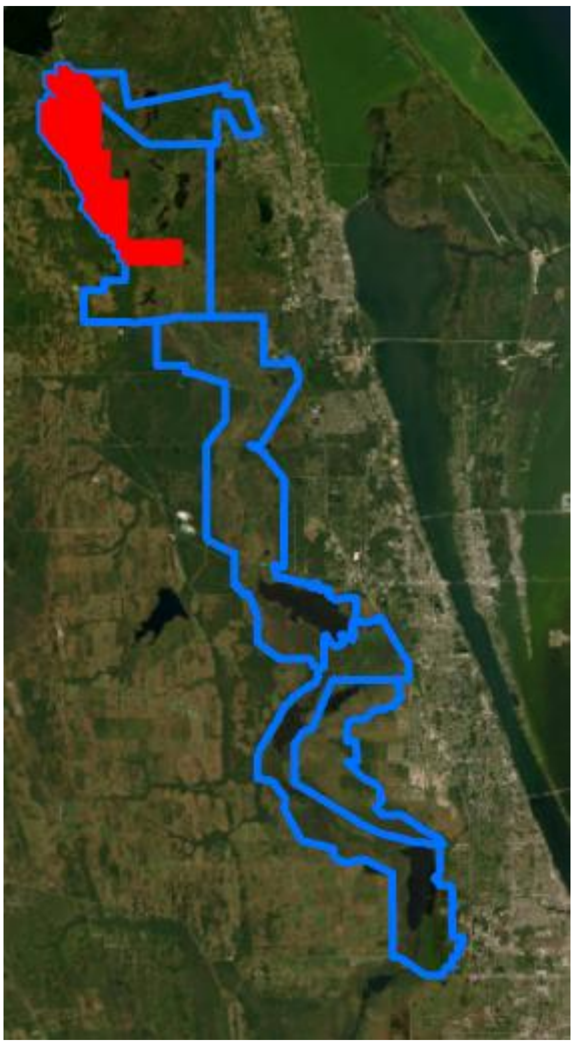


Figure 20 Location of SRCA2.

Table 9 Error matrix for SRCA3.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1		HM	GS	PA	SP	SS	WS	CY	HS	UH	OW	Column Total	UA
2	HM	51	0	0	6	1	1	2	0	0	1	62	0.823
3	GS	2	59	1	7	0	0	0	0	0	0	69	0.855
4	PA	0	0	72	0	0	0	0	0	0	0	72	1
5	SP	4	2	0	149	0	0	0	0	0	0	155	0.961
6	SS	1	0	0	1	43	0	1	4	6	0	56	0.768
7	WS	0	0	0	1	2	27	0	0	0	0	30	0.9
8	CY	0	0	0	0	0	1	69	4	0	0	74	0.932
9	HS	0	0	0	0	0	1	8	74	28	0	111	0.667
10	UH	0	0	0	0	1	0	1	21	101	0	124	0.815
11	OW	0	0	0	0	0	0	0	0	0	19	19	1
12	Row Total	58	61	73	164	47	30	81	103	135	20	772	0
13	PA	0.879	0.967	0.986	0.909	0.915	0.9	0.852	0.718	0.748	0.95	0	0
14	Overall Accuracy	0.86	0	0	0	0	0	0	0	0	0	0	0
15	Kappa	0.839	0	0	0	0	0	0	0	0	0	0	0

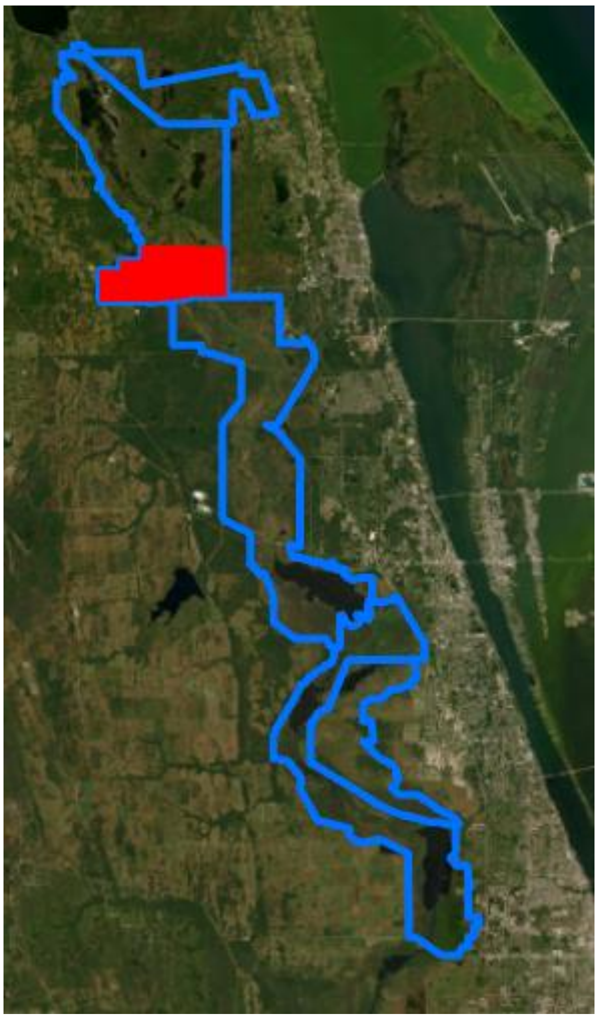


Figure 21 Location of SRCA3.

Table 10 Error matrix for South RLCA.

	A	B	C	D	E	F	G	H	I	J	K	L
1		HM	GS	SP	PH	SS	WS	OW	HS	CP	Column Total	UA
2	HM	66	2	6	2	0	2	1	2	4	85	0.776
3	GS	0	41	4	0	0	0	0	0	4	49	0.837
4	SP	2	5	103	2	0	3	1	0	0	116	0.888
5	PH	6	0	2	37	0	1	0	0	1	47	0.787
6	SS	0	0	0	0	0	1	0	5	1	7	0
7	WS	4	0	2	0	0	67	0	0	0	73	0.918
8	OW	1	0	0	0	0	0	9	1	0	11	0.818
9	HS	0	0	0	0	1	1	0	36	0	38	0.947
10	CP	2	0	0	0	0	0	0	0	34	36	0.944
11	Row Total	81	48	117	41	1	75	11	44	44	462	0
12	PA	0.815	0.854	0.88	0.902	0	0.893	0.818	0.818	0.773	0	0
13	Overall Accuracy	0.851	0	0	0	0	0	0	0	0	0	0
14	Kappa	0.823	0	0	0	0	0	0	0	0	0	0

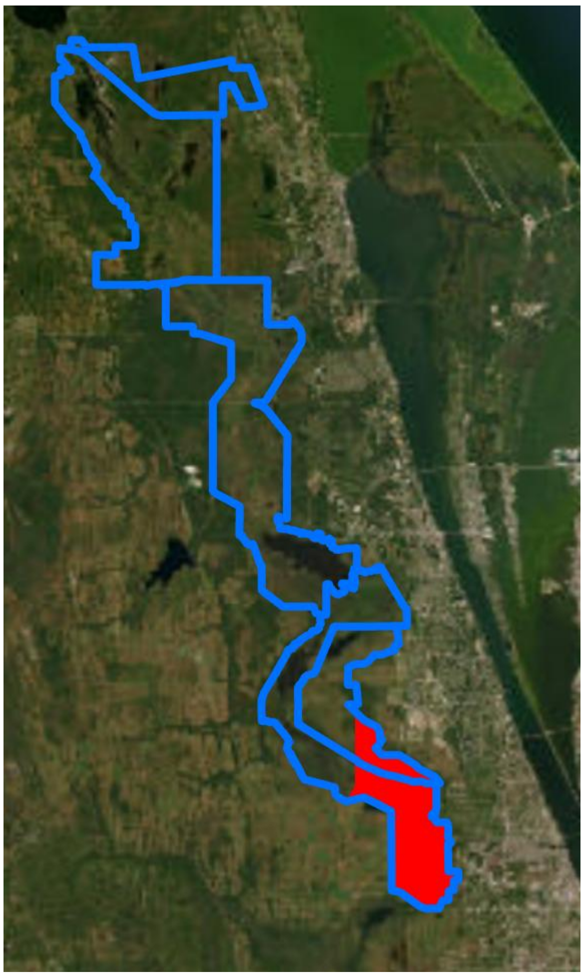


Figure 22 Location of South RLCA.

Table 11 Error matrix for North RLCA_MIMRA.

	PA	HM	WP	CT	GS	SP	SG	PH	SS	WS	FF	OW	UH	PF	HH	HS	CY	CP	Column Total	UA
PA	90	1	3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	96	0.938
HM	1	186	6	13	2	13	1	2	0	0	1	0	1	2	0	0	0	0	228	0.816
WP	0	2	226	3	2	4	2	0	1	0	0	0	2	2	0	0	0	9	253	0.893
CT	0	4	3	171	0	5	1	0	0	0	0	0	0	0	0	0	0	0	184	0.929
GS	2	1	2	3	168	23	1	0	0	0	2	0	0	0	0	0	0	0	202	0.832
SP	0	6	1	4	5	289	0	5	0	1	0	0	0	0	0	0	0	0	311	0.929
SG	0	5	1	0	0	0	77	0	3	0	0	0	0	0	0	0	0	0	86	0.895
PH	0	6	0	0	0	5	0	85	0	0	0	0	0	0	0	0	0	0	96	0.885
SS	0	1	0	1	0	0	0	0	200	3	0	0	2	1	1	2	1	1	213	0.939
WS	0	0	0	0	0	0	0	0	10	195	0	0	3	1	0	0	1	1	211	0.924
FF	0	1	2	1	3	1	0	0	2	2	44	3	0	2	0	0	0	0	61	0.721
OW	0	0	0	0	0	0	0	0	0	0	9	41	0	0	0	0	0	0	50	0.82
UH	0	2	4	0	0	0	0	0	3	0	0	0	215	14	0	0	1	21	260	0.827
PF	0	0	2	0	0	0	0	0	0	0	0	0	4	170	0	0	0	3	179	0.95
HH	0	0	0	0	0	0	0	0	0	0	0	0	3	0	61	12	0	5	81	0.753
HS	0	0	0	0	1	0	0	0	3	0	0	0	4	0	9	88	6	3	114	0.772
CY	0	0	0	0	0	0	0	0	1	4	0	0	0	0	0	7	86	0	98	0.878
CP	0	1	5	0	0	0	0	0	0	2	0	0	15	3	5	0	0	165	196	0.842
Row Total	93	216	255	196	181	341	82	92	223	207	56	44	249	195	76	109	95	209	2919	0
PA	0.968	0.861	0.886	0.872	0.928	0.848	0.939	0.924	0.897	0.942	0.786	0.932	0.863	0.872	0.803	0.807	0.905	0.789	0	0
Overall Accura	0.876	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Kappa	0.867	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

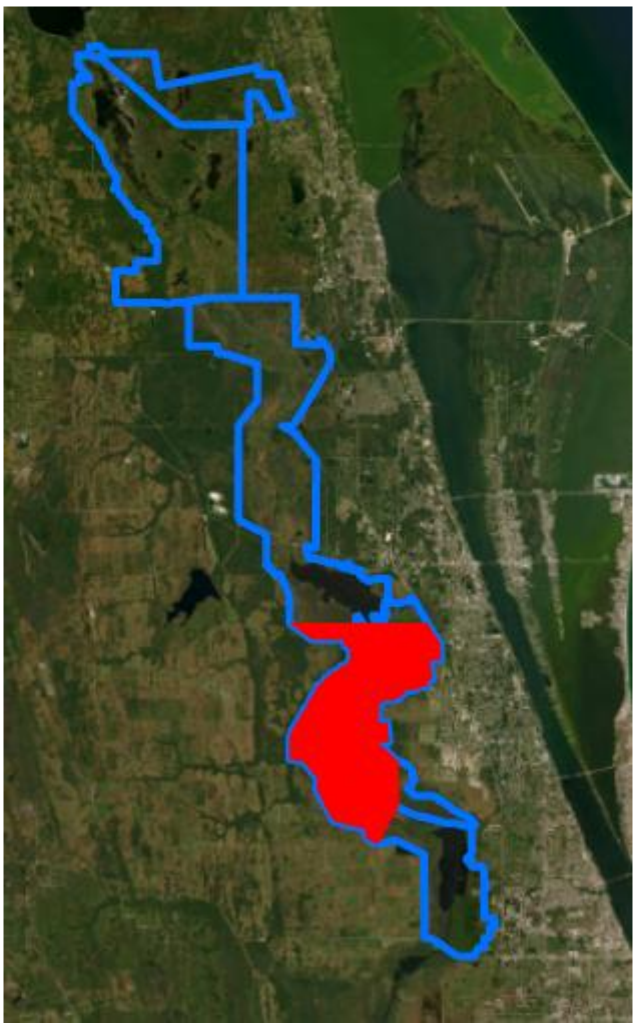


Figure 23 Location of North RLCA_MIMRA.

4.3 Final map

Figure 24 shows the final map of year 3. This map shows the expansive extent of Mixed Herbaceous Marsh in this portion of the USJRB (>25%). In combination with Spartina, Grass/Sedge and Willow, these communities account for over 60% of the area. Table 12 shows the coverage and percentage of each community in descending order.

Two communities Salt Marsh/Salt flat, and Phragmites are present in the mapping area but were not present in the previous two mapping phases. Salt Marsh/Salt flat (SM) is caused by salty groundwater release. It is smooth and looks like grass/sedge on the imagery because these areas are covered with very short salt grasses or salt-loving vegetation that runs very close to the ground. On color infrared (CIR) composite, they show up as pink or orange. Adjacent areas of salt marsh are almost completely devoid of vegetation and are recognized as salt flats.

Table 12 The coverage of each plant community based upon the map of year 3 in descending order. Bare Soil, Anthropogenic, Levee/Road, and Water are excluded.

Community	Coverage (Acre)	%
Mixed Herbaceous Marsh	28829	25.4
Spartina	13682	12.0
Grass/Sedge Marsh	13401	11.8
Willow Swamp	12945	11.4
Shrub Swamp	10883	9.6
Cabbage Palm Hammock	5555	4.9
Upland Hardwood	5344	4.7
Wet Prairie/Wet Pasture	4757	4.2
Pine Flatwoods	4515	4.0
Hydric Hammock	3968	3.5
Pasture	1763	1.6
Cypress	1541	1.4
Palmetto Prairie	1411	1.2
Phragmites	1373	1.2
Hardwood Swamp	1253	1.1
Salt Marsh/Salt flat	901	0.8
Sawgrass	727	0.6
Scrub	267	0.2
Cattail	224	0.2
Deep Marsh	203	0.2
Free Floating plants	60	0.1
Bayhead/gall	5	0.0
Total	**113607**	

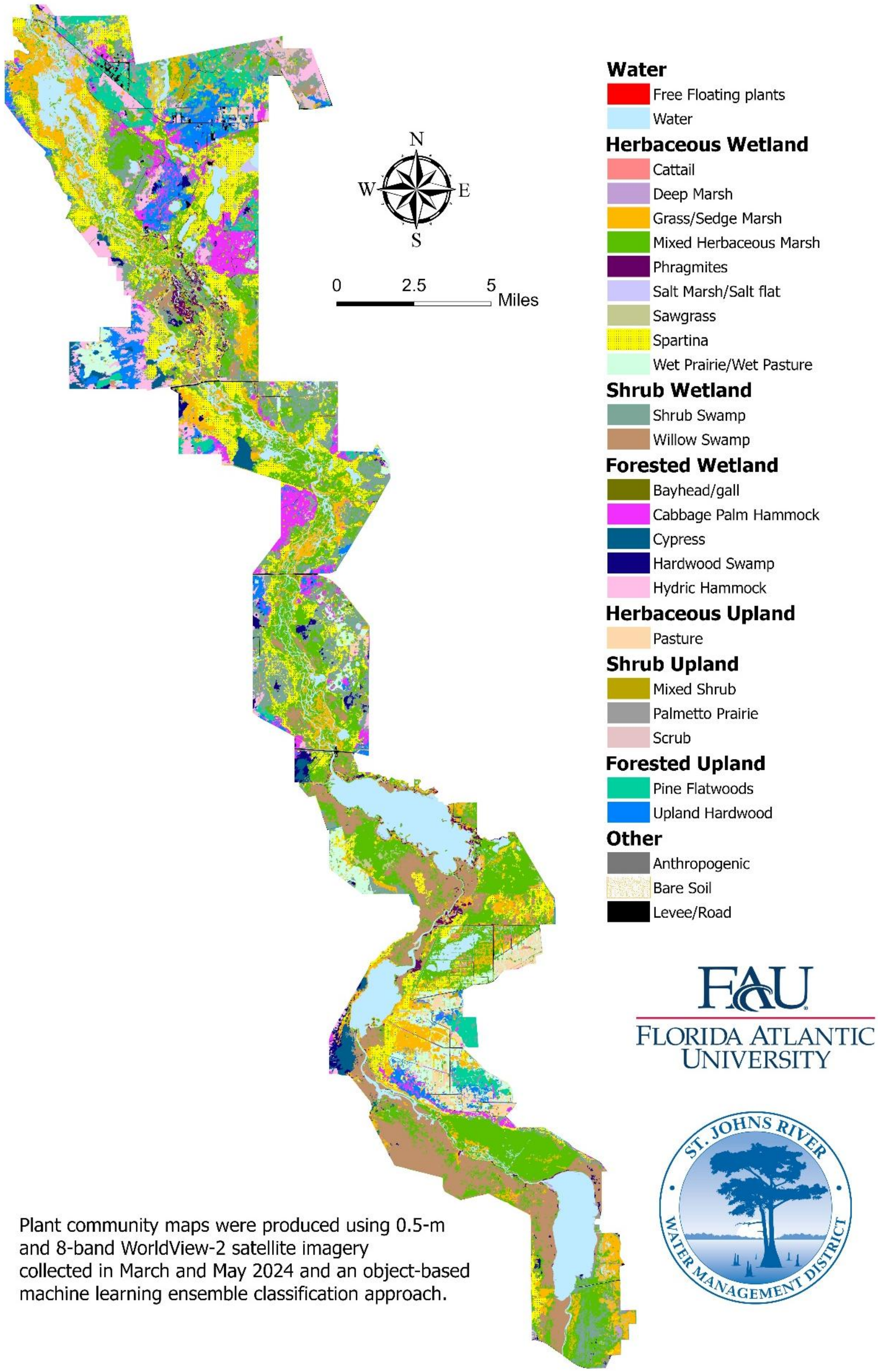


Figure 24 Map of year 3 covering 130966 acres.

4.4 Hard copy maps

One of the deliverables of this project is a hard copy of each year's map product on the matte laminated (42×60 inch). We initially used Office Depot but the maps did not meet the required quality. This year after discussions with Dr. Hall, we tried PosterNinja (https://posterninja.com/) (Figure 25). We updated year 1 and year 2 maps to be consistent across all three years and ordered the map poster from PosterNinja to complete this task. Year 1 and year 2 finalized maps are displayed in Figures 26 and 27. The parameters used in PosterNinja via its web are:

- Large Poster Printing
- Material: Matte Photo
- Lamination: No Lamination
- Width: 42 inch
- Height: 60 inch

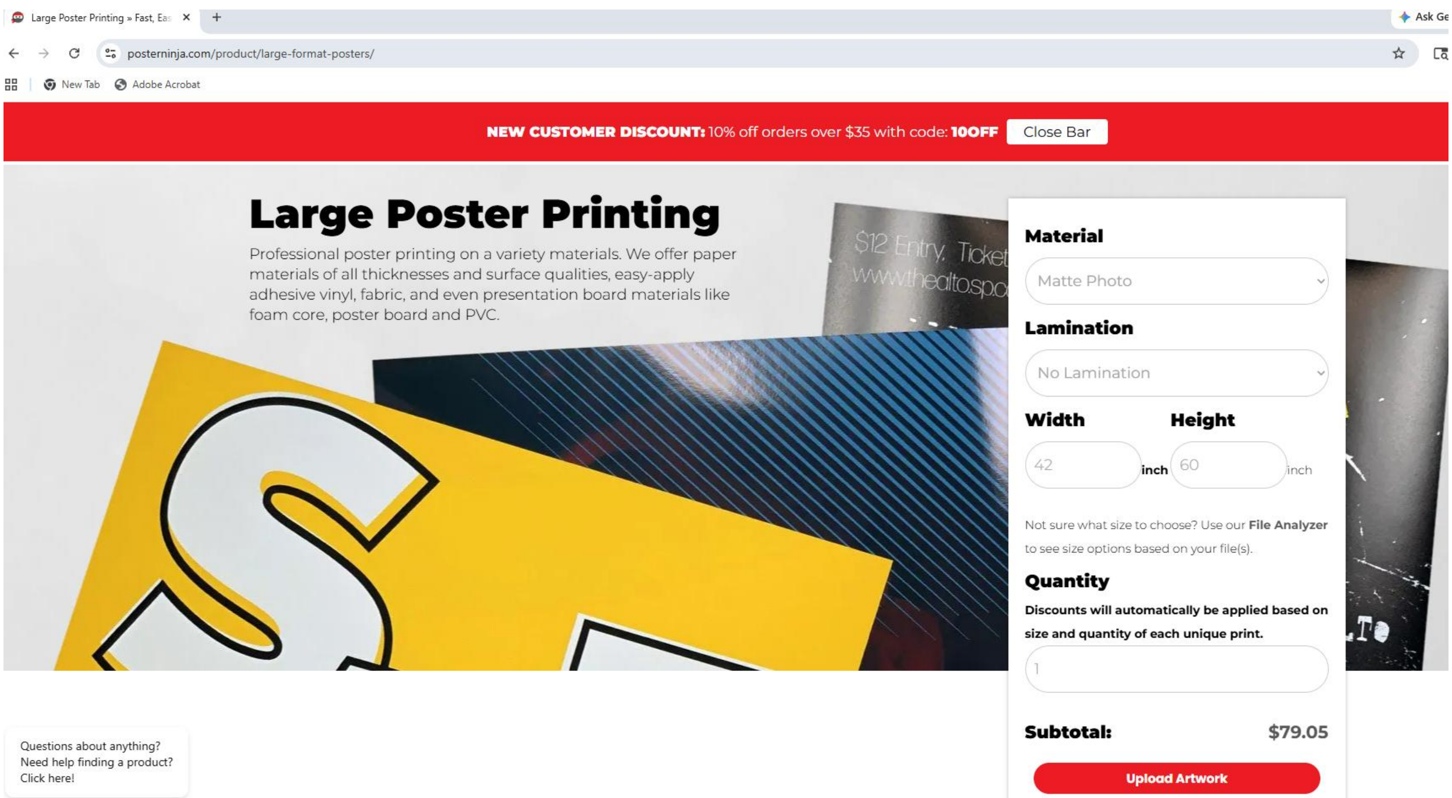


Figure 25 Setting parameters for map poster on PosterNinja.

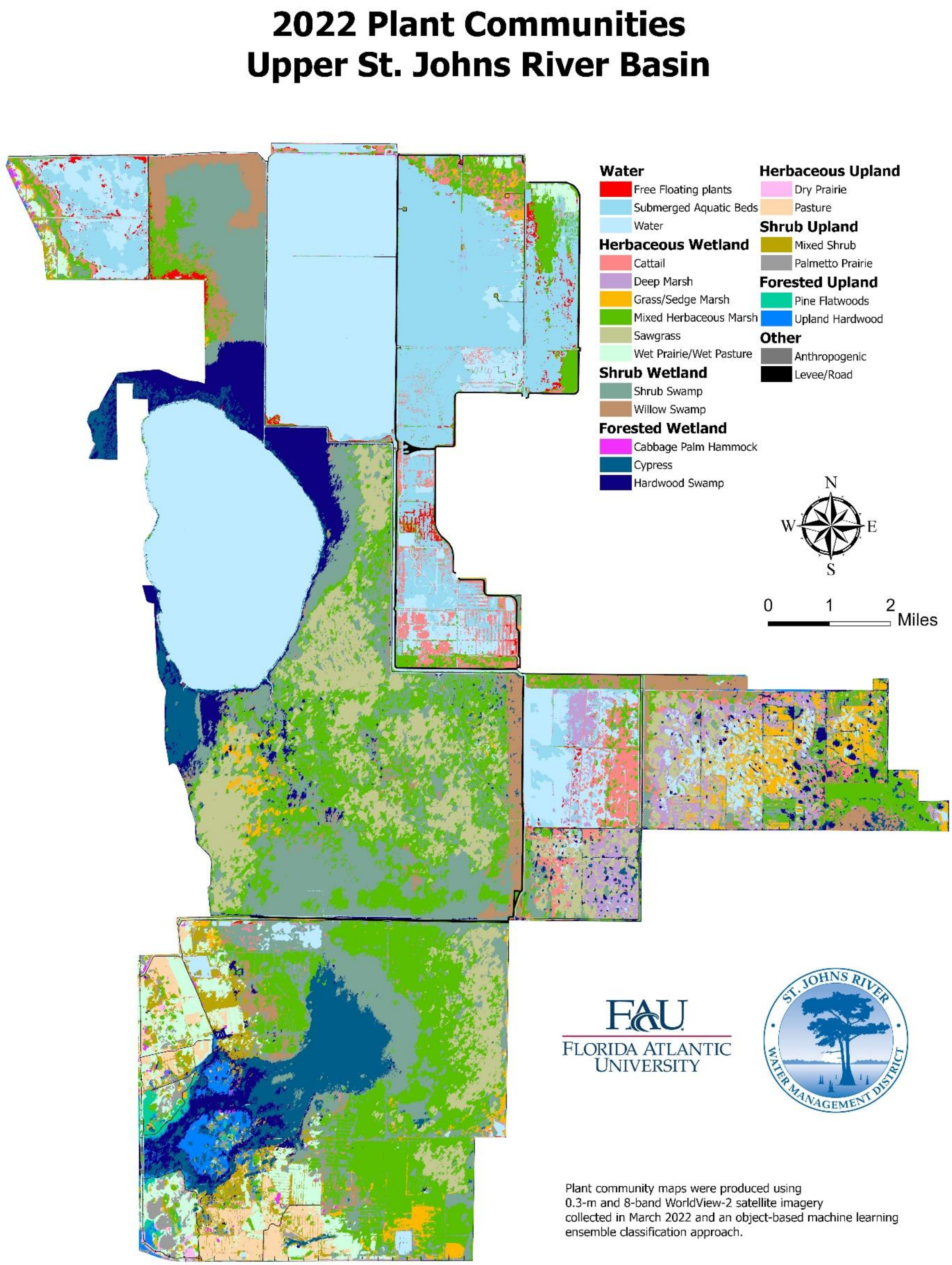


Figure 26 Map of year 1 covering 81896 acres.

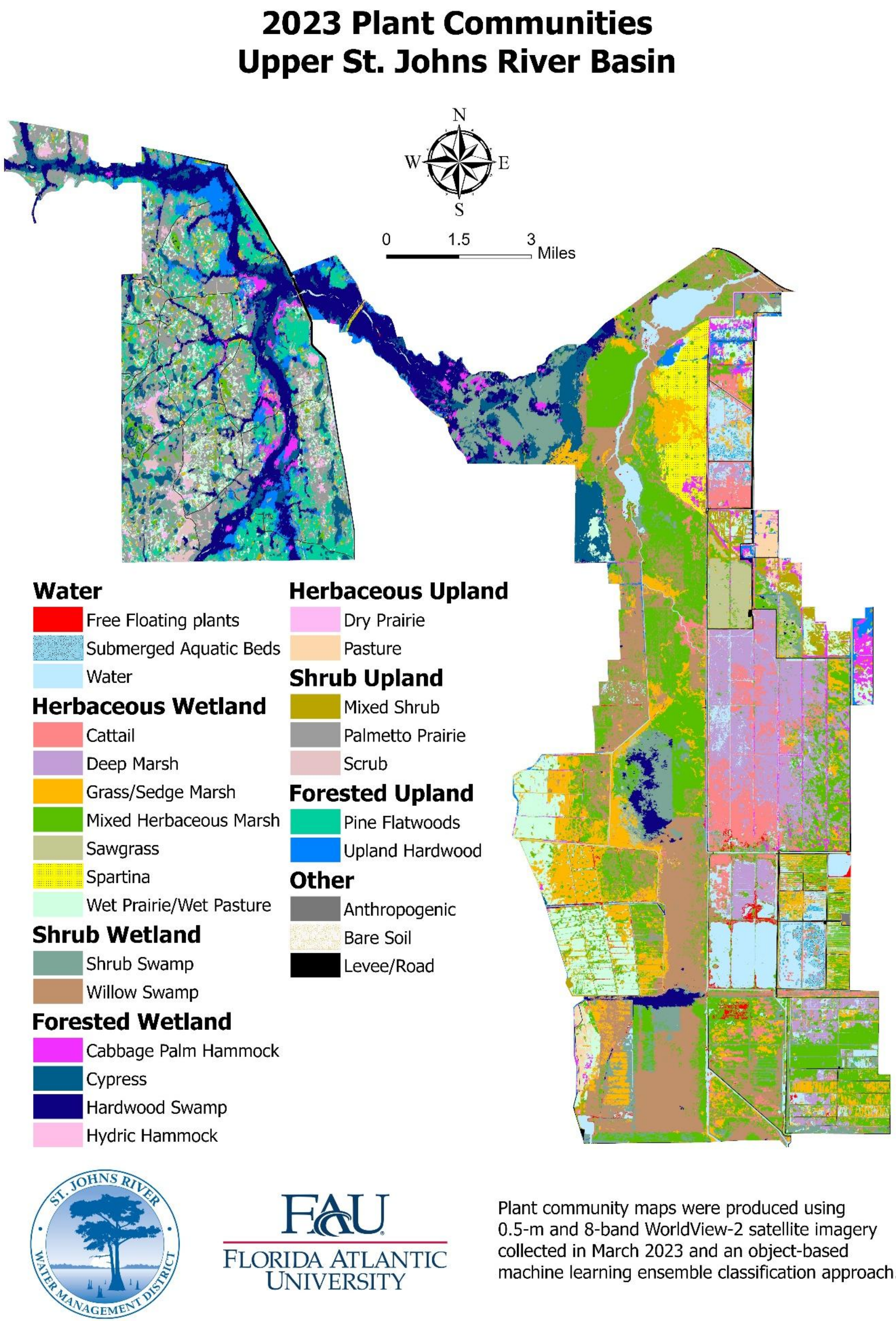


Figure 27 Map of year 2 covering 88016 acres.

5. Discussion

5.1 Factors impacting map quality

For each mapping piece, we achieved an overall accuracy larger than 80% based on the classification model except BLCA1, but we believe that the integrity of the final maps was higher after the post-classification manual refinement, especially using keys for identifying trees developed this year by including NAIP imagery collected in winter. A lower accuracy for an individual community for a specific area occurred when there were fewer training samples due to difficulties in collecting samples caused by the small size coverage or narrow linear features, or the degree of mixture levels with other communities. These communities often cover less than 5% of each individual project area and thus their effects are minor considering the entire area being mapped. A qualitative examination of each map laid over the imagery and using the swipe function in ArcGIS Pro was also conducted in addition to the quantitative error matrix techniques. The general pattern of each map was consistent with the visual observation of the imagery.

The most critical factor impacting mapping accuracy is the degree of complexity of the area of interest. In general, more classes, more heterogeneity within a class, and more mixture between classes will be more difficult to map. From a methodology perspective, a major step impacting the map accuracy and results is the training sample selection. Ideally, training samples should be selected based on a stratified sample selection strategy through field visits, but, in practice, field sample collection is difficult especially in inaccessible areas. Misalignment between field samples and imagery can cause issues too. The time of field visit should also be considered, and a large time gap between field visit and acquisition of WV-2 imagery will result in more uncertainties in both field training sample selection and post-mapping ground-truth accuracy assessment. For example, in project year 2, WV-2 imagery was acquired in March 2023, but field spectral keys were collected in June. During the field visit, change was observed between imagery and field observations over some areas. Therefore, a timely field visit is recommended. The WV-2/3 imagery products have a very fine resolution (0.5 m in this project), which allows reference sample collection by a visual interpretation procedure based upon old maps and current imagery. However, we must be careful not to perpetuate errors from the old map into the new one. A combination of this visual interpretation with samples collected by field visits is more effective than the application of imagery-based or field-based sample collection alone. Special care should be paid in obtaining training samples from communities containing similar groups of species. For example, Mixed Herbaceous Marsh (HM) communities, may contain cattail and small shrubs, which will be present in the Shrub Swamp and Cattail communities as well. Training points should be selected over homogeneous areas where only one community is present. For instance, training samples for Cattails should be taken in areas where cattail is at least 70% of the community. Likewise, training points for Shrub Swamp should only be taken from areas where shrubs are at least 70% of the community. Mislabeling of any training samples will lead to misclassifications on the map and be reflected in the error matrix.

Selection of the scale parameter in image segmentation also impacts mapping results. In project year 1, we selected the scale of 300 to avoid the “salt-and-pepper” effect, reduce the size of the dataset for future processing and use, and in consideration of the areal constraints on management activities. The application of this scale created a lot of mixture issues and missed the delineation of small patches or linear features. In project year 2, we decreased the scale to 150 to solve the mixture issue. This year, we used the scale of 150. With the decreased scale, features were segmented better. However, this one-scale for the entire project area may not work for heterogeneous landscapes which can still generate segments with mixtures of plant communities, leading to confusion in the classification. Segmentation refinement is a complicated procedure and, so far, there are no automated methods for this improvement.

Map quality is also influenced by the boundary effects. Ideally, single-date imagery should be used for each individual area. This is easier for an area with a small size but for a large project area with a narrow shape, imagery often comes from a mosaic of multiple image scenes or images collected on different dates. Inconsistency will occur at the boundary of the mosaic lines. Similarly, when mapping a large area, an image needs to be split so that the computer or software packages can handle the dataset. This can cause boundary inconsistencies and misalignments among the segments across the splitting line, leading to map artifacts. A solution for this is the manual editing/revision of these boundary segments. This is a time-consuming procedure.

5.2 Challenges in the project

One challenge in the mapping project was to collect field data within a project area. We have collected data along levees and airboat trails but to better train our own brain to label communities on the imagery, especially for areas we are not sure what they are, a field visit is the best solution. Unfortunately, many of these areas are inaccessible to humans under most conditions. To mitigate this, we met with District's personnel such as Dr. Hall online to validate spots where we wanted to put training samples. The District's personnel have rich knowledge across all the project areas and were invaluable in assisting with the labeling of many samples on the imagery to be used as training data to develop the machine learning models. Knowledge of what plant communities should or should not appear in a specific area, and what a community looks like on the imagery and in the field was vital for us to acquire effective training samples for classification.

The other challenge was in training the students. In the PI's team, a total of eight graduate students have been involved in this project including six PhD students (David Brodylo, Mizanur Rahman, Sandip Rijal, Abdullah Ai-Fazari, Fiona Benzi, and Rabindra Parajuli) and two MS students (David Ramirez, and Madan Thapa Chhetri). Exposure of graduate students to a research project and their participation in it is critical for their graduate training and future careers. For this project, students needed to be trained to identify each plant community in the field and on the imagery. They needed to learn satellite imagery processing, data editing, how to run machine learning models, and how to generate the final map products. Although the project PI has developed detailed tutorials and generated a plant inventory with descriptions and pictures, it is still challenging for students to correctly label training samples. In project year 1, none of these students collected effective training samples on the imagery nor generated acceptable map products for their assigned project area. However, during the first phase of the mapping project, most students have become proficient in the entire mapping process and gained field experience. They have increased their skills using ArcGIS Pro, creating, and running *R* scripts, and using ESRI's Field Map software. They have also become proficient at eCognition image segmentation and data preprocessing, and in organizing, sharing, and backing up data. Students have also learned how to work on a project as a team member, how to communicate with others, as well as how to appreciate the beauty of imagery and maps. In project year 2, PhD students Sandip Rijal, Fiona Benzi, and Rabindra Parajuli, and MS student Madan Thapa Chhetri were hired in summer 2023. They all created map products though their maps need further revision and editing by the PI. Students may have incorrectly labeled misclassified segments in the map refinement procedure, forgot to include required attributes, or are confused about the label codes used. There should be two sets of label codes with one set to be used in the machine learning classification, and one set to be used for final map generation. The label code for final map generation should add the minor communities which are manually labeled and do not come into the machine classification procedure. For project year 3, PhD student Fiona Benzi was the only one who helped with the map generation because most of the trained students including Sandip Rijal, Mizanur Rahman, Abdullah Ai-Fazari, Rabindra Parajuli, and Madan Thapa Chhetri could not work on the project anymore due to graduation or lack of time.

5.3 Estimated time cost

The previous mapping method using manual interpretation of aerial photograph by the District would take over a year to generate the map products covering around 80,000 acres. Our estimated time cost is around 10 weeks (2-3 months) after we receive the data from the District, if one person, proficient in plant community identification and the mapping procedure works solely on this project. The largely reduced time length in map generation will guide timely management activities for preserving the District's natural systems. A detailed time cost for major steps in our computer-based machine learning classification procedure is provided below (40 hours/week fully dedicated to the project by the PI).

- Preparation of field plan: 1 week
- Field visit: 1 week
- On-line meeting with District's personnel: 1 week
- Map generation: 1 week per project area, a total of 10 weeks for 10 areas
- Wrap up of deliverables: 1 week including generating levee/road and AN layers

6. Summary and deliverables

We have completed the required tasks in project year 3 (2024-2026) for mapping five project areas with a total coverage of 130,966 acres. We conducted a 3-day field trip to the project area, collected 2228 field points, and took 378 pictures. A summary of the deliverables is provided below:

- Field samples, photos, and notes
- Map products of testing plots and accuracies
- Map products of ten areas and accuracies
- Map product of year 3
- Annual report (this file)
- Map plots

References

Zhang, C., 2014. Combining hyperspectral and lidar data for vegetation mapping in the Florida Everglades. Photogrammetric Engineering & Remote Sensing 80:733–743.

Zhang, C., and Z. Xie. 2014. Data Fusion and classifier ensemble techniques for vegetation mapping in the Everglades. Geocarto International 29: 228–243.

Zhang, C., D. Selch, and H. Cooper. 2016. A framework to combine three remotely sensed data sources for vegetation mapping in the central Florida Everglades. Wetlands 36: 201–213.

Zhang, C., S. Denka, and D. R. Mishra, 2018. Mapping freshwater marsh species in the wetlands of Lake Okeechobee using very high-resolution aerial photography and lidar data. International Journal of Remote Sensing 39: 5600–5618.

Acknowledgement

We are grateful that the District has provided this project as an opportunity for FAU's graduate students: David Brodylo (PhD, graduated Summer 2023), Mizanur Rahman (PhD, graduated Summer 2025), Rabindra Parajuli (PhD, graduated Summer 2024), David Ramirez (MS, graduated Spring 2024), Madan Thapa Chhetri (MS, graduated Summer 2024), Abdullah Ai-Fazari (PhD, graduated Spring 2026), Sandip Rijal (PhD, ongoing), and Fiona Benzi (PhD, ongoing) to put their classroom learning into a real field project, allowing for the application of geospatial techniques, and generating industry level map products. Some students (Mizanur Rahman and Fiona Benzi) have been working on their thesis/dissertation based upon this project. We also would like to extend our gratitude to the District's Project Manager, Dr. Dianne Hall, for her rich knowledge over the project area, patience to teach the students and PI to identify each community and understand their ecological significance, for providing detailed considerations and logistics for the field visit and improving the final map products and project report. District personnel Christy Akers, Kimberly Ponzio, Jodi Slater, Jonny Baker, Doug Voltolina, Graham Williams, and Chris O'Hara, and retired District employee Ken Snyder made the field survey a great success.

Appendix 1 Classification system used in the project

PLANT COMMUNITY CLASSIFICATIONS AND DEFINITIONS

Community Type	Plant Community	Definition
Other (O)	Anthropogenic (AN)	Areas of agricultural land (including orchards, groves, and row crops, but NOT pasture or pine plantations), and buildings, parking lots, spoil piles, development, etc. Includes bare areas associated with anthropogenic disturbance.
	Levee/Road (LR)	Paved or unpaved roads or levees with grassed, gravel, limerock or dirt roads at their apex; levees without roads should be classified based on the vegetation they support.
	Bare Soil (BS)	Open areas with > 70% cover of bare soil with no vegetation (e.g., shoreline, beach, mudflats, barrens); not associated with anthropogenic disturbance or salt flats.
Water (W)	Water (OW)	Areas such as lakes, impoundments, rivers, canals, ditches, and other areas of open water which may support free-floating plant species (e.g., *Eichhornia, Pistia, Salvinia, Lemna*).
	Submerged Aquatic Beds (SAB)	Areas containing rooted aquatic plants with photosynthetic tissues below the water surface (e.g., *Vallisneria, Najas, Hydrilla, Potamogeton*).
	Free floating plants (FF)	Areas that are flooded and dominated by floating plant species (e.g., *Eichhornia, Pistia, Salvinia, Lemna*) that are not attached or rooted to the substrate of a water body.
Herbaceous Wetland (HW)	Salt Marsh/Salt flat (SM)	Areas where salty groundwater seeps to the surface and supports salt-tolerant plants (e.g., *Spartina, Sesuvium, Salicornia, Iva, Juncus roemarinus,* and small *Baccharis* shrubs); bare soil is often a significant part of this community and should not be mapped separately.
	Deep Marsh (DM)	Areas containing 2: 40% cover of bottom-rooted species with floating leaves (e.g., *Nymphaea, Nuphar, Nelumbo, Brasenia, Nymphoides*) or deep -water emergent species (e.g., *Schoenoplectus*); may also include *Utricularia* spp and may occur as a littoral zone around lakes.
	Grass/Sedge Marsh (GS)	Areas containing 2: 70% cover of obligate or facultative-wet grass or sedge spp. (e.g., *Panicum, Sacciolepsis, Eleocharis, Rhynchospora, Cyperus*); other non-graminoid species, such as *Typha* and small shrubs may be present in small amounts.
	Mixed Herbaceous Marsh (HM)	Areas containing a mixture of broadleaf emergents, grasses, sedges, and other spp. (e.g., *Pontederia, Sagittaria, Hydrocotyle, Persicaria);* small shrubs may be included as a small part of the community (e.g., *Cephalanthus, Kosteletzkya, Hibiscus*).
	Cattail (CT)	Areas containing 2: 70% cover of *Typha* spp.
	Phragmites (PH)	Areas containing 2: 70% cover of *Phagmites berlandieri.*
	Sawgrass (SG)	Areas containing 2: 70% cover of *Cladium jamaicense.*
	Spartina (SP)	Areas containing 2: 70% cover of *Spartina bakeri.*
	Wet prairie/wet pasture (WP)	Areas containing a mixture of grasses, sedges, rushes, and forbs (e.g., *Spartina, Juncus, Panicum*) typically classified as facultative-wet or facultative; long-hydroperiod species (e.g., *Typha*, water lilies) should not be present; category should also be used for reflooded pastures and wet, unimproved pastures.
Shrub Wetland (SW)	Shrub Swamp (SS)	Areas containing 2: 70% cover of mixed shrub species (e.g., *Salix, Morella, Baccharis, Sambucus, Ludwigia, Cephalanthus, Kosteletzkya, Hibiscus*); may include small trees (e.g., *Acer, Gordonia, Persea, Ilex, Sabal, Schinus*).
	Willow Swamp (WS)	Areas containing 2: 70% cover of *Salix caroliniana.*
Forested Wetland (FW)	Cypress (CY)	Areas containing 2: 70% cover of *Taxodium* spp. (bald or pond cypress); includes cypress domes, swamps, strands and lakeshore variants.
	Hardwood Swamp (HS)	Areas containing 2: 70% mixed wetland tree species (e.g., *Acer, Taxodium, Fraxinus, Nyssa, Ulmus, Annona*), cypress may be a significant component, but < 70%; includes swamps and communities lying in the floodplain of rivers and streams; understory typically doesn't include *Serenoa repens* (saw palmetto).

Community Type	Plant Community	Definition
Forested Wetland (FW) cont.	Bayhead/gall (BG)	Areas containing > 50% cover by one or more evergreen bay trees (e.g., *Gordonia, Persea, Magnolia*); may be in combination with *Pinus*, typically *Pinus serotina.* Ilex cassine may also be present. Subcanopy and understory may be dominated by *Serenoa repens* or bays. Ferns (e.g., *Osmunda cinnamomea, Woodwardia virginica, Thelypteris* spp.) may also be common.
	Hydric Hammock (HH)	Areas containing 2: 70% canopy cover of *Quercus laurifolia, Sabal palmetto, Magnolia virginiana, Juniperus, Celtis, Liquidamber*, and/or *Ulmus spp.* and having shorter hydroperiods than Hardwood Swamp; tree canopy may commonly include *Pinus*, but will rarely include *Taxodium* spp.; understory may include *Serenoa repens*, *Callicarpa americana* and *Psychotria nervosa* or ferns
	Cabbage Palm Hammock (CP)	Areas similar in species composition to Hydric Hammocks, but containing 2: 70% cover of *Sabal palmetto*
	Forested Flatwood Depressions (FD)	Areas containing mixed communities of *Taxodium, Pinus, Sabal*, bays or deciduous hardwoods in shallow depressions; may be located within areas of mesic hardwoods or pine flatwoods.
Herbaceous Upland (HU)	Dry Prairie (DP)	Areas containing > 50% cover of mixed upland grasses and other herbaceous species (e.g., *Aristida, Andropogon, Xyris, Rhexia*) with < 50% cover of low shrubs (e.g., *Serenoa, Ilex glabra, Lyonia, Vaccinium, Quercus minima*) and few trees.
	Pasture (PA)	Areas similar in composition to Dry Prairie, but with recent evidence of pasture/cattle management (e.g., fencing, feeding or water troughs) and the presence of exotic forage grasses (*Paspalum notatum, Hemarthria, Panicum repens, Cynodon*).
Shrub Upland (SU)	Palmetto Prairie (PP)	Areas containing > 50% cover of *Serenoa repens* and low shrubs (e.g., *Ilex glabra, Lyonia, Quercus minima, Vaccinium*) with few to no trees; < 50% cover of mixed upland grasses and herbs.
	Mixed Shrub (MS)	Areas containing 2: 50% mixed low shrub cover (e.g., Serenoa, Lyonia, Tlex glabra, etc.) interspersed with grasses and herbaceous vegetation with few to no trees. Includes overgrown pasture areas.
	Scrub (SC)	Areas containing 2: 70% cover of scrub species (e.g., *Ceratiola ericoides, Garberia fruticosa, Sabal etonia*) and scrub oak species (e.g., *Quercus geminata, Q. chapmanii, Q. inopina*), withor without an overstory of *Pinus clausa*; areas of bare white sand may be visible and should be included as part of the community.
Forested Upland (FU)	Sandhill (SH)	Areas containing < 50% cover of mixed upland grasses and forbs (e.g., *Aristida* spp., *Garberia, Licania, Pityopsis*) with widely spaced *Pinus palustris, Quercus laevis, Q. incana, and/or Q. stellata*; areas of bare sand may be visible and should be included as part of the community.
	Pine Flatwoods (PF)	Areas typically containing > 40% cover of *Pinus* spp. with an understory of low shrubs (e.g., *Serenoa repens, Ilex glabra*), grasses (e.g., *Aristida, Andropogon*) and forbs; where intensive burns have occurred, trees may be defoliated and understory vegetation may dominate.
	Pine Plantation (PI)	Areas where rows of planted pines (*Pinus elliottii, P. palustris, P. taeda, P. clausa*, etc.) are visible. Understory vegetation is variable.
	Upland Hardwood (UH)	Areas containing a mixture of hardwood species with pines < 40% and palms < 70%; may be dominated by mesic oak species (e.g., *Quercus virginiana, Q. laurifolia*).