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

Year 1 (2022-2023) Report (Contract 38076)

Submitted to: St. Johns River Water Management District

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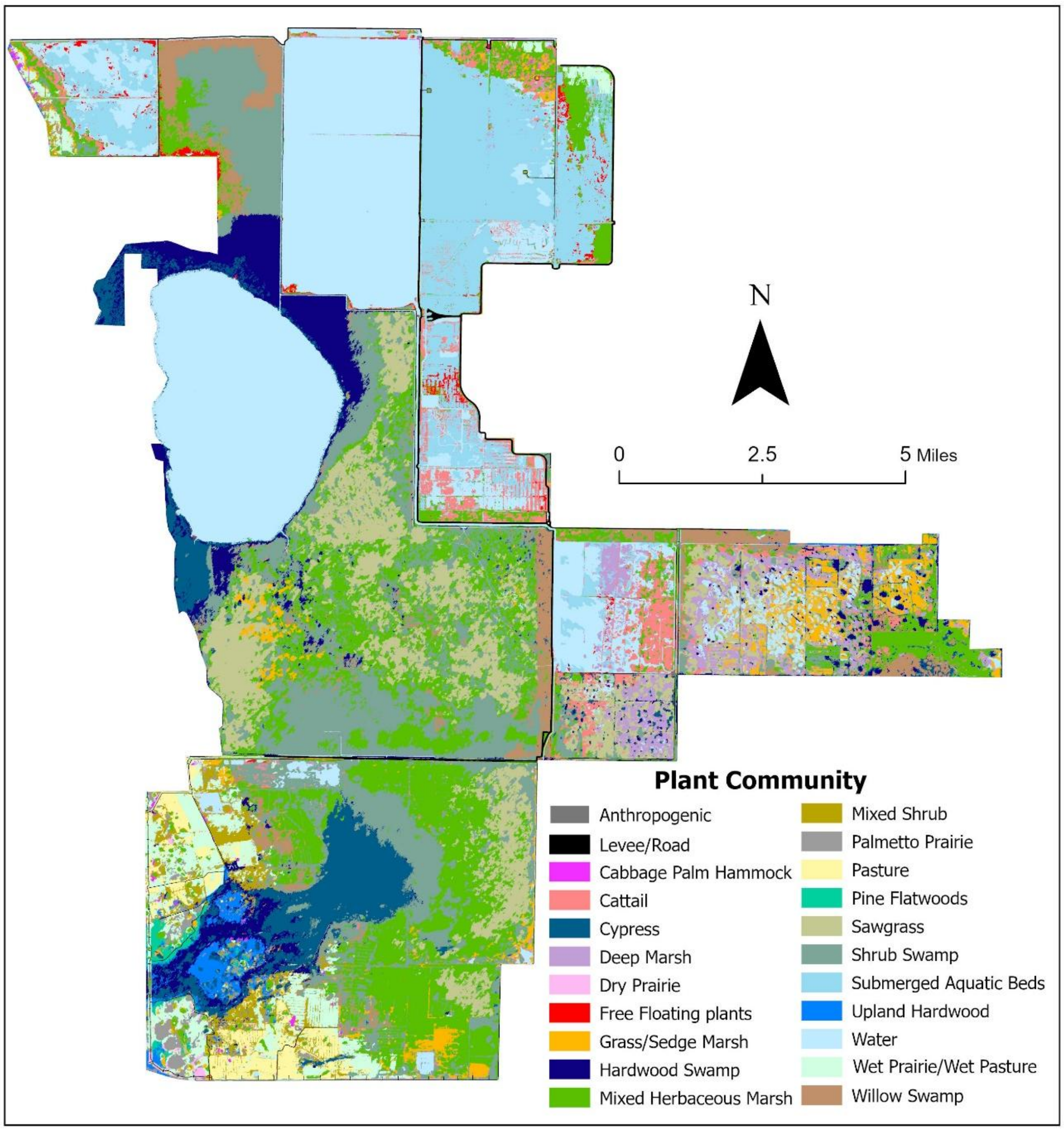

Map of wetland communities in 2022 with a coverage of 81,895 acres generated from an ensemble of machine learning classifications and WorldView-2 satellite imagery.

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 latest 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-regenerated 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), 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 Area, Moccasin Island Area, and Buck Lake Area. The developed methods are effective and efficient across several test wetland areas on District land. In the current contract project (Contract 38076), we further improved our machine learning procedures, and generated map products covering 81,895 acres of natural wetland areas during Project Year 1 (2022-2023). This annual report includes information on the data we received from the District, data we collected in the field, methods we used in generating these maps, methodological improvements we made during this period, map products we created, issues we encountered and how they were solved, and suggestions to the District such as timely field visit, supply of accurate project boundaries, and other ancillary data required in the project.

2. Project areas and data

2.1 Project areas

In Project Year 1, we mapped six areas: Kenansville Lake (KENAN - 2,565 acres), Blue Cypress Marsh Conservation Area (BCMCA - 29,387 acres), St. Johns Water Management Area (SJWMA - 6,323 acres); Fellsmere Water Management Area (FWMA -11,189 acres), Blue Cypress Water Management Area (BCWMA - 11,777 acres), and Ft. Drum Marsh Conservation Area (FDMCA - 20, 655). These areas are displayed as a color infrared composite of the WV-2 imagery collected on March 2, 2022, in Figure 1.

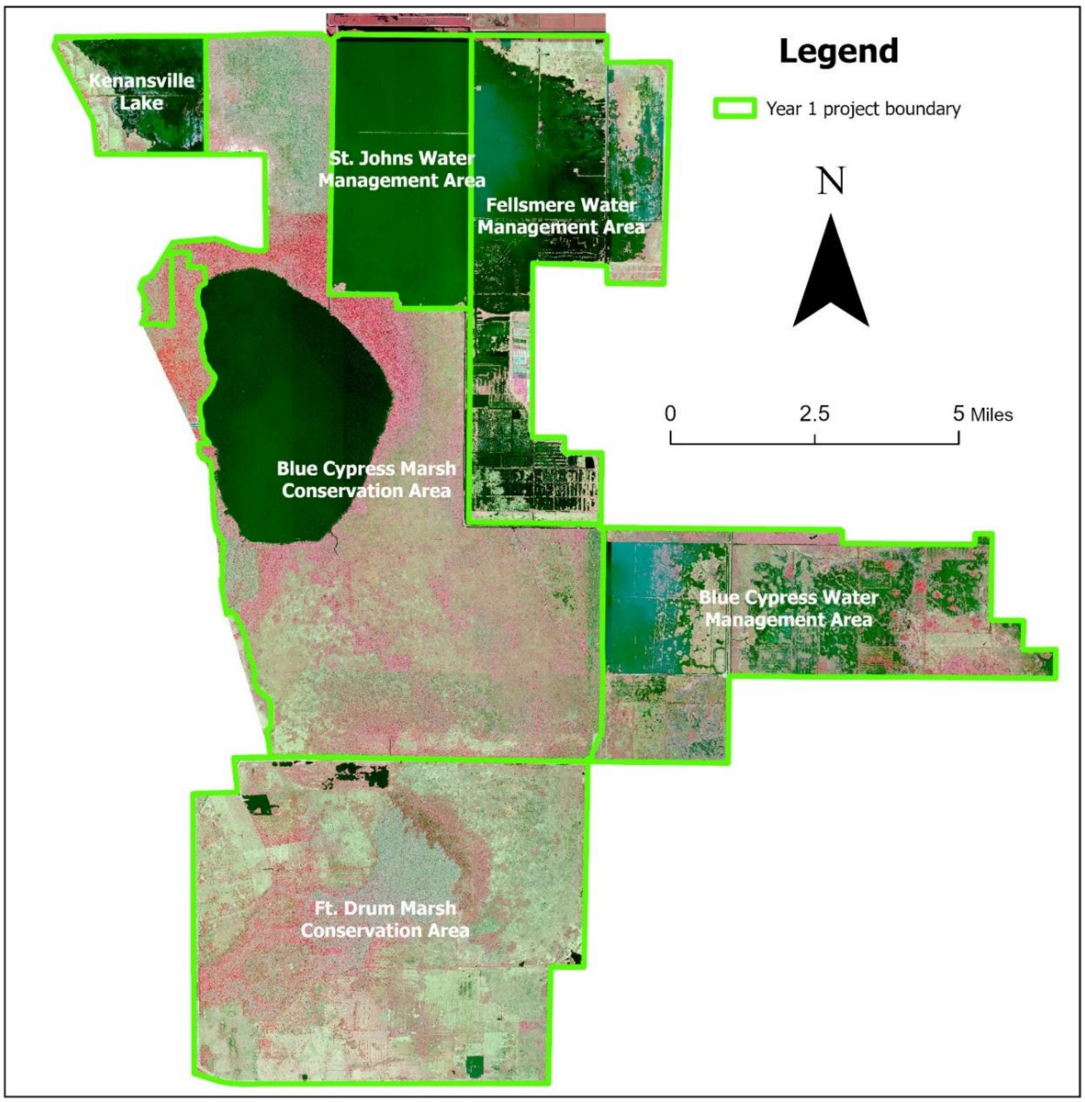

Figure 1 Project areas displayed in a color infrared composite of WorldView-2 imagery collected in March 2022. The imagery is the major input for generating the maps in the project.

2.2 Data provided by the District

The District delivered a hard drive with satellite imagery, historical aerial photography collected in 2015, lidar Digital Elevation Models (DEMs), historical vegetation maps created in 2015 by manual interpretation of the aerial photography, road map data, project boundary, elevation contour maps, 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, 360 GB data were received from the District, as shown in Figure 2 of the screenshot of the data.

Name	Date modified	Type	Size
District_Roads	11/17/2022 3:14 PM	File folder	
QA_QC LiDAR reports	2/23/2023 10:53 AM	File folder	
SJWMA Flowway Imagery	1/11/2023 1:39 PM	File folder	
Upper Basin DEMs 2013-2018	12/13/2022 9:06 AM	File folder	
Upper Basin Imagery 2015-2017	12/19/2022 8:58 AM	File folder	
22MAR02161632-PS-014792549010_02_P001_PS_8Band_16bit.prj	4/13/2022 11:40 AM	PRJ File	1 KB
22MAR02161632-PS-014792549010_02_P001_PS_8Band_16bit.tfw	4/13/2022 11:40 AM	TFW File	1 KB
22MAR02161632-PS-014792549010_02_P001_PS_8Band_16bit.tif	4/13/2022 12:23 PM	TIF File	69,512,830 ...
22MAR28162348-PS-014792549010_02_P002_PS_8Band_16bit.prj	4/13/2022 12:23 PM	PRJ File	1 KB
22MAR28162348-PS-014792549010_02_P002_PS_8Band_16bit.tfw	4/13/2022 12:23 PM	TFW File	1 KB
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2020 BCWMA Plant Comm.lpk	11/14/2022 2:24 PM	ArcGIS Layer Pack...	1,769 KB
2020 BCWMA Sat Imagery.lpk	11/14/2022 5:40 PM	ArcGIS Layer Pack...	3,910,124 KB
2022 PLANT COMM CLASSIF AND DEFINITIONS with symbols.docx	9/7/2022 11:32 AM	Microsoft Word D...	90 KB
MappingArea.lpk	11/14/2022 2:22 PM	ArcGIS Layer Pack...	35 KB
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Mosaic_22MAR02161632_PS_014792549010_02_8Band_16bit.tif	10/13/2022 3:52 AM	TIF File	37,287,851 ...
Mosaic_22MAR02161632_PS_014792549010_02_8Band_16bit.tif.aux.xml	10/12/2022 7:23 PM	XML Document	15 KB
Mosaic_22MAR02161632_PS_014792549010_02_8Band_16bit.tif.ovr	10/13/2022 3:52 AM	ERDAS IMAGINE D...	10,145,633 ...
Mosaic_22MAR02161632_PS_014792549010_02_8Band_16bit.tif.xml	10/13/2022 3:52 AM	XML Document	8 KB
New Imagery Capture Area.lpk	11/14/2022 2:23 PM	ArcGIS Layer Pack...	28 KB
Plant Community Maps.lpk	11/14/2022 2:19 PM	ArcGIS Layer Pack...	23,842 KB
PlantCommunityCrosswalk.2022.xlsx	2/27/2023 11:04 AM	Microsoft Excel W...	15 KB
Sandra Fox.DEM QAQC reports.msg	2/23/2023 10:53 AM	Outlook Item	230 KB
Training Plots.lpk	11/14/2022 2:21 PM	ArcGIS Layer Pack...	17 KB
Upper Basin elevation contours.lpk	11/14/2022 2:30 PM	ArcGIS Layer Pack...	36,166 KB

Figure 2 Data received from the District.

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 the 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. We also collected very high-resolution drone imagery for selected sites within the project area to increase our ability to select appropriate training samples.

The plant communities, corresponding community type, and abbreviations that we mapped for are listed in Table 1. Their definitions are provided in Appendix 1.

Table 1 Plant community mapped in this project.

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

We made a detailed field plan to collect training samples with District personnel Dr. Dianne Hall (Dr. Hall, Project Manager), Christy Akers, and Jonny Baker, and former District employee Ken Snyder, whose airboat was employed to access certain areas. The group considered waterfowl hunting dates, site accessibility by the District's truck and FAU's 11-seat van, suitability for ground target setup for drone data collection, distribution of sites across the project area, vegetation communities, capacity of the drone batteries, safety, and the logistics of planned field time schedule (time and cost budget). The selected sites are displayed in Figure 3. The District provided a 3-seat airboat with Christy Akers as the driver, and we rented a 7-seat airboat with Ken Snyder as the driver. In total, we collected drone data across 15 sites along the levees, and 6 sites along airboat trails, with a total of 6205 field points collected (Figure 3). We also took 187 pictures during the visit to document the signatures of each vegetation community with our notes. Figures 4-10 show some of the field pictures.

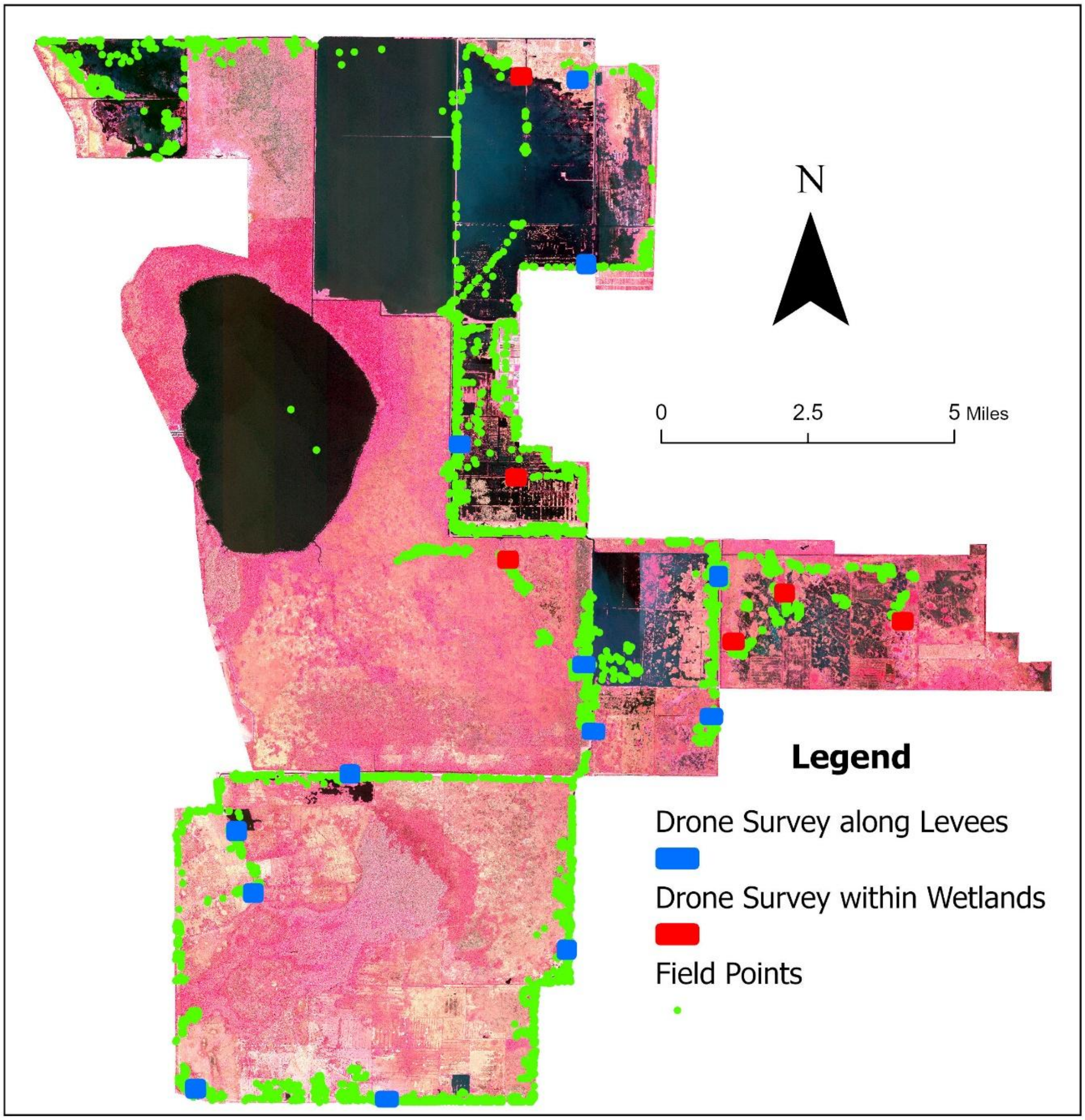

Figure 3 Field drone survey sites and point data collected in the project.

Figure 4 Wet prairie (WP) with shrubs invading at FDMCA.

Figure 5 Deep marsh (DM) and cattail (CT) at BCWMA.

Figure 6 Cattail (CT) with shrub swamp (SS) behind at BCWMA.

Figure 7 Submerged aquatic bed (SAB hydrilla), with small areas of deep marsh (DM) and floating plants, and cattails (CT) in the background at KENAN.

Figure 8 Mixed herbaceous marsh (HM) at BCMCA. Airboat driver Ken Snyder was examining the depth of water.

Figure 9 FAU students set up ground targets for drone data collection from a levee.

Figure 10 FAU crew in the field on the airboat with Ken Snyder as the driver (upper left), van stuck in the mud (upper right), and crew at FDMCA (bottom).

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 a large number of 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 0.3-m and 8-band pansharpened WV-2 imagery products in eCognition 10 with the scale set to 300. After segmentation, we fused lidar DEM features including mean and standard deviation of elevation with image features to be used for classification. Project areas KENAN, SJWMA, FWMA and BCWMA have a large water coverage and lidar DEM would not provide values for mapping these areas and thus were not included. 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 vote from three classifiers is achieved, then the segment will be assigned as the voted class, else, it will assign the segment to the class which has the highest individual accuracy among three classifiers. We collected both field-based and imagery-based reference samples to train and test the classification models.

3.2 Selection of scale parameter in image segmentation

In our first contract with the District, we mapped multiple wetland areas on District land and set the scale parameter in the multiresolution segmentation process at 150. The setting of this parameter is important. A smaller value will lead to a greater number of segments/patches and may lead to "salt-and-pepper" effects in the final maps similar to the pixel-based mapping method. In addition, the large number of small segments will largely increase the dataset requiring more computer memory, resulting in difficulties in further data processing. The small segments are also not reasonable for management activities compared to the minimum mapping unit used in the historical maps. In the current contract, we experimented with different scale parameters (e.g., 150, 300, 500) in a small test area (500 acres) within FDMCA and discussed the results with Dr. Hall. The results using the different scale parameters are displayed in Figure 11.

The scale of 150 generated more "salt-and-pepper" effects in which small shrubs or patches appeared within a large community (Figure 11a). These small patches are not very relevant for management purposes. Increasing the scale parameter to 300 largely reduced this effect and the map looked much smoother (Figure 11b) and was similar to the resolution of previous plant community maps. Further increasing the scale parameter to 500 made the map even smoother but disregarded important plant communities with restricted extents. Based upon the evaluation of different scale parameters, and in consultation with the District, we selected the scale of 300 for the entire Project Area mapped during the 2022-2023 FY. This scale will continue to be used in subsequent years of this contract unless plant community distributions and extents suggest otherwise.

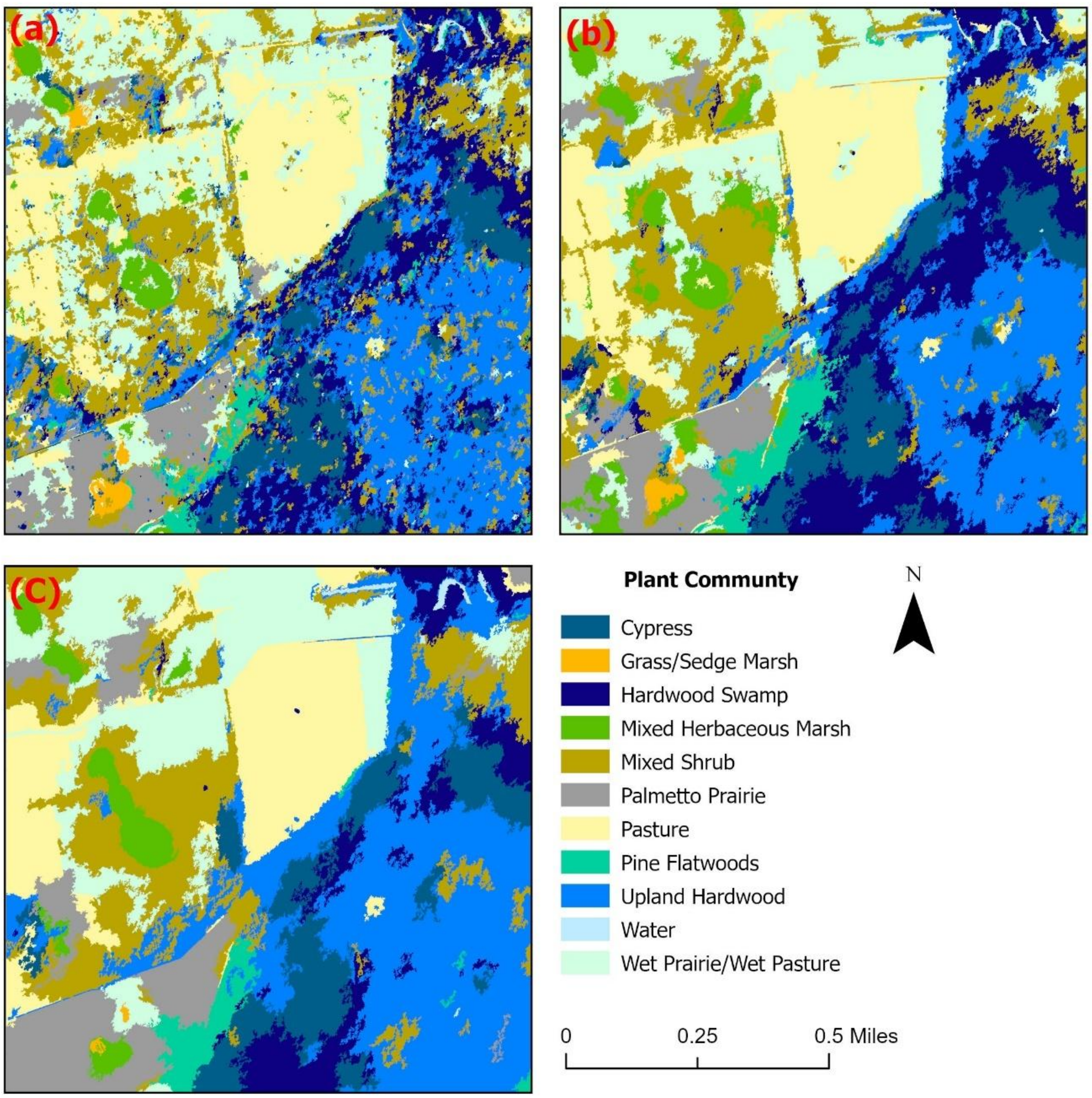

Figure 11 Mapping a 500-acre area within the FDMCA using different scale parameters, 150 (a), 300 (b), and 500 (c).

3.3 Acceleration of image segmentation using eCognition server

A big challenge using the multiresolution image segmentation in eCognition Developer 10 for object-based wetland mapping is the time cost. There are no comparable software packages to the state-of-the-art OBIA of eCognition Developer which has been secured by the District.

Generating the image objects and exporting relevant image-based features may take over 10 hours for an area of 10,000 acres. Interruption of this procedure will lead to a complete loss of the generated segments and exported features, and thus the procedure needs to restart. In this contract, we found a solution to reduce the segmentation time and save the segments if the procedure is interrupted. We applied the eCognition Server tiling and batch processing functions to solve this issue. Applying the multiple server function is similar to parallel computation using multicore processing, and the batching function segments image task by task. The segmentation and export function can be saved as a batch rule set to be applied in the batch processing, then the server will process and apply the batch rule to analyzed image. Large images can be split into smaller tiles and the server will process the data tile by tile. Though this current contract does not require tutorials for the mapping procedure as in the previous contract, we can provide a detailed manual for the District to use the eCognition Server batching and tiling function using the WV-2 imagery as an example. This approach improved the segmentation procedure and largely reduced the time cost in the project.

3.4 Modification of project boundary for FWMA and SJWMA

The original project boundary provided by the District was not correct for FWMA and SJWMA. The boundary missed a small portion of the north part called flow-away in SJWMA and included crop areas along the southern boundary of Area 2 and the eastern boundary of Area 3 which do not belong to the District. The provided WV-2 imagery is larger than the project boundary. A correct definition of the project boundary is important because it defines where we should collect reference samples as well as other data processing procedures. A final makeup to account for the missing part by providing a small piece of the imagery made the entire mapping procedure more complicated and added another week to fix this issue because this missing part needs to be stitched to the bigger imagery, and rerun the segmentation for the merged imagery, and further classification and mapping. This also added a boundary issue in the final map. We manually corrected the FWMA and SJWMA boundaries and stitched the segmented results to FWMA and SJWMA and re-ran the entire classification procedure to fix the incorrect boundary and flow-away issues in this project. Thus, we suggest the District refine and improve each project area and check corresponding imagery before the mapping project starts.

3.5 Mapping of 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 example, grassed levees can be confused with pasture (PA) areas, boat ramp areas can be confused with paved roads. The District has an existing levee/road dataset in line features, and the anthropogenic areas are sparse. Both levees/roads and anthropogenic features can be clearly identified on the imagery, and thus we manually mapped these two classes. For the levee/road features, we revised the District's levee/road line features by measuring the width of different roads on the imagery, then applied a buffer with different width (50 feet, 100 feet, 150 feet, and 200 feet) to generate a polygon feature of the levee/road map layer. For the anthropogenic areas, we manually digitized anthropogenic features if they were not completely covered by the levee/road map layer. 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.

3.6 Automation of map product generation

In our previous contract, we developed a detailed tutorial to implement the developed object-based machine learning mapping procedure using ArcMap, eCognition, open-source WEKA, and alternative *R* packages. In this contract, we made major steps more automated to speed up the entire mapping procedure. We designed data preparation modules to generate inputs for our *R* script, and map product generation modules using ArcGIS model builder. We implemented the entire machine learning and classification process using *R* script to reduce the manual input procedure of WEKA. In this way, the inputs and outputs are consistent in data format, and product attributes, making the process more efficient. An example model we developed for the FDMCA is displayed in Figure 12.

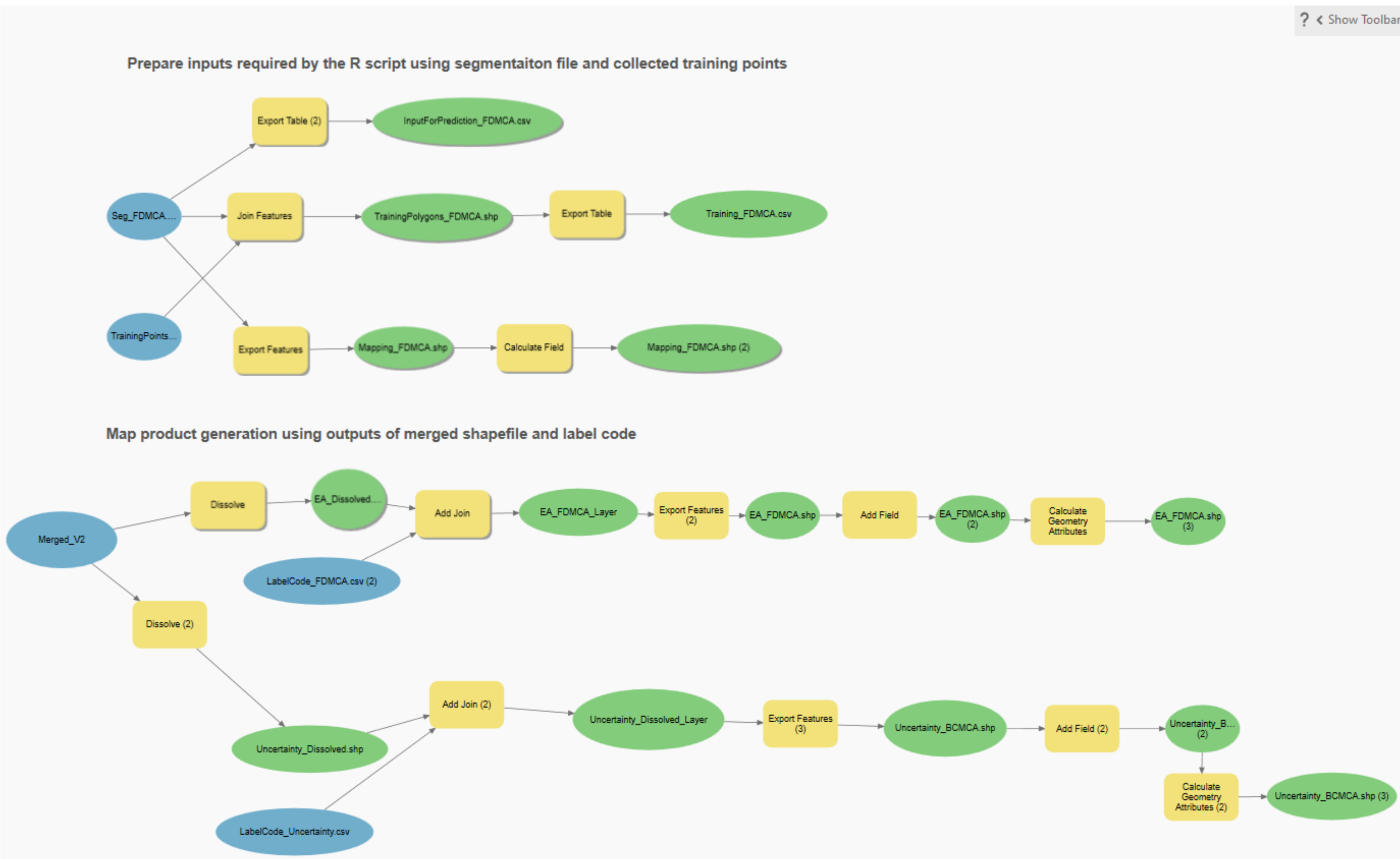

Figure 12 Models developed for preparation of the inputs and processing outputs of *R* for map product generation using model builder in ArcGIS Pro.

3.7 Post-classification refinement

The automated digital procedure generated encouraging results for delineating communities for each project area, however, confusions 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.

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 next to them. Small patches such as shrubs appeared in a big patch such as Upland Hardwood (UH) are often suspected to be misclassified. By examining the historical map 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 actually greater than the error matrices indicate.

4. Results

4.1 Three testing plots

As required by the District, the developed procedures need to be tested over selected plots to meet the accuracy requirement before going further to map the entire project area. We selected three 500-acre test plots with a diverse plant community within the FDMCA, BCWMA and BCMCA and 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.

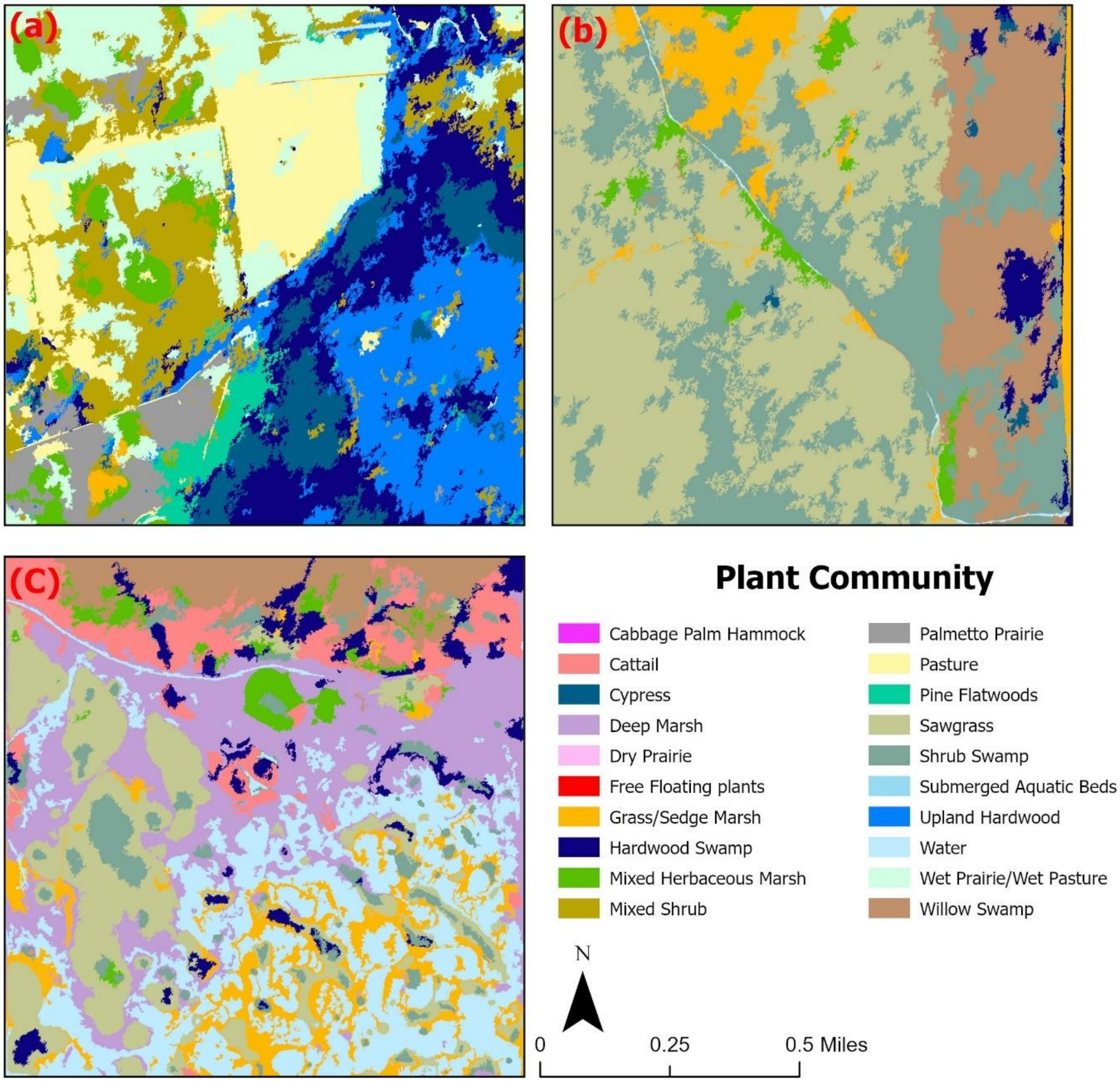

Figure 13 Maps of three 500-acre testing plots within (a) FDMCA, (b) BCMCA, and (c) BCWMA.

4.2 Mapping results of KENAN

The classified map for KENAN is displayed in Figure 14, and error matrix for this area is displayed in Table 2. This area is dominated by aquatic communities such as Submerged Aquatic Beds (SAB), Free Floating Plants (FF), or a mixture of SAB and FF for most areas. SAB shows different signatures across this area. Some have a smooth pattern with airboat trails across them, while others have a very different color on imagery when they emerge from the water and mix with FF, or Mixed Herbaceous Marsh (HM). Sparse DM appears at the edge of the lake or canal, and it is confused with FF by spectral signature. Woody-dominated communities are mainly present at the western side of the lake including Upland Hardwood (UH), Shrub Swamp (SS), Mixed Shrub (MS), Willow Swamp (WS), and Cabbage Palm Hammock (CP). These communities are mixed and appeared as small patches. Their training sample collection was difficult. Patches were labeled by the dominant community though they might be a mixture of multiple communities. Grass/sedge (GS) was confused with HM because HM is a mixture of grass, shrubs, and others. An overall accuracy (OA) of 88% was achieved and a Kappa value of 0.85 was obtained for this area. The User's Accuracy (UA) showed the lowest accuracy was the classification of UH (44%) which was misclassified as MS or CP, while Producer's Accuracy (PA) revealed the same pattern that CP and MS were misclassified as UH. This was expected because CP, MS and UH are mixed in the upland area. Lidar DEM was not included in this area for mapping because most areas are covered by water and there is more uncertainty of lidar data when used in areas dominated by water.

Table 2 Error matrix for KENAN from the ensemble classification. UA=User's Accuracy, PA=Producer's Accuracy. Plant community abbreviations are listed in Table 1.

	CP	CT	DM	DP	FF	GS	HM	MS	OW	SAB	SS	UH	WS	Row Total	UA
CP	36	0	0	0	1	0	0	8	0	0	0	8	0	53	0.68
CT	0	79	0	2	0	1	10	0	0	0	0	0	0	92	0.86
DM	0	0	21	0	6	0	0	0	0	0	0	0	0	27	0.78
DP	0	1	0	65	0	4	2	0	0	0	0	0	0	72	0.90
FF	0	0	2	0	236	0	1	0	0	22	1	0	0	262	0.90
GS	0	1	0	3	2	22	16	0	0	1	0	0	0	45	0.49
HM	0	11	0	1	5	1	185	3	0	2	4	0	2	214	0.86
MS	5	0	0	0	5	0	5	52	0	1	7	11	0	86	0.61
OW	0	0	0	0	1	0	0	0	184	12	0	0	0	197	0.93
SAB	0	0	0	0	11	0	0	0	8	869	0	0	0	888	0.98
SS	2	0	0	0	3	0	5	8	0	0	42	0	0	60	0.70
UH	19	0	0	0	1	0	2	11	0	0	0	26	0	59	0.44
WS	0	2	0	0	0	0	10	0	0	0	0	0	24	36	0.67
Column Total	62	94	23	71	271	28	236	82	192	907	54	45	26	2091	
PA	0.58	0.84	0.91	0.92	0.87	0.79	0.78	0.63	0.96	0.96	0.78	0.58	0.92		
Overall Accuracy: 0.88 Kappa: 0.85															

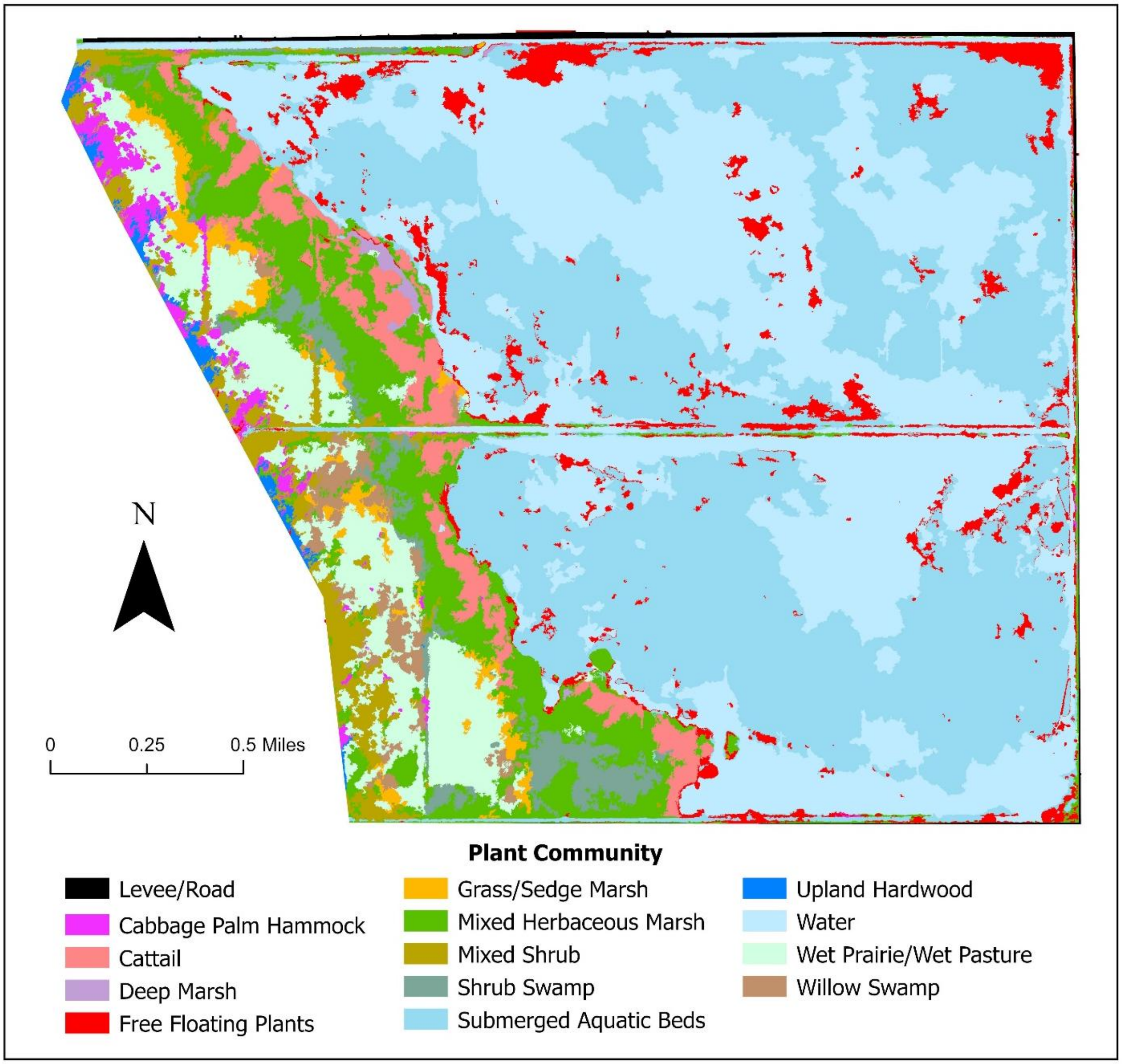

Figure 14 Classified map for KENAN.

4.3 Mapping results of BCMCA

The classified map for BCMCA is displayed in Figure 15, and error matrix for this area is displayed in Table 3. The challenge for mapping this area was the huge dataset covering the entire BCMCA which was the largest area with a size of 29,387 acres among project areas that were mapped. The size of the 0.3-m WV-2 imagery is 12.9 GB. Processing such a large image using normal Dell Workstations is difficult. We thus split the imagery into two pieces to map but the training/reference sample collection was conducted across the entire area to catch the spectral signature variation within this big area. Shrubs, Hardwood Swamp (HS), CY, and Willow Swamp (WS) dominated the north part, while Sawgrass (SG), HM, and Shrubs dominated the south part. Cypress trees lining the perimeter of Blue Cypress Lake were delineated well by the fine resolution imagery. A small coverage of FF was observed on the imagery and was labeled for corresponding segments manually due to limited training samples. A high accuracy for all the mapped plant communities, with an overall accuracy of 89% and Kappa value of 0.87, was achieved for this area due to the relatively small number of communities within this area.

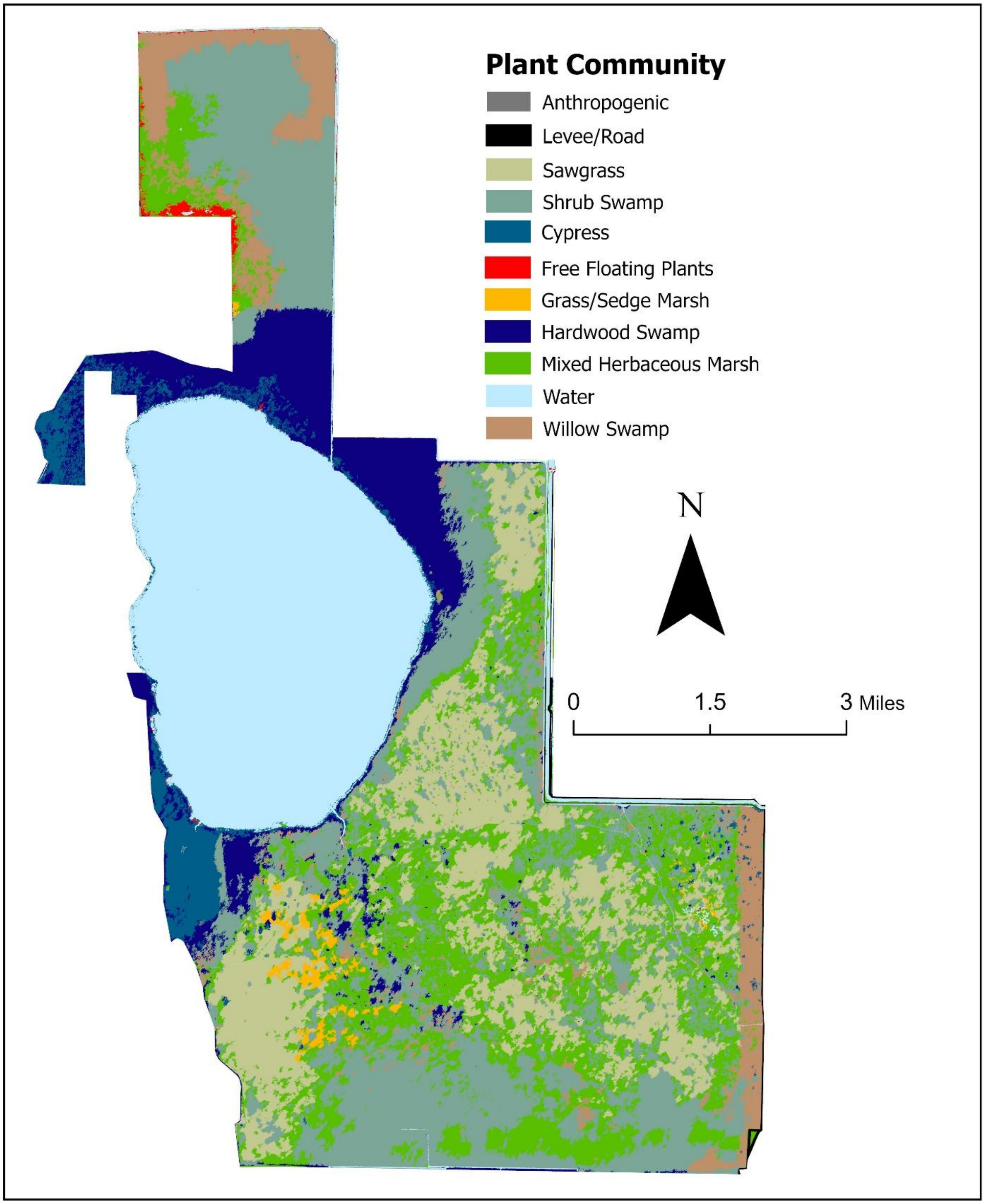

Figure 15 Classified map for BCMCA.

Table 3 Error matrix for the BCMCA from the ensemble classification. UA=User's Accuracy, PA=Producer's Accuracy. Plant community abbreviations are listed in Table 1.

	SG	SS	HM	WS	GS	HS	CY	OW	Row Total	UA
SG	187	0	24	0	3	0	0	0	214	0.87
SS	1	200	9	6	0	3	1	0	220	0.91
HM	27	6	269	3	9	0	0	0	314	0.86
WS	0	26	5	187	1	1	3	0	223	0.84
GS	3	0	8	1	78	0	0	1	91	0.86
HS	0	3	0	1	0	117	2	0	123	0.95
CY	0	3	0	2	0	0	116	0	121	0.96
OW	0	0	0	0	0	0	0	67	67	1.00
Column Total	218	238	315	200	91	121	122	68	1373	
PA	0.86	0.84	0.85	0.94	0.86	0.97	0.95	0.99		
Overall Accuracy: 0.89 Kappa: 0.87										

4.4 Mapping results of SJWMA

The SJWMA is mainly occupied by water bordered by a levee capped with crushed coquina on the east side and a grassed levee on the west side. It is adjacent to the FWMA, and thus we collected training/reference samples and developed the same classification model for SJWMA and FWMA. However, we mapped the two areas separately due to the large dataset that would result if the two areas were combined (i.e., we conducted segmentation and final classification for each individual area). SJWMA and FWMA shared the same error matrix as shown in Table 4 (see discussion of accuracy and error matrix under FWMA), and the final classified map for SJWMA is displayed in Figure 16. Free Floating plants (FF), HM, and Cattail (CT) are present at the edge of the water body.

Table 4 Error matrix for SJWMA and FWMA from the ensemble classification. UA=User's Accuracy, PA=Producer's Accuracy. Plant community abbreviations are listed in Table 1.

	CT	WP	HM	DM	GS	SAB	FF	CP	SS	OW	Row Total	UA
CT	269	1	34	0	2	1	0	0	1	0	308	0.87
WP	0	70	18	0	0	0	0	0	0	0	88	0.80
HM	35	5	214	1	8	8	5	0	5	0	281	0.76
DM	1	0	2	62	0	6	3	2	2	0	78	0.80
GS	15	5	29	0	44	0	13	0	3	0	109	0.40
SAB	0	0	0	0	1	361	3	0	2	12	379	0.95
FF	0	2	6	4	3	5	131	1	6	1	159	0.82
CP	5	0	3	0	0	1	0	26	6	0	41	0.63
SS	8	1	10	5	1	1	4	5	52	0	87	0.60
OW	0	0	0	0	0	13	0	0	0	175	188	0.93
Column Total	333	84	316	72	59	396	159	34	77	188	1718	
PA	0.81	0.83	0.68	0.86	0.75	0.91	0.82	0.77	0.68	0.93		
Overall Accuracy: 0.82 Kappa: 0.79												

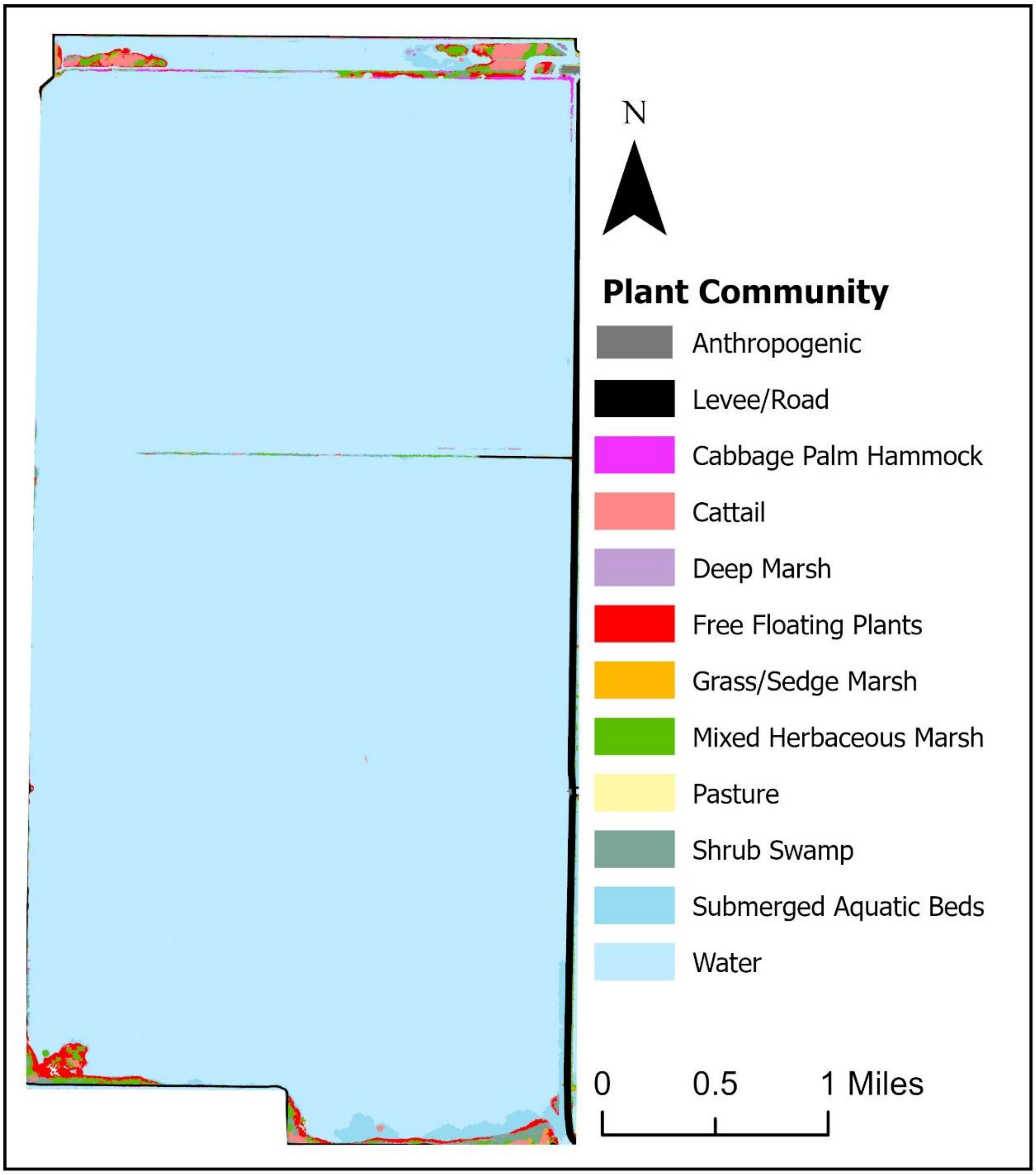

Figure 16 Classified map for SJWMA.

4.5 Mapping results of FWMA

Figure 17 shows the classified map for FWMA. This area was difficult to map. Large changes have occurred in this area since the last mapping in 2015. This area was dominated by Pasture (PA), Grass/Sedge Marsh (GS), and HM before flooded, and now is occupied by tons of Cattail (CT) islands, SAB, and FF. Relatively dry areas are now covered by Wet Prairie/Wet Pasture (WP), HM and sparse GS. Increased inundation at the southern end contributed to the conversion of HS to CT and HM.

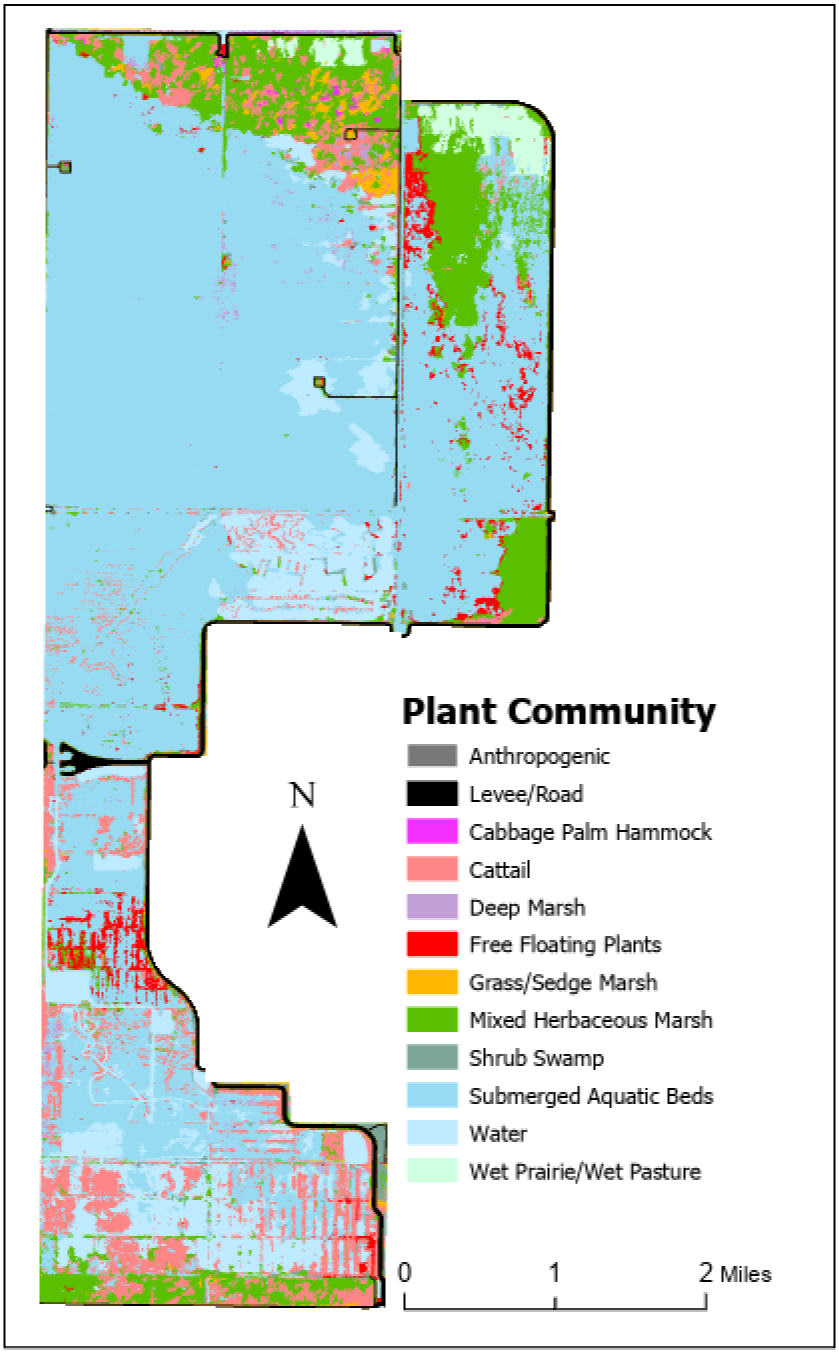

Figure 17 Classified map for FWMA.

The challenge in mapping this area was the difficulty in collecting spectral signatures from the imagery because the 2015 map provided less information in this area relative to other areas which only saw small changes. Flooded vegetation was mixed with SAB and floating plants, and deep dark water was barely seen over this area. Pasture was converted into other land cover types, but low farm berms that were subsequently inundated still support emergent vegetation. We carefully selected spectral signatures and training samples during multiple collaboration events with Dr. Hall to confirm each community on the imagery and reviewed data taken during field visits before developing the model. Accurate spectral signature collection and training/reference sample acquisition is critical in the mapping procedure, since mislabeled training samples will directly cause misclassification of communities.

As shown in Table 4, an overall accuracy of 82% and Kappa value of 0.79 was obtained for mapping this area. Major communities all achieved a high accuracy (>80%) in the identification such as SAB and CT. Minor communities such as Cabbage Palms (CP) and GS had a lower accuracy. CP distribution was limited, which made the training sample selection difficult. CP was only found up along the levee and in the extreme northern and northeastern portions of FWMA and SJWMA. Individual CP trees were observed in larger HM areas in FWMA, but they were not a dominant component of the plant communities and thus were not mapped. Homogeneous GS patches were also barely seen on the imagery and in the field. GS was confused with CT and HM, as expected because HM is a mixture of herbaceous plants, grasses, sedges, and small shrubs (Appendix 1).

4.6 Mapping results of BCWMA

The classified map for BCWMA is displayed in Figure 18 and the error matrix is displayed in Table 5. DM, GS, SS, WS, CT, Sawgrass (SG) and HM are dominant communities over this area. Hardwood Swamp (HS) is present at tree islands and cypress domes are also observed. An overall accuracy of 84% and a Kappa value of 0.83 was generated in classifying 13 plant communities in this area. Upland Hardwood (UH) had the lowest accuracy (60%) due to confusion with Hardwood Swamp (HS). UH was only found along higher parts of the northern levees, and any UH communities mapped in the middle of wetlands were manually revised into HS. Selection of SS training samples based upon the old map were difficult because SS would be changed into HS after seven year’s growth.

The challenge in mapping this area is the heterogeneity of communities. This resulted in under segmentation and sever mixture within a segment. In addition, many segments were bordered by narrow segments with a mixture of water and plants, leading to the need to manually fix these misclassifications. In general, with automated classification and manual refinement, the map captures the heterogeneity of this wetland landscape well.

Table 5 Error matrix for the classification of BCWMA from the ensemble classification. UA=User's Accuracy, PA=Producer's Accuracy. Plant community abbreviations are listed in Table 1.

	GS	HM	SG	CT	DM	SS	WS	HS	CY	UH	SAB	OW	FF	Row Total	UA
GS	83	14	8	0	1	1	1	0	0	0	0	1	0	109	0.76
HM	12	317	5	10	2	2	8	1	7	0	0	0	0	364	0.87
SG	12	8	262	12	5	5	0	0	1	0	0	0	0	305	0.86
CT	2	15	13	206	1	0	0	1	0	0	0	0	0	238	0.87
DM	1	0	1	0	326	2	0	0	1	0	0	1	1	333	0.98
SS	0	6	4	3	5	138	15	35	4	0	0	0	0	210	0.66
WS	0	5	0	0	2	13	288	5	5	0	0	0	0	318	0.91
HS	0	2	2	1	3	19	18	201	17	12	0	0	0	275	0.73
CY	0	4	1	0	1	6	5	14	106	0	0	0	0	137	0.77
UH	0	0	0	0	0	6	2	17	0	37	0	0	0	62	0.60
SAB	1	0	0	0	0	0	0	0	0	0	22	4	0	27	0.82
OW	0	0	0	0	1	0	0	0	0	0	0	111	0	112	0.99
FF	0	0	0	0	1	0	1	0	0	0	0	0	28	30	0.93
Column Total	111	371	296	232	348	192	338	274	141	49	22	117	29	2520	
PA	0.75	0.85	0.89	0.89	0.94	0.72	0.85	0.73	0.75	0.76	1.00	0.95	0.97		
Overall Accuracy: 0.84; Kappa: 0.83															

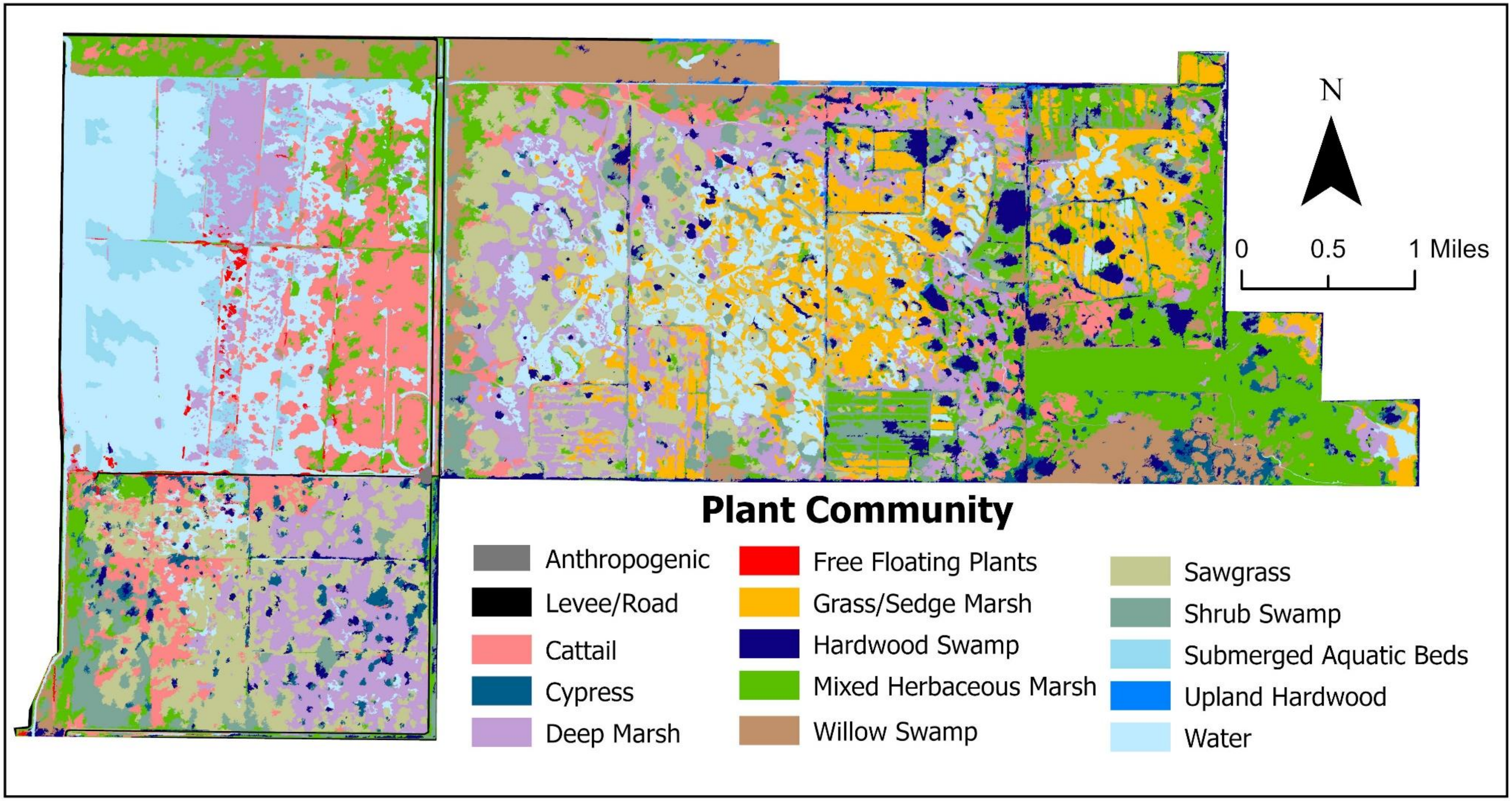

Figure 18 Classified map for BCWMA.

4.7 Mapping results of FDMCA

Table 6 and Figure 19 show the mapping results for the FDMCA. In total this area had 19 communities to be mapped using the classification procedure, the largest number of communities among six project areas. This area is a mosaic of wetland and upland communities including large homogeneous areas of CY, UH, and HS, with a mixture of smaller areas of SS, MS, PA, Wet Pasture (WP), Palmetto Prairie (PP), and other communities. In general, the classification procedure performed well and could accurately identify the large patches with an overall accuracy of 82% and a Kappa value of 0.80. Cabbage Palm hammocks (CP) obtained the lowest User's Accuracy (UA) (37%) due to misclassification with UH and MS, of which cabbage palms can be a part. From the imagery it was observed that the major forested area is a mixture of CY, HS and UH but dominated by CY, which was mapped well as shown in Figure 19. PA and WP were slightly confused and misclassified with each other, which has been seen with manual interpretation of these communities as well. The challenge for mapping this area is the labeling of Mixed Shrub (MS) and Shrub Swamp (SS). MS is present over drier uplands while SS appears over wetter areas. The inclusion of lidar DEM helped the improvement of MS and SS in the training sample selection procedure and was included in the classification. Shadows beside trees or shrubs were misclassified as water. This was manually corrected. Small patches of PA or WP appeared within larger HM communities due to the confusion of WP/PA and HM. These misclassifications were also manually corrected. Similarly, small patches of shrubs that appeared in the big patches of forests or vice versa were suspected misclassifications and were manually revised if needed. Change over this area was small since the last mapping in 2015, therefore the historical map was valuable for spectral signature and training sample selection.

Table 6 Error matrix for the classification of FDMCA from the ensemble classification. UA=User's Accuracy, PA=Producer's Accuracy. Plant community abbreviations are listed in Table 1.

	CP	CT	CY	DM	DP	WS	GS	HM	HS	MS	OW	PA	PF	PP	SG	SS	UH	WP	FF	Row Total	UA
CP	19	0	0	0	0	0	0	0	0	15	0	1	1	1	0	2	13	0	0	52	0.37
CT	0	22	0	0	0	1	0	7	0	0	0	0	0	0	0	2	0	0	0	32	0.69
CY	0	0	269	0	0	1	0	1	3	0	0	0	0	0	0	1	1	0	0	276	0.98
DM	0	0	0	45	0	0	0	0	0	0	1	0	0	1	0	7	0	1	0	55	0.82
DP	0	0	0	0	18	0	0	1	0	0	0	0	0	2	0	0	0	3	0	24	0.75
WS	0	1	3	0	0	75	0	7	0	0	0	0	0	0	0	3	0	0	0	89	0.84
GS	0	2	1	0	0	2	80	78	0	1	0	0	0	0	1	2	0	9	0	176	0.46
HM	0	1	1	1	0	3	10	700	0	1	0	11	0	0	20	9	0	18	0	775	0.90
HS	2	0	7	0	0	1	0	0	104	25	0	0	1	0	0	9	12	2	0	163	0.64
MS	2	0	1	0	0	0	0	1	13	210	0	3	6	2	0	9	6	15	0	268	0.78
OW	0	0	0	0	0	0	0	0	0	0	76	0	0	0	0	0	0	0	0	76	1.00
PA	0	0	0	0	0	0	0	3	0	3	0	184	0	2	0	0	0	30	0	222	0.83
PF	0	0	1	0	0	0	0	0	0	1	0	0	78	0	0	0	10	1	0	91	0.86
PP	0	0	0	0	0	0	0	0	0	5	0	2	0	87	0	0	2	3	0	99	0.88
SG	0	0	5	0	0	0	0	44	0	0	0	0	0	0	133	4	0	0	0	186	0.72
SS	0	1	0	0	0	0	0	14	3	8	0	1	0	0	2	389	0	2	0	420	0.93
UH	0	0	6	0	0	0	0	1	12	17	0	0	14	1	0	0	104	0	0	155	0.67
WP	0	0	1	0	3	1	3	24	0	9	0	32	0	2	0	5	0	311	0	391	0.80
FF	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	15	18	0.83
Column Total	23	27	295	48	21	84	93	882	135	295	77	234	100	98	156	442	148	395	15	3568	
PA	0.83	0.82	0.91	0.94	0.86	0.89	0.86	0.79	0.77	0.71	0.99	0.79	0.78	0.89	0.85	0.88	0.70	0.79	1.00		
Overall Accuracy: 0.82; Kappa: 0.80																					

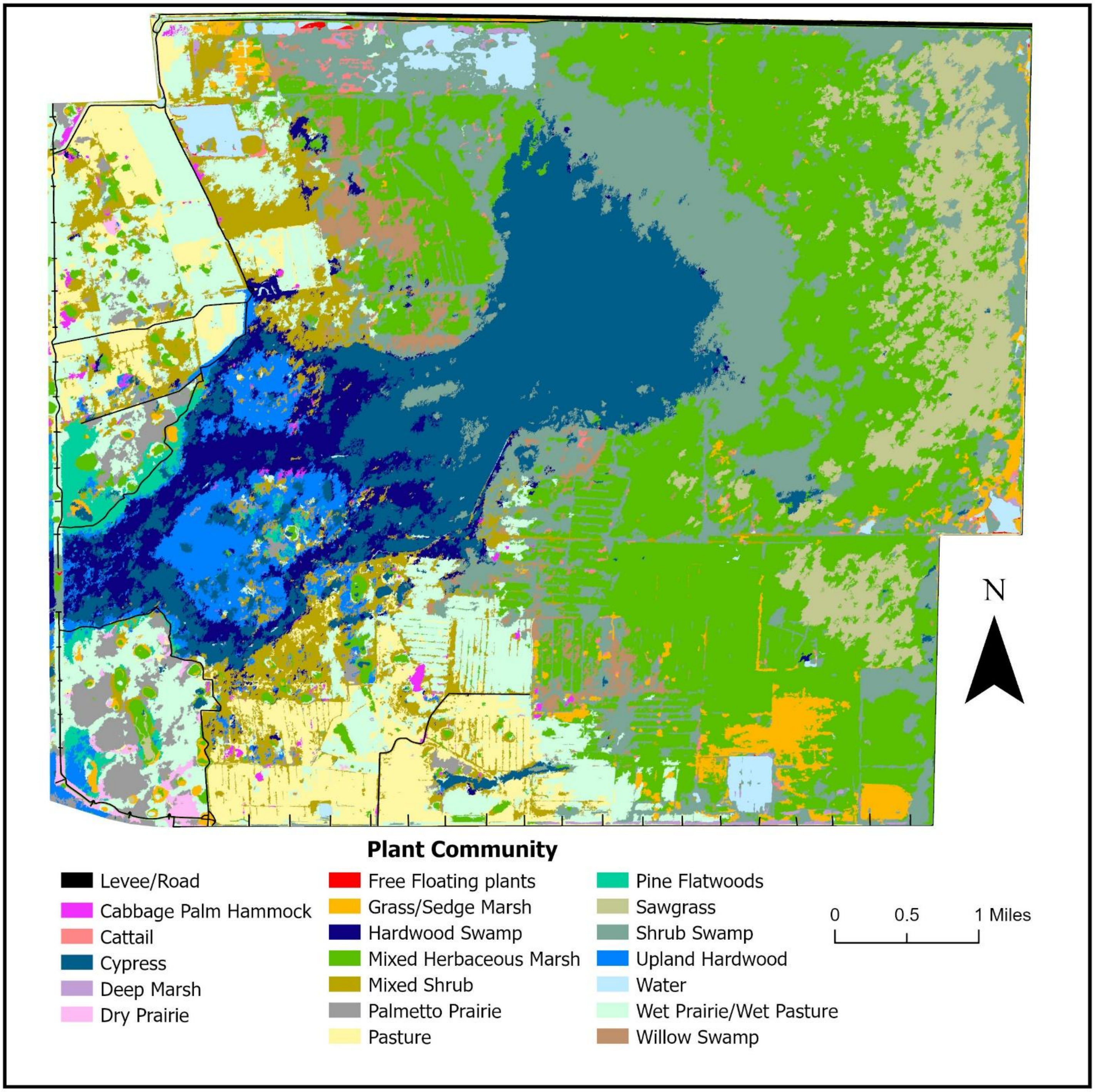

Figure 19 Classified map for FDMCA.

5. Discussion

5.1 Factors impacting map quality

For each project area, we achieved an overall accuracy larger than 80% based on the classification model, but we believe that the integrity of the final maps was higher after the post-classification manual refinement. A lower accuracy for an individual community for a specific area occurred when there were less 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 for the entire area mapping. A qualitative examination of each map laid over the imagery and using the swipe function in ArcGIS 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 the 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 1, WV-2 imagery was acquired in March 2022, but field spectral keys were collected in November 2022. During the field visit, change was observed between the imagery and field observations over some areas, thus only when imagery keys and field observations were consistent, and these areas could be labeled for training or testing in the project. Therefore, a timely field visit is recommended. The WV-2/3 imagery products have a very fine resolution (0.3 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 the mapping results. In this contract, we selected the scale of 300 to avoid the "salt-and-pepper" effect, trade off of the size of the dataset for further processing, and consider the effects on management activities. This one-scale for the entire project area may not work as well for heterogeneous landscapes which will generate segments with more 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 such as BCMCA, imagery often comes from a mosaic of multiple image scenes or images collected from 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, most areas are inaccessible to humans. To mitigate this, we conducted drone surveys for selected sites, but drones could only be launched along a solid levee with a limited coverage (40 acres or smaller). We also tried launching our drone on the airboat, but we could not set up ground control points in the wetlands. Prior knowledge of a project area is valuable to mitigate limited field visits. 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. None of these students had collected effective training samples on the imagery and generated acceptable map products for their assigned project area. However, during this 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 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. I believe that in project year 2 (2023-2024), students will be able to generate map products more accurately and efficiently and learn how to train new students for this project.

5.3 Estimated time cost

The previous mapping method using manual interpretation of aerial photograph by the District would take almost two years 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. 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 6 weeks for 6 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 1 (2022-2023) for mapping six project areas with a total coverage of 81,895 acres. We conducted a 5-day field trip to the project area, collected 6205 field points, and took 187 pictures. A summary of the deliverables is provided below:

- Field samples, photos, and notes
- Drone imagery products
- Map products of testing plots and accuracies
- Map products of six project areas and accuracies
- Map product of a mosaic of all six project areas
- Annual report (this file)
- Map plots (in preparation, need the Project Manager's confirmation)

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, Mizanur Rahman, Sandip Rijal, Abdullah Ai-Fazari, Fiona Benzi, Rabindra Parajuli, David Ramirez, and Madan Thapa Chhetri, 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 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 students and PI to identify each community and understand their ecological significance, providing detailed considerations and logistics for the field visit, and improving the final map products and project report. District's Christy Akers, Jonny Baker, Doug Voltolina and Chris O'Hara, and retired 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*).