

Utilization of Unmanned Aerial Systems (UAS) for Vegetation Mapping and Restoration

Jon Morton

Invasive Species Management Branch

South Florida Restoration Office

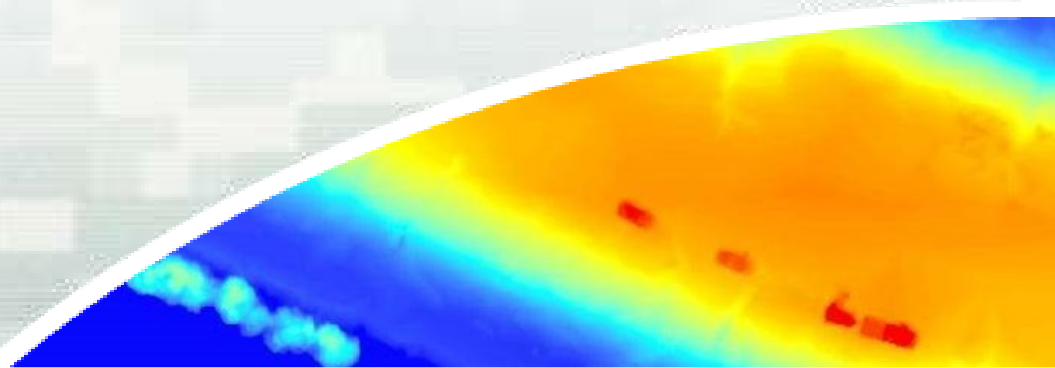
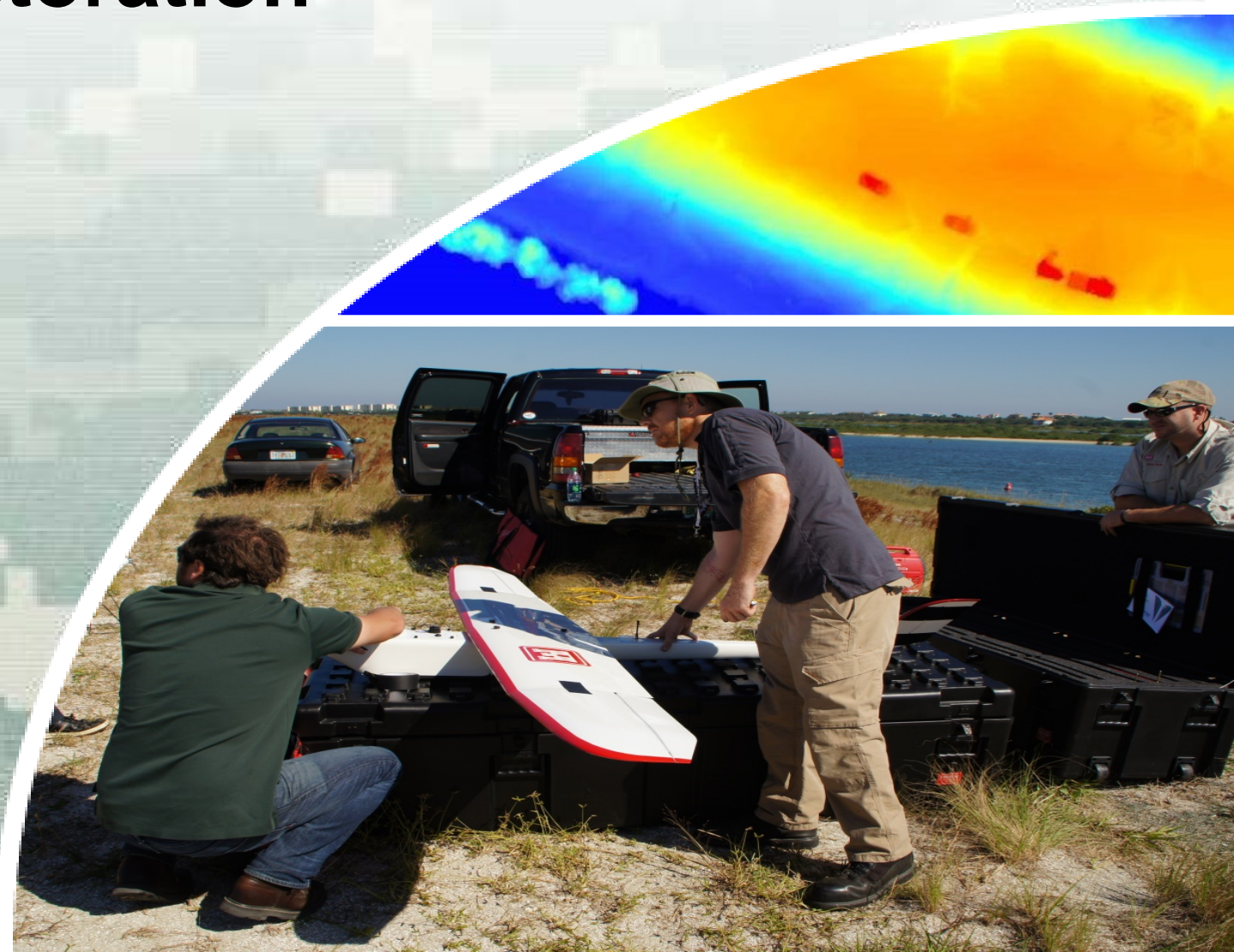
West Palm Beach, Florida



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UAV – THE NEED

- High resolution imagery for invasive species management and environmental restoration
- High temporal resolution (ability to quickly reacquire)
- Waterproof landing
- Responsive to users
- Sufficient payload capacity for future development



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USACE Program Mission

Provide a Reliable Data Collection Tool to Support
Aerial Mapping and Environmental Reconnaissance
Missions



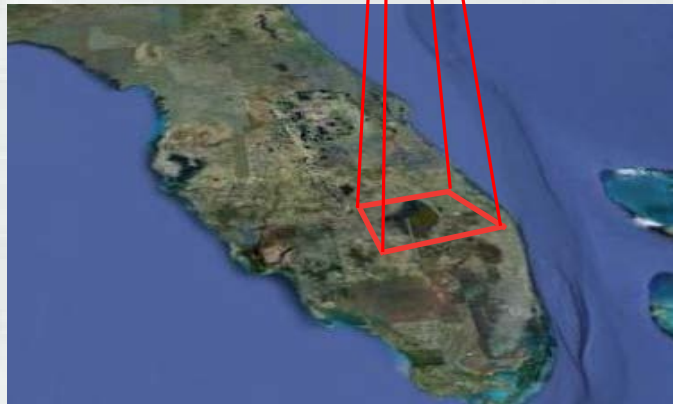
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Airframe Evolution



2006-2008: Polaris

- Airframe development
- “Truck” for geospatial payload



2008-2009: Shoe/NOVA



2009-2010: NOVA/NOVA Block II



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NOVA System



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NOVA System Components



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NOVA BLOCK III



- “Commercialized” version of the Block II
- 6 cell lithium battery
- Connection improvements
- Established safety record with AED
- Procerus Kestrel Autopilot



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NOVA Specifications



- Fully Autonomous
- 2.7 m Wingspan
- 15 lbs. w/ Payload
- ~750 acres per lift @ 300m altitude
- ~50 kilometers per lift @ 300m altitude
- ~3.5cm @ 300m altitude
- Absolute spatial accuracy typically 2-4 meters (no ground control)
- Block II = 60 minute duration
- Block III = 90 minute duration



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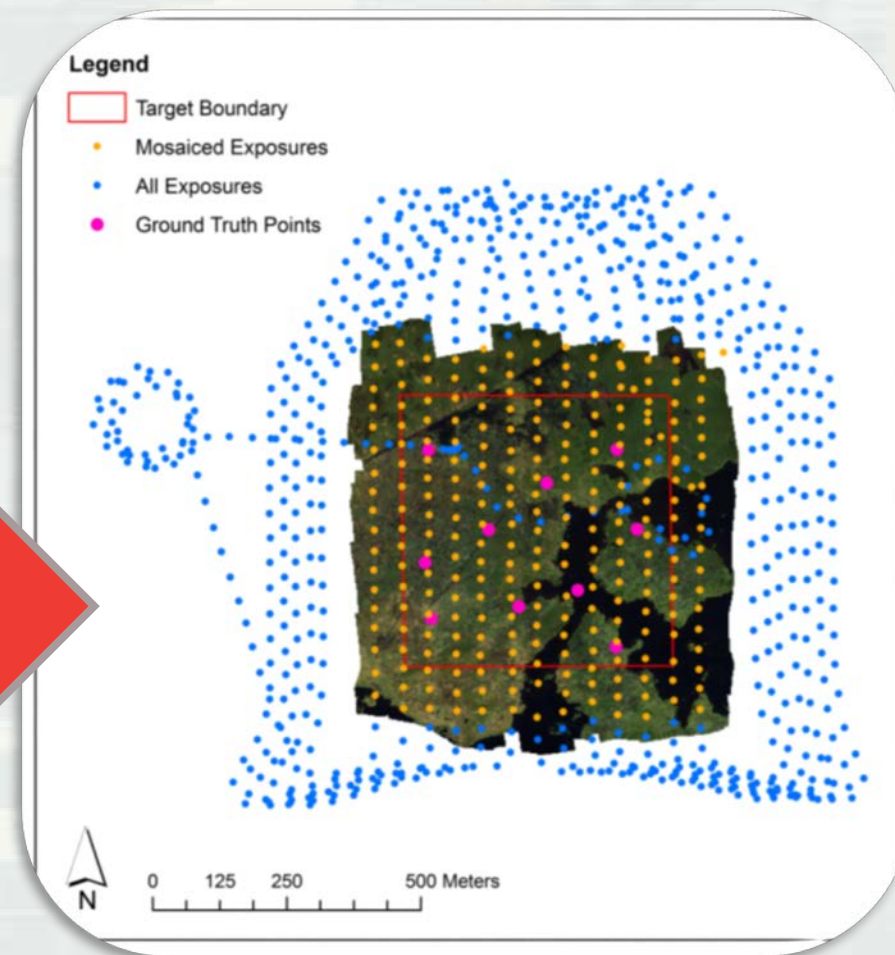
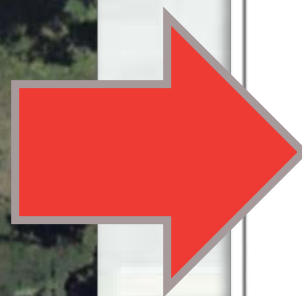
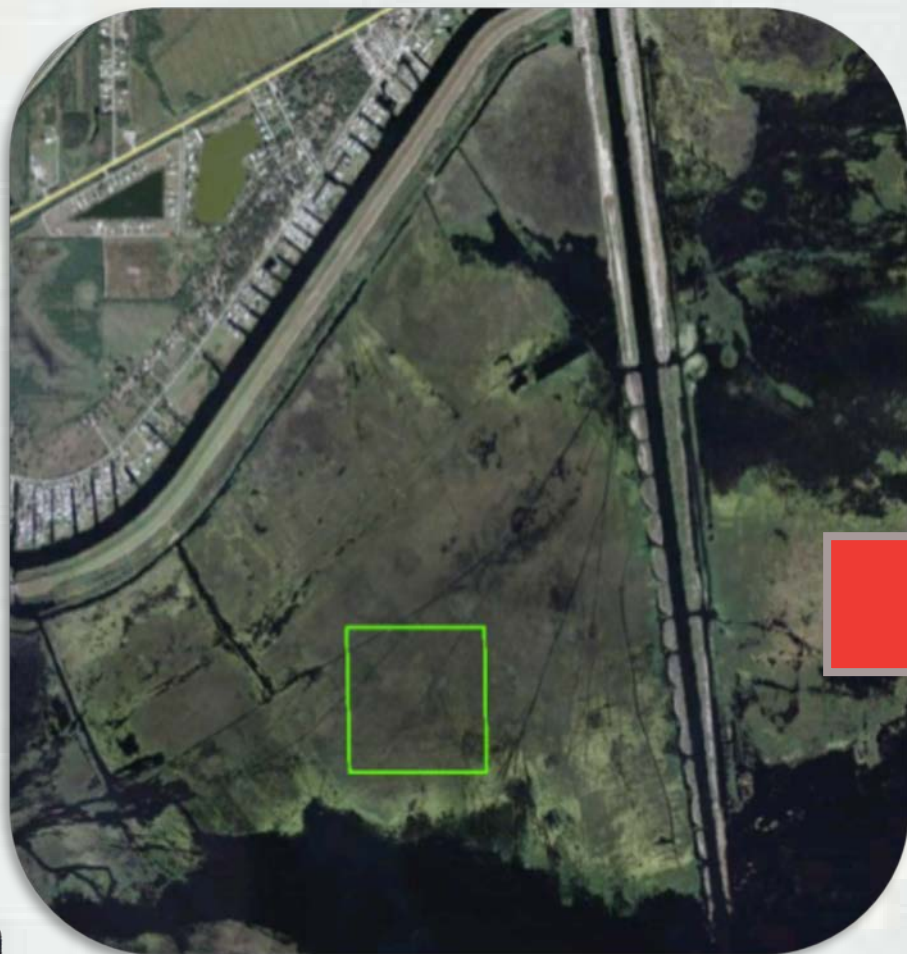
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NOVA - Airboat Launch



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Image Capture



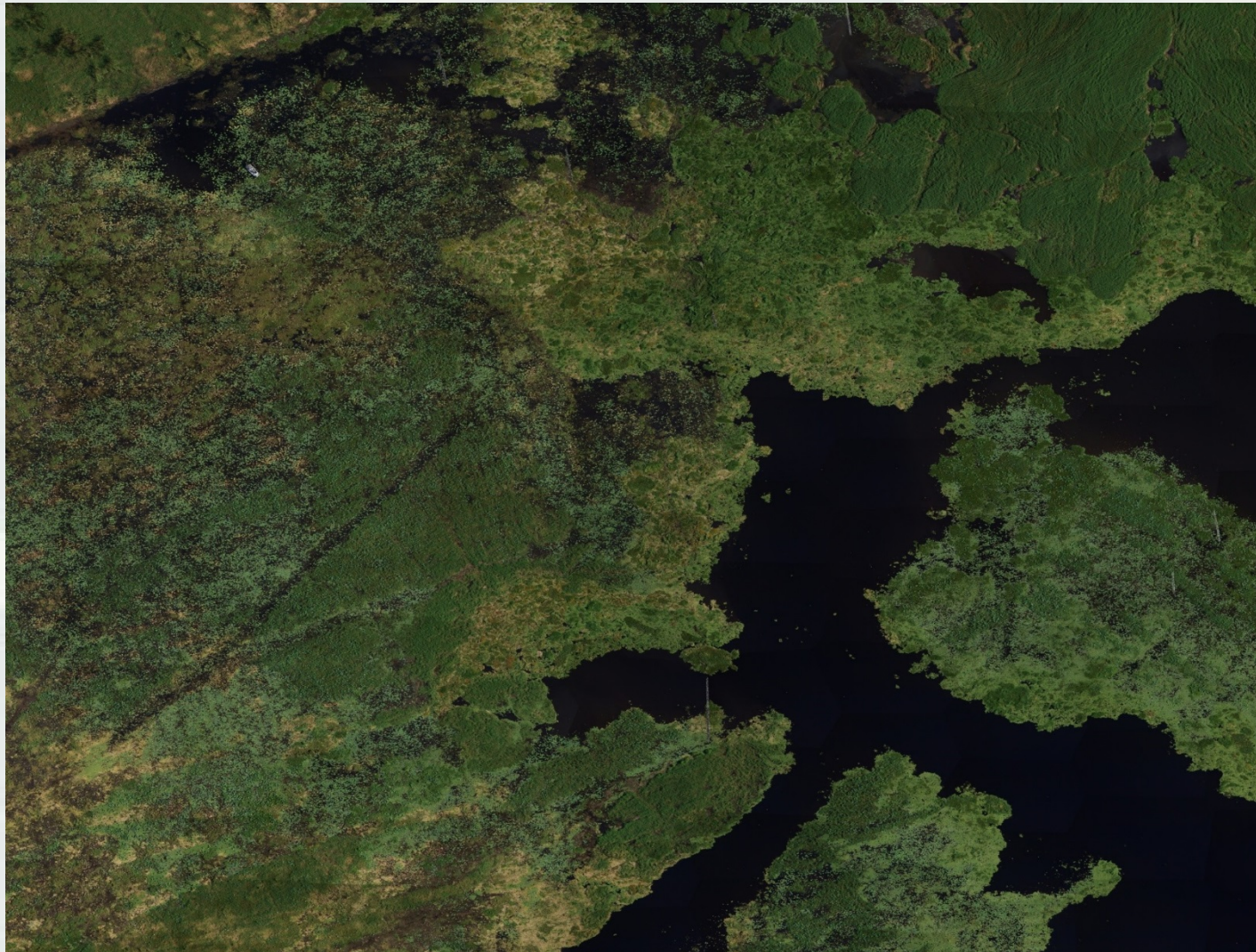
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High Resolution Mosaic – 250 images



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Mosaic Enlargement



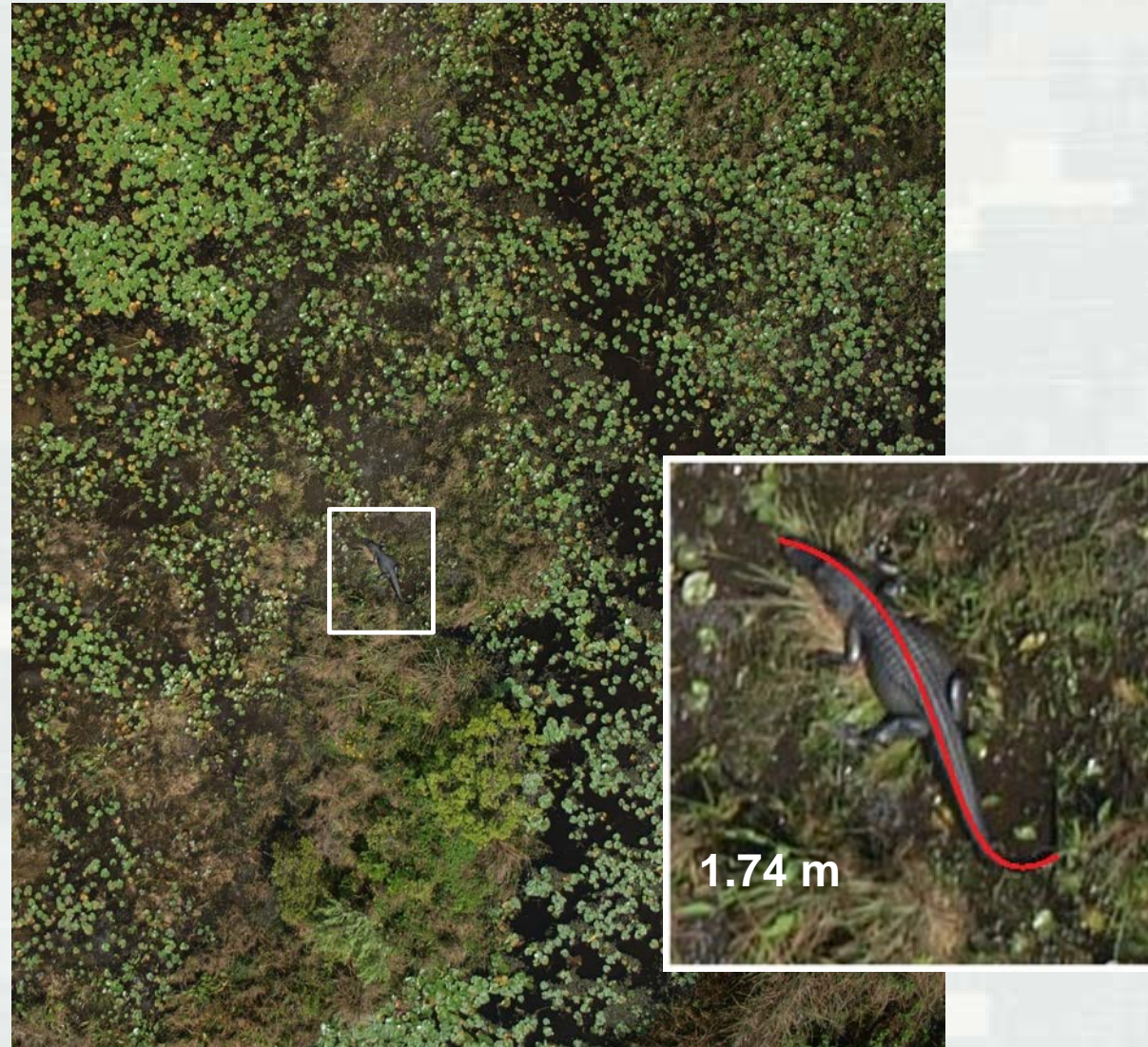
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Spatial Measurement



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Constraints



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Constraints

We only fly in approved airspace, typically:

- Below 1200'
- 5 nm outside of airports
- 30 nm for large airports (MIA, TPA).
- Flight in this airspace possible, requires COA

AR 70-62 requires AWR:

- Airworthiness Qualification Level (AQL) 3
- Not undergone rigorous airworthiness qualification
- Avoid flying over people, roads, homes, etc.
- Limited to Line Of Sight operation (LOS)
- Depends on conditions, typically 1.5km



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Airspace



Class G Airspace = GOOD for the most part.



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NOVA: Applications



- Pre/active/post construction monitoring
- Asset/infrastructure management
- Invasive species surveillance and monitoring***
- Vegetation community mapping***
- Environmental restoration/engineering***



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Untreated Cogongrass (*Imperata cylindrical*)



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U.S. ARMY

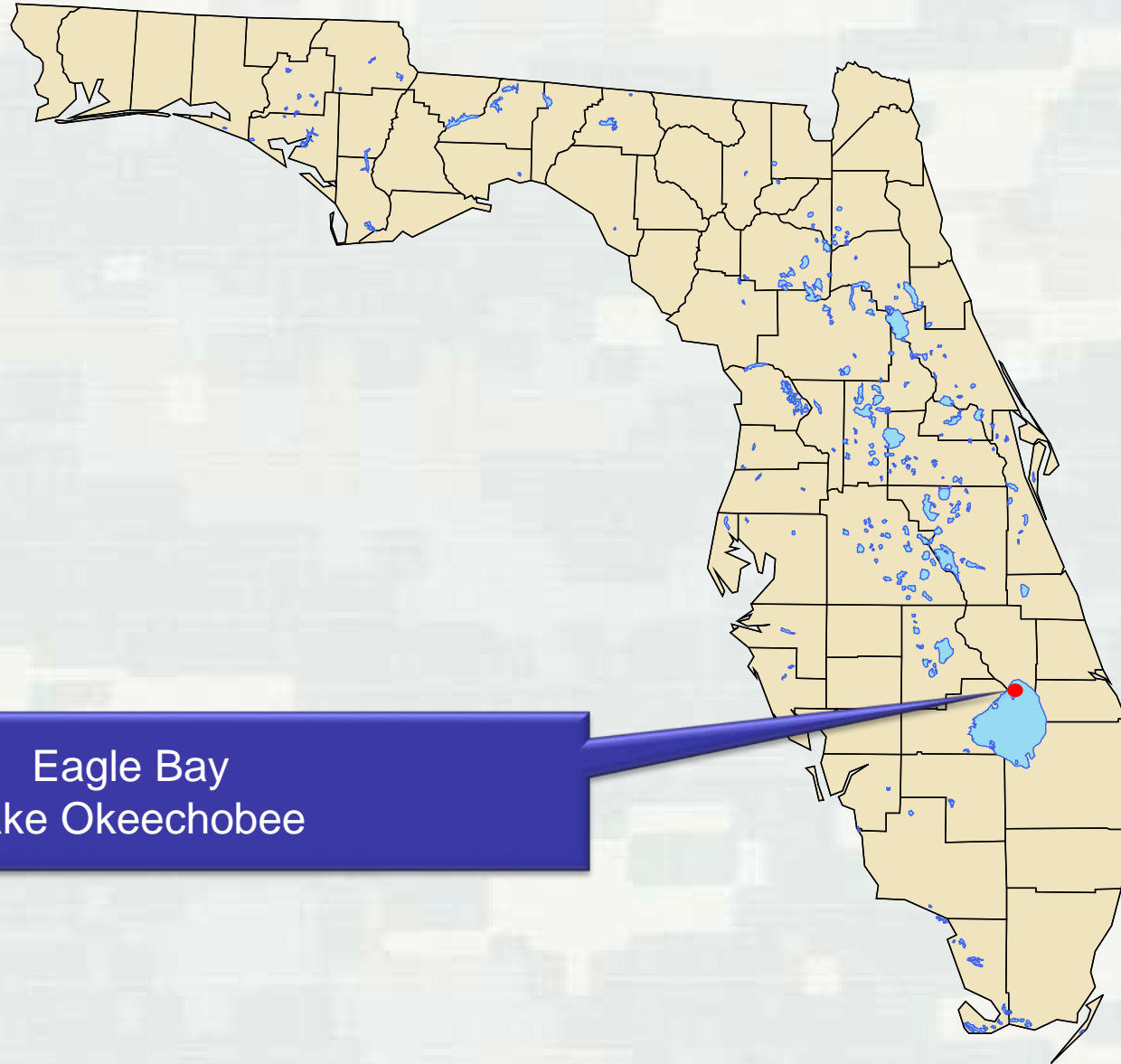
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Eagle Bay
Lake Okeechobee

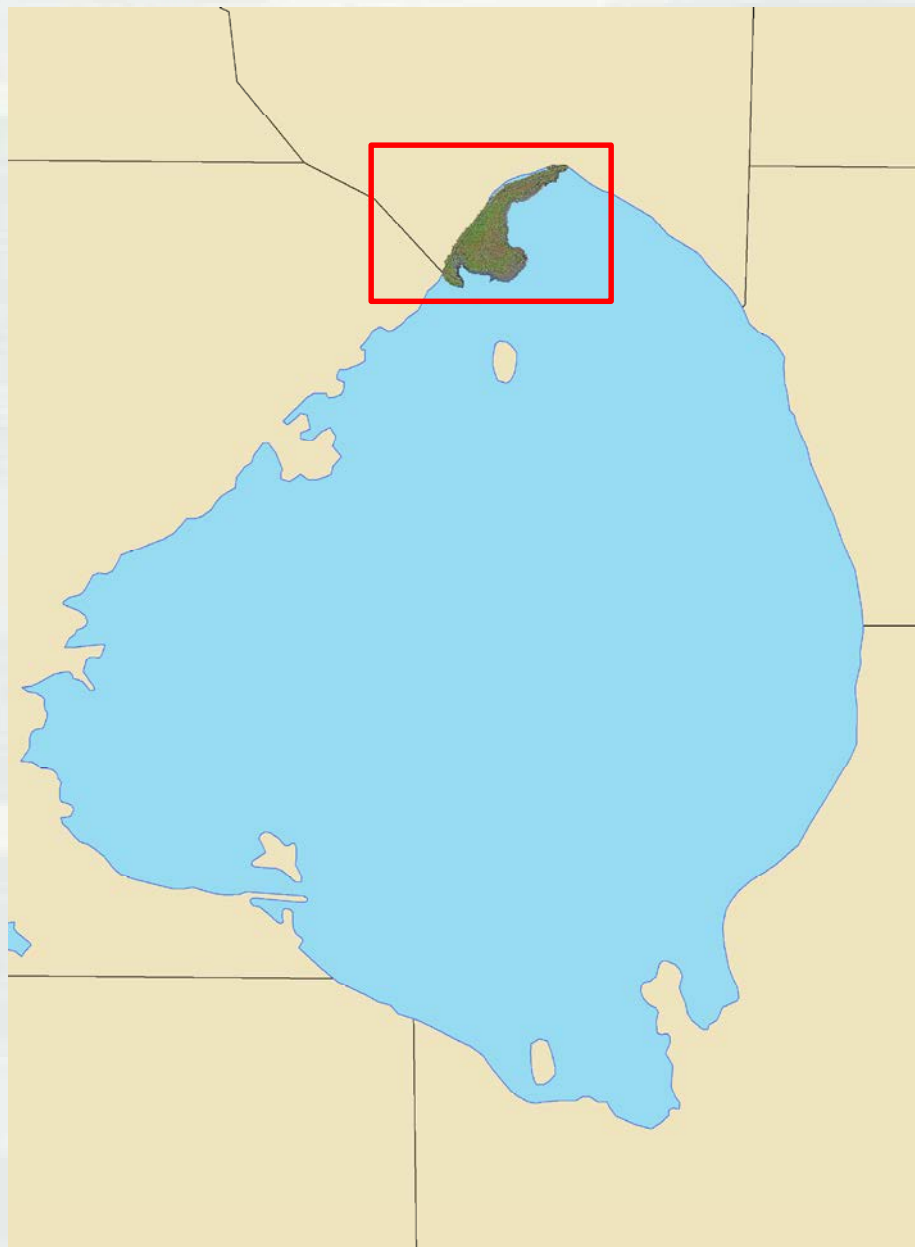


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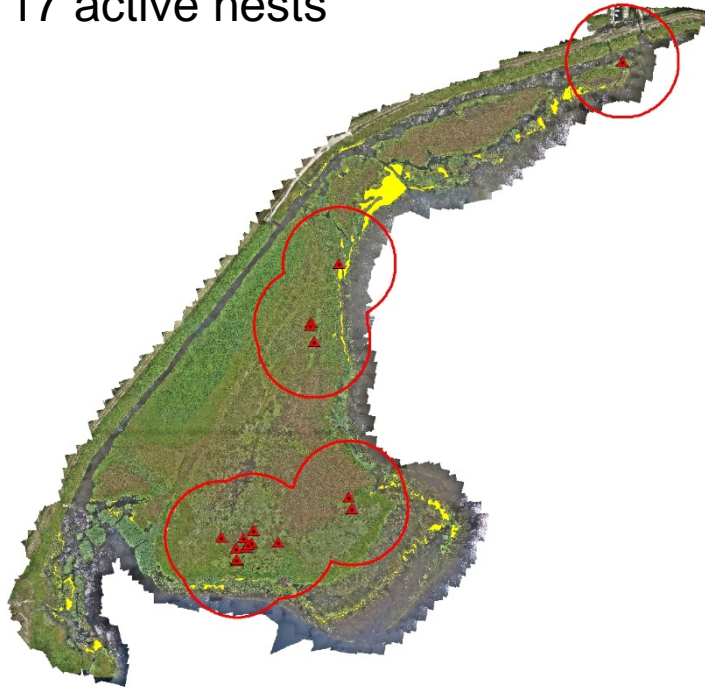
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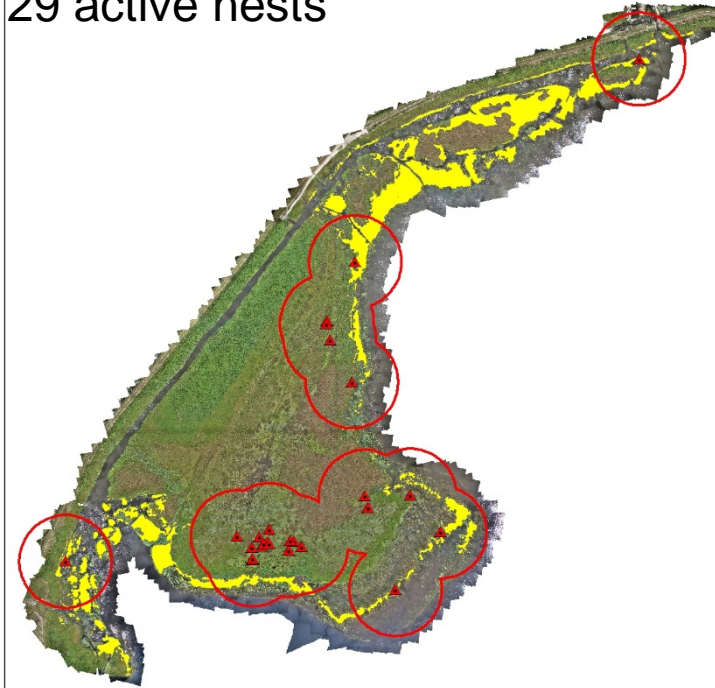
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Invasive Species Management/Everglades Snail Kite Nesting Area

March 2012
142 acres
17 active nests



July 2012
537 acres
29 active nests

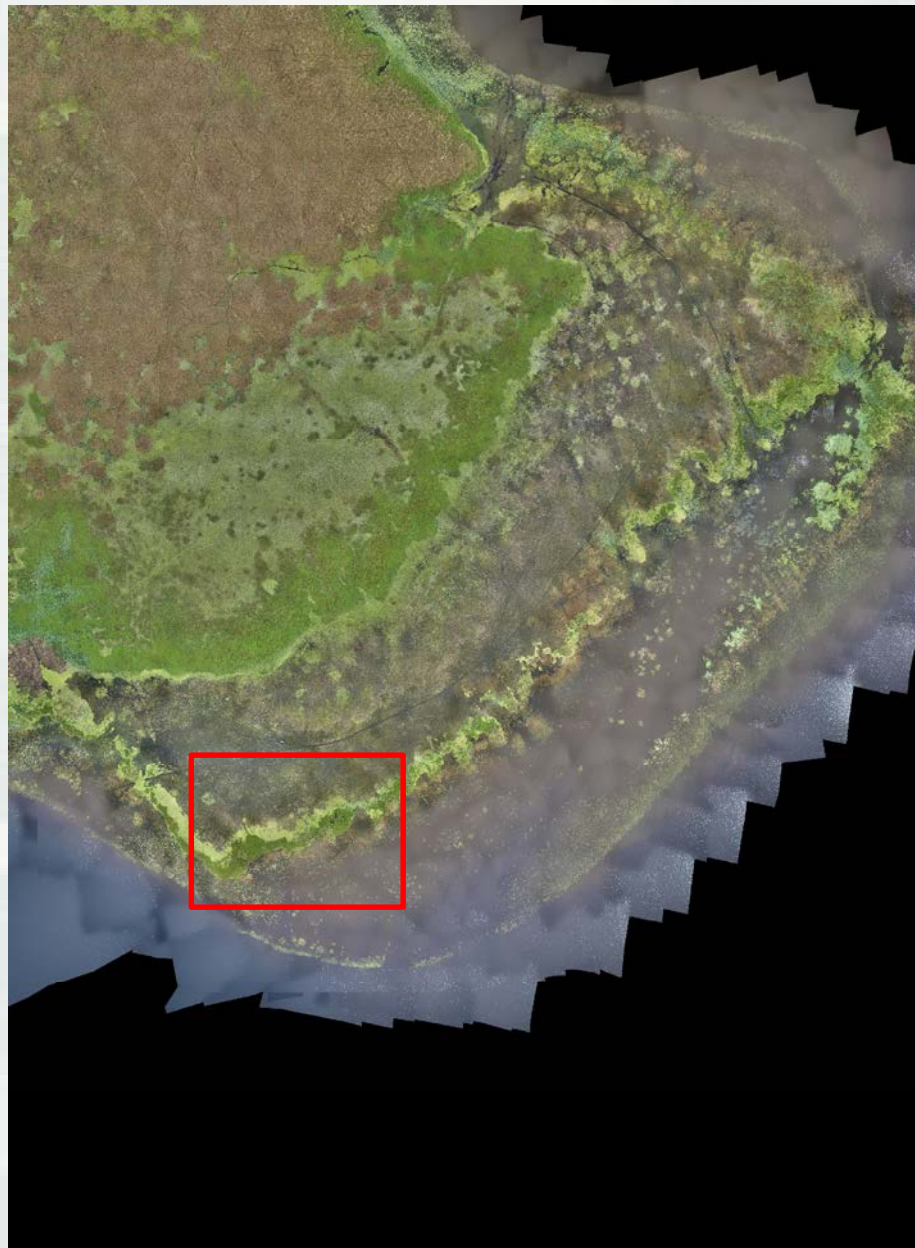


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The need for auto-classification



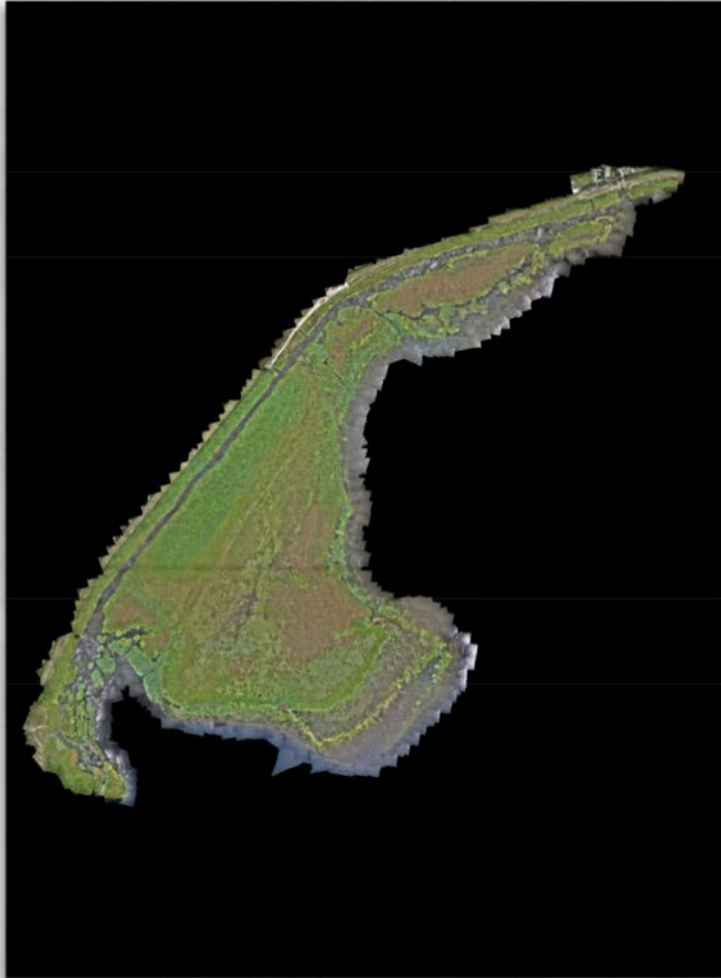
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Research



Dr Amr Abd-Elrahman, PhD

Geomatics Lead

University of Florida

Gulf Coast Research & Education Center

Roshan Pande, Post-Doc

Tao Liu, Post-Doc



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Object-based Classification



Goal:

- Map Invasive plants using spectral, textural and contextual object-based classification

Objectives:

- Identify best spectral and textural features and segmentation scale(s)
- Test different machine learning classifiers e.g. Regression Tree (CART), Support Vector Machine (SVM), and Artificial Neural Network (ANN)
- Develop spectral, textural and contextual rules based on multi-scale segmentation



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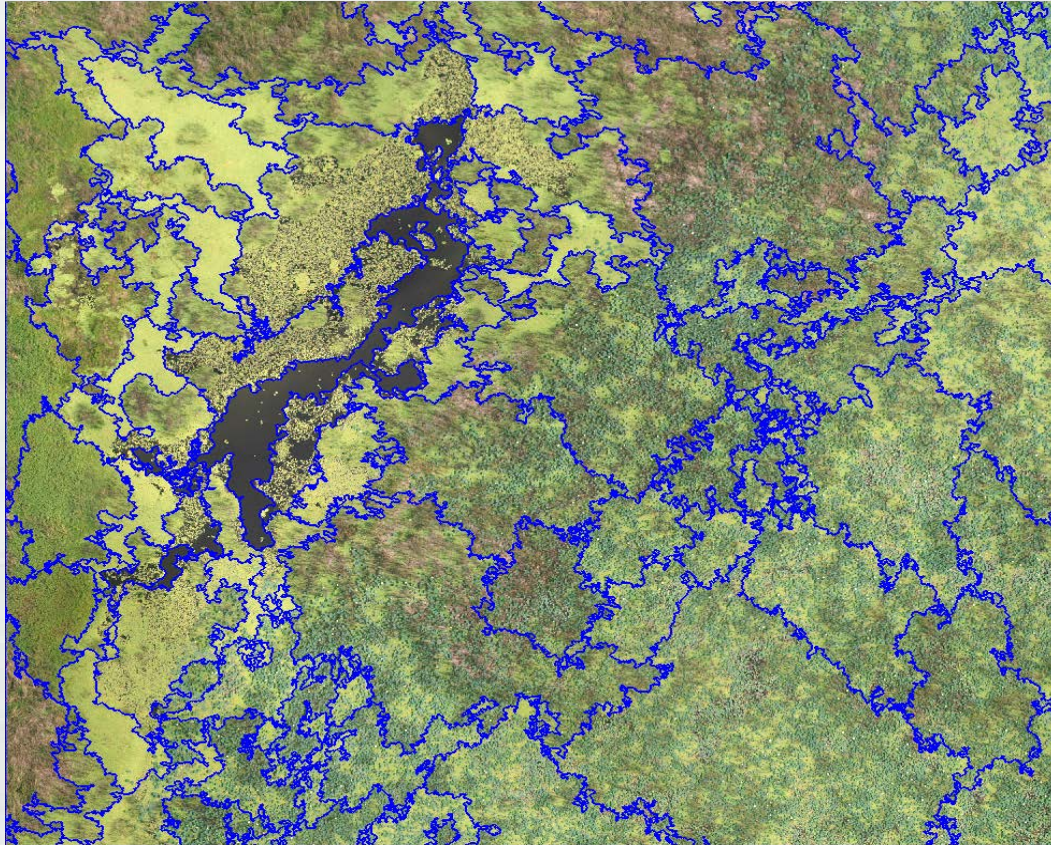
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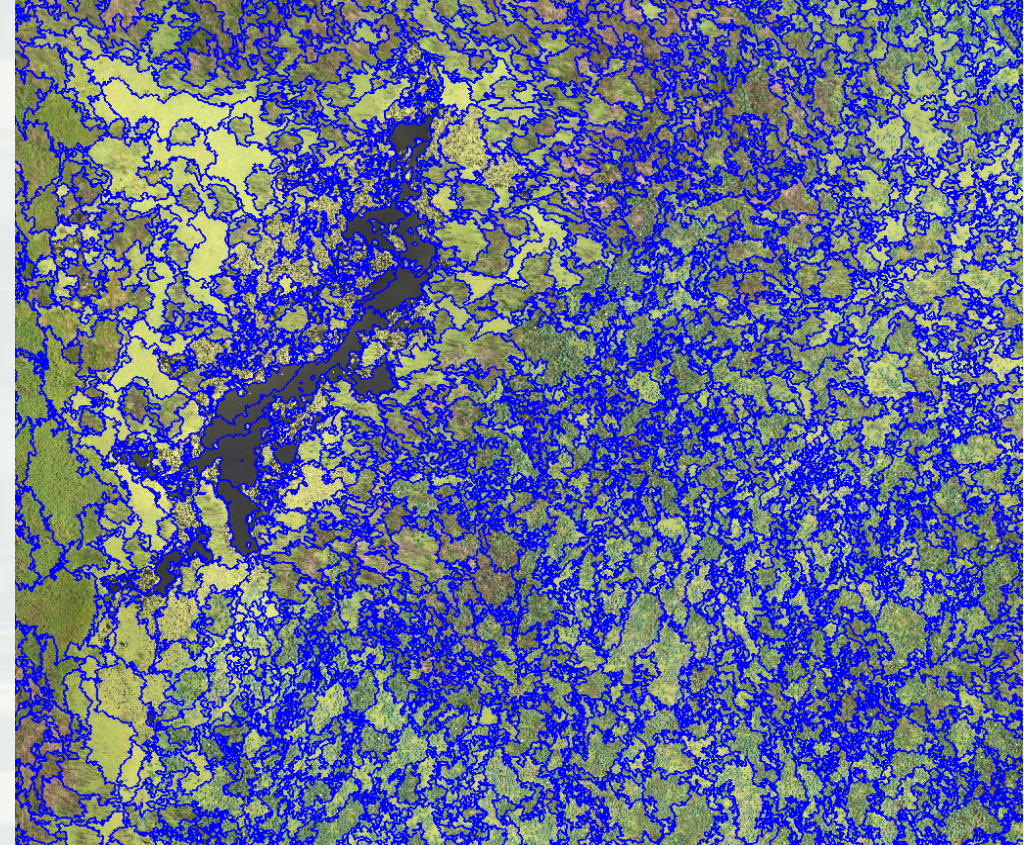
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Examples of Segmentation at different scales



Segmentation : course (300) scale



Segmentation: medium (75)scale

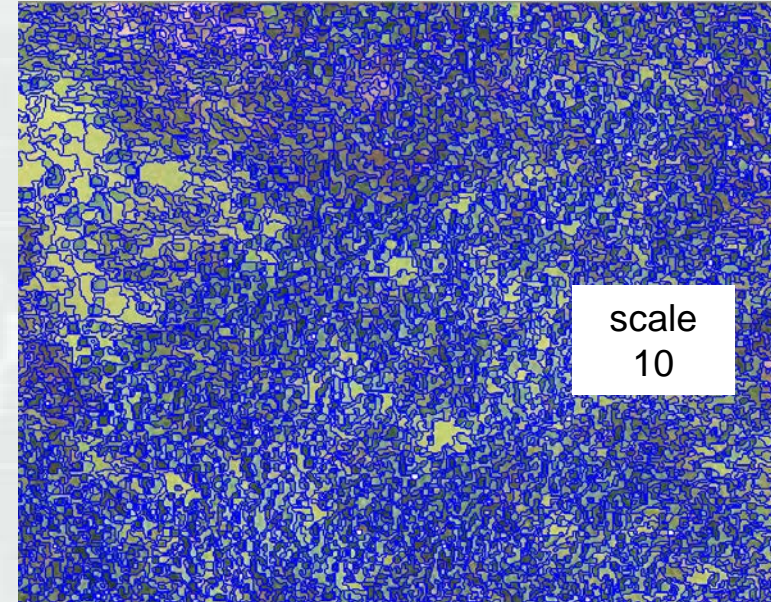
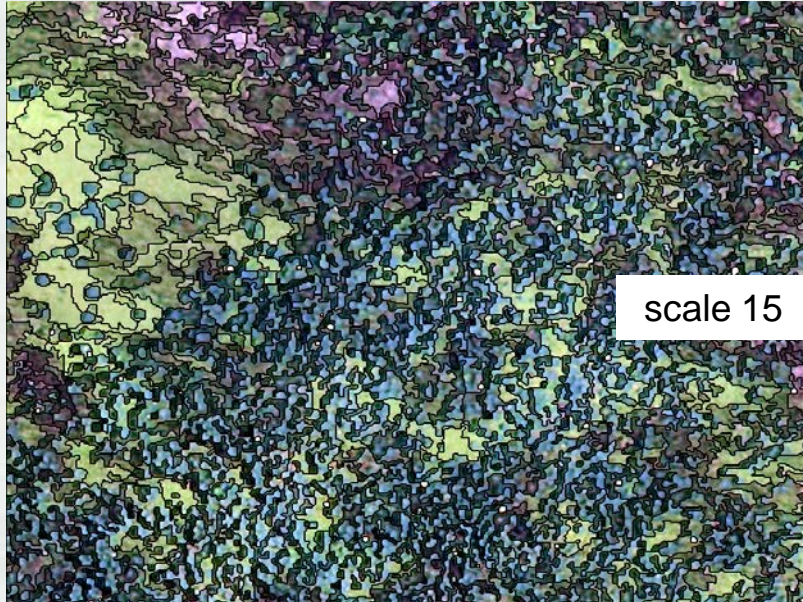
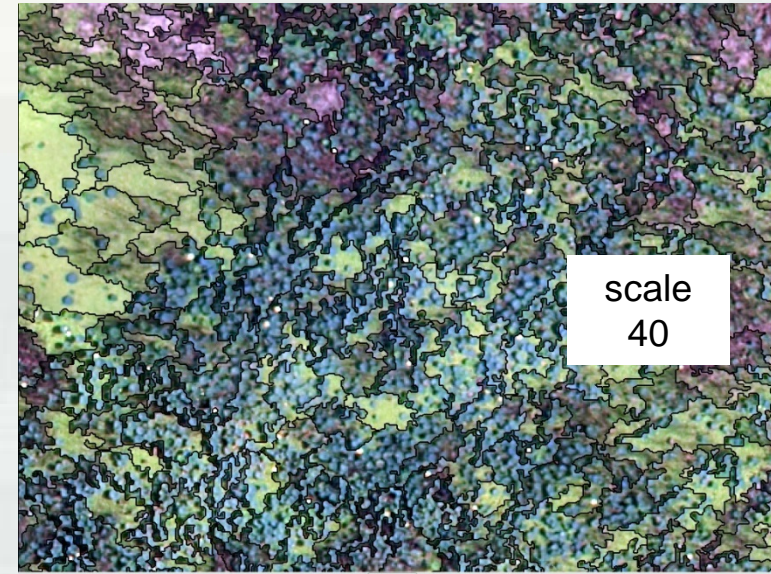


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Accuracy Assessment

- Classified maps were matched against assessment data set and error matrices were developed.
- Accuracy values (overall accuracy and Kappa coefficients) were computed and used for assessment and comparison.

| Classifier | Overall | Kappa |
|--------------------------------|---------|-------|
| SVM | 70.32% | 0.654 |
| ANN | 69.44% | 0.643 |
| M L | 58.18% | 0.516 |
| Pixel based SVM (downsized) | 57.37% | 0.513 |
| Pixel based ML | 50.94% | 0.451 |
| Pixel based ANN | 53.62% | 0.476 |



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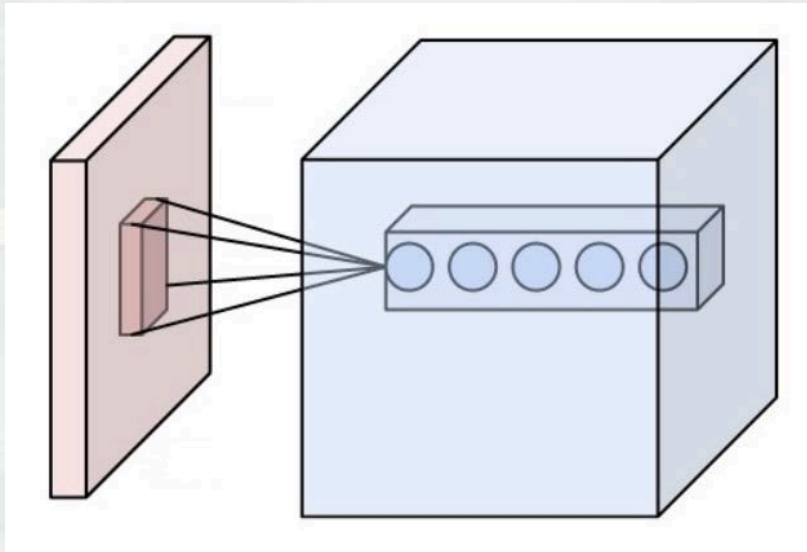


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Classification Using Convolutional Neural Network(CNN)

- One type of feed-forward artificial neural network
- Workhorse for a lot of recording-breaking deep learning frameworks for computer vision tasks



https://en.wikipedia.org/wiki/Convolutional_neural_network

Distinguish features:
3D volumes of neurons

One single layer can be extended to multiple layers

Local connectivity

Allow locally learned features to combine together to represent global feature

Shared weights

Each filter is applied to the entire image to create one layer



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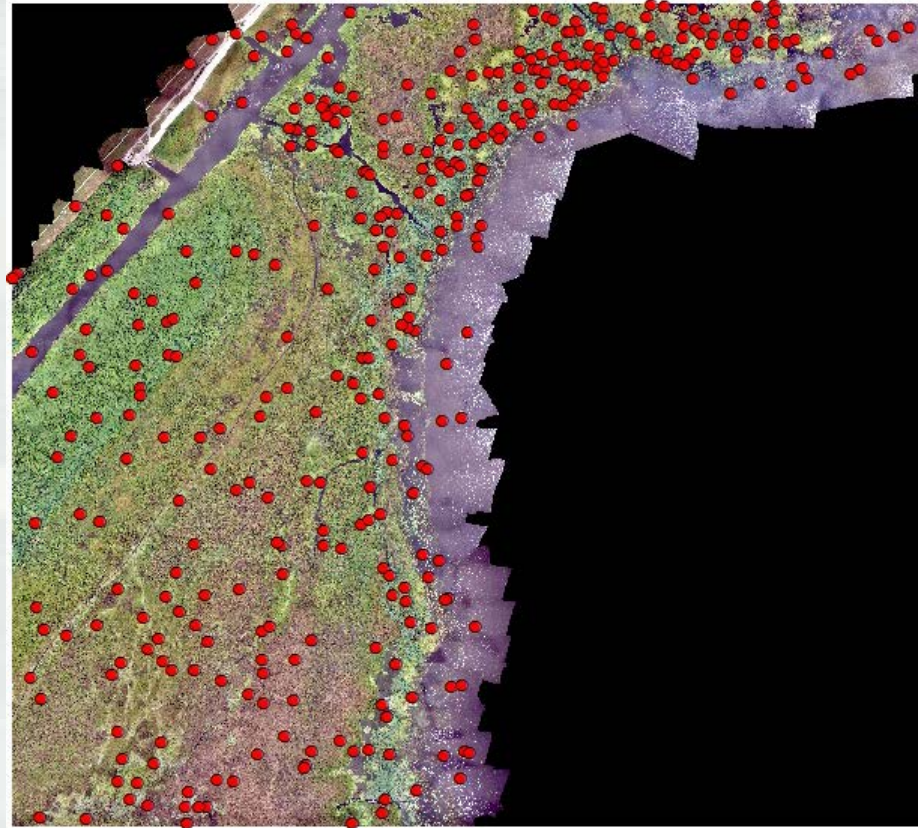
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Second Testing Set



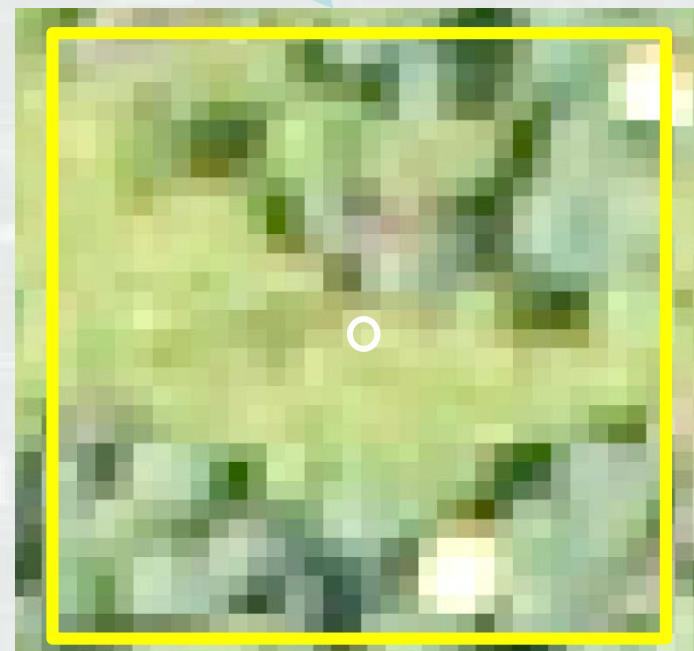
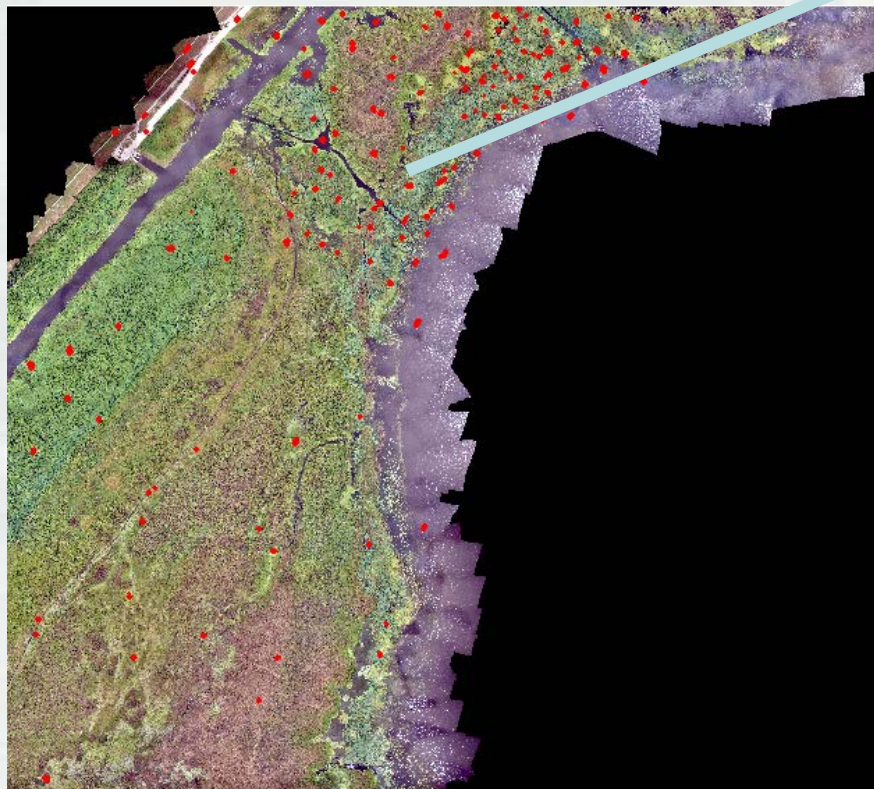
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Extract training data



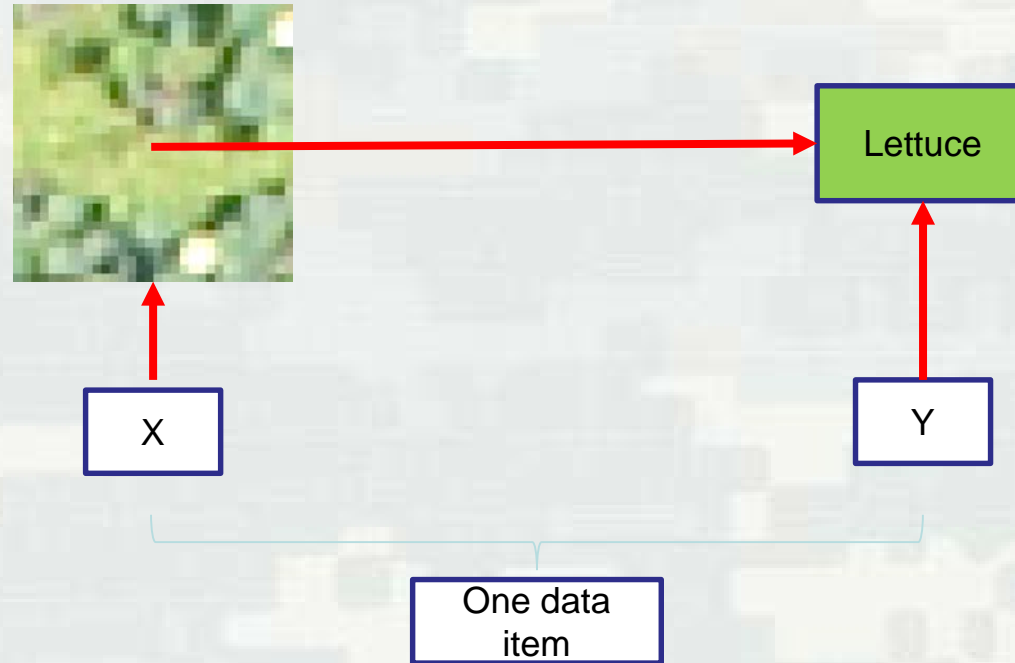
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One data item



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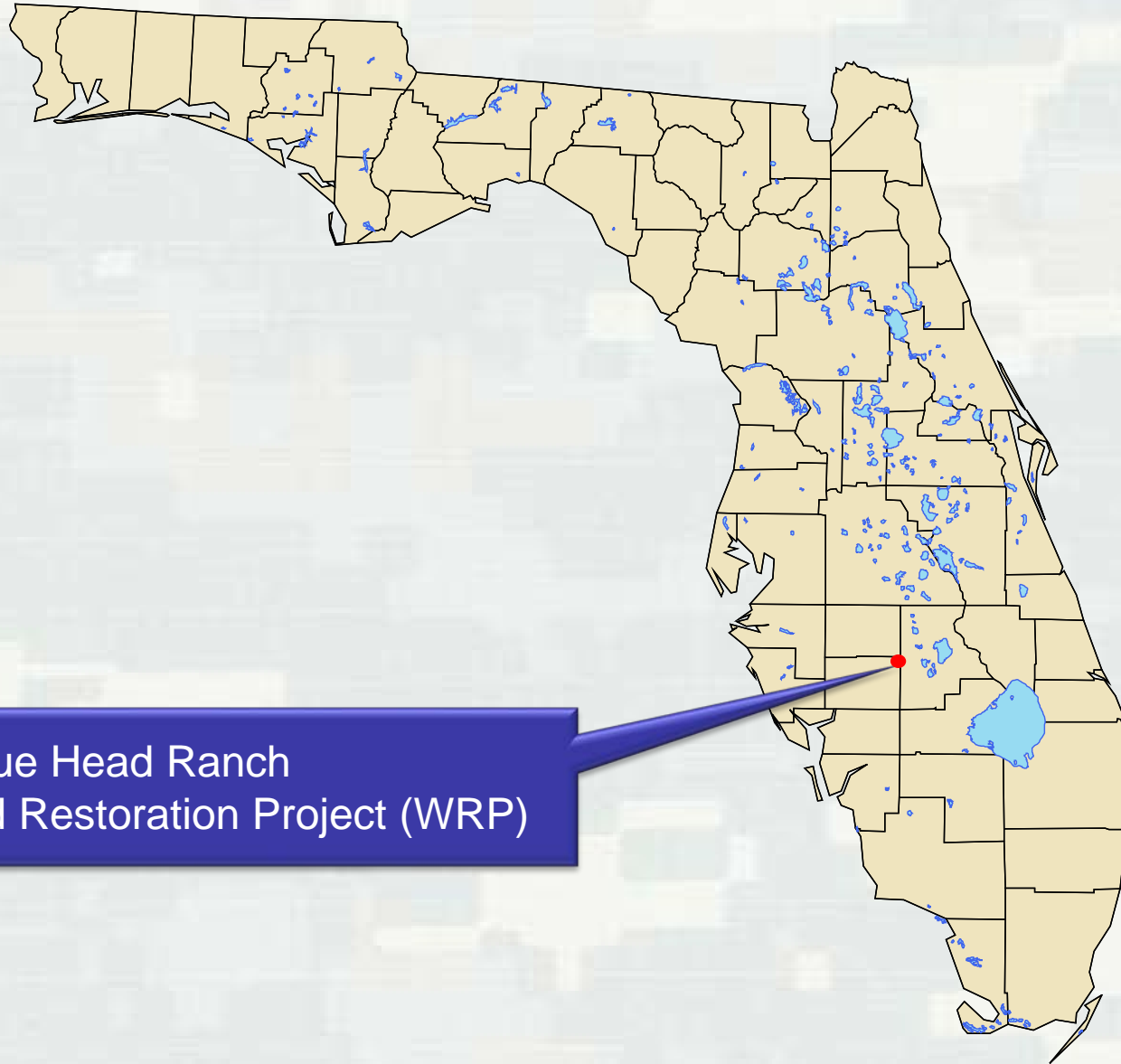
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Result

Table 1 Accuracy of CNN result of first testing set

| Approach | | Overall Accuracy | |
|---|------------|------------------|--------------|
| CNN approach based on the first testing data set | | 79.88% | |
| Best accuracy of object approach on the second testing data set | | 70.78% | |
| Approach | Classifier | Overall accuracy | Kappa coeff. |
| Object based | SVM | 70.78% | 0.659 |
| | ANN | 69.44% | 0.643 |
| | ML | 58.18% | 0.512 |
| Pixel based on high resolution (8 cm) images | SVM | 56.84% | 0.503 |
| | ANN | 50.94% | 0.441 |
| | ML | 53.62% | 0.471 |
| Pixel based on low resolution (30 cm) image | SVM | 61.93% | 0.560 |
| | ANN | 53.89% | 0.474 |
| | ML | 52.81% | 0.464 |





Blue Head Ranch
NRCS Wetland Restoration Project (WRP)

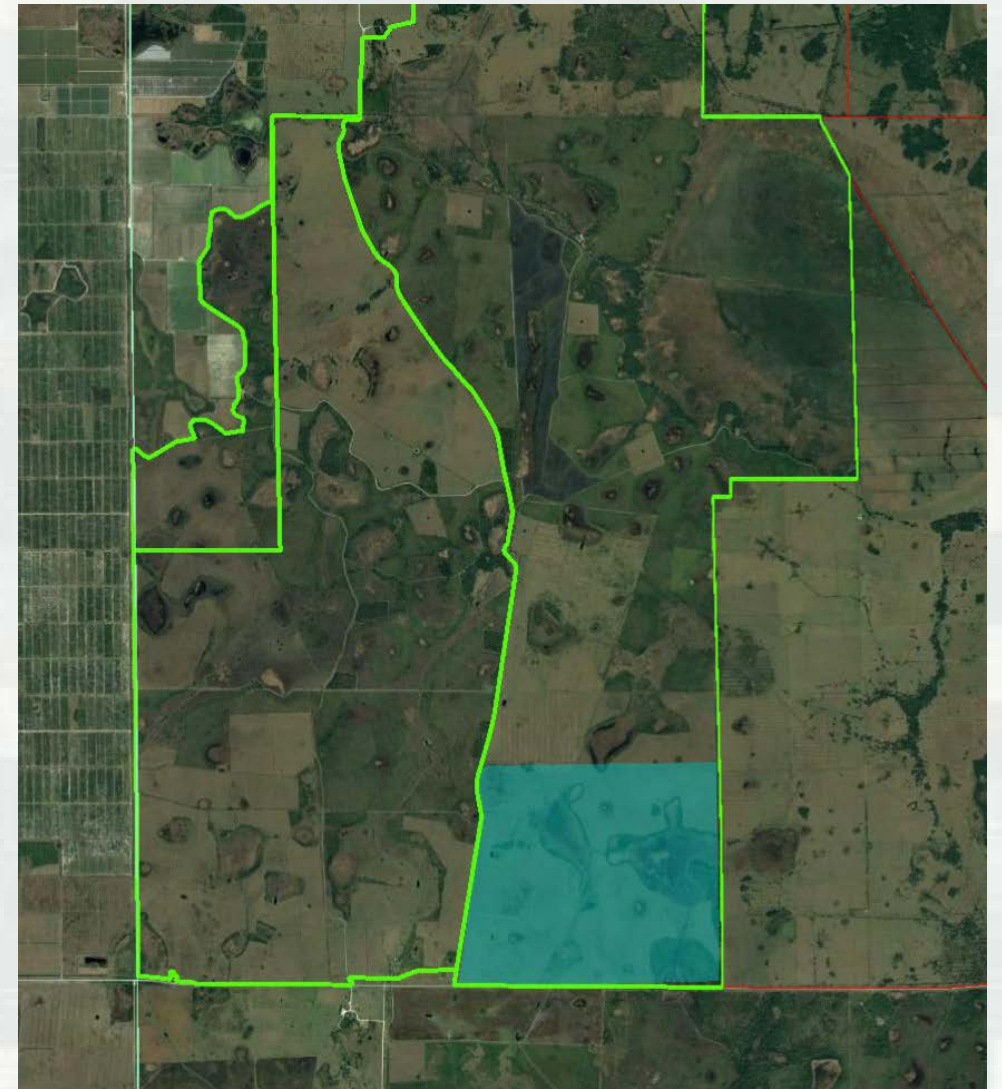
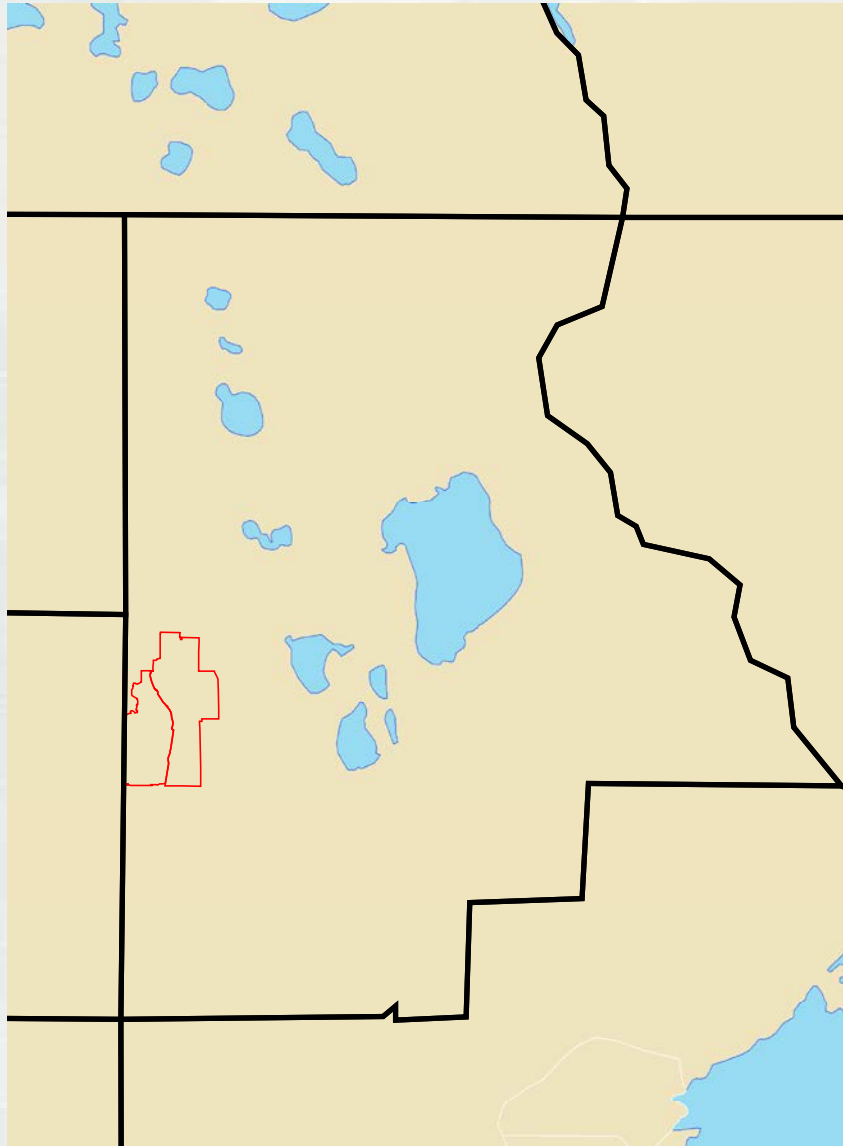


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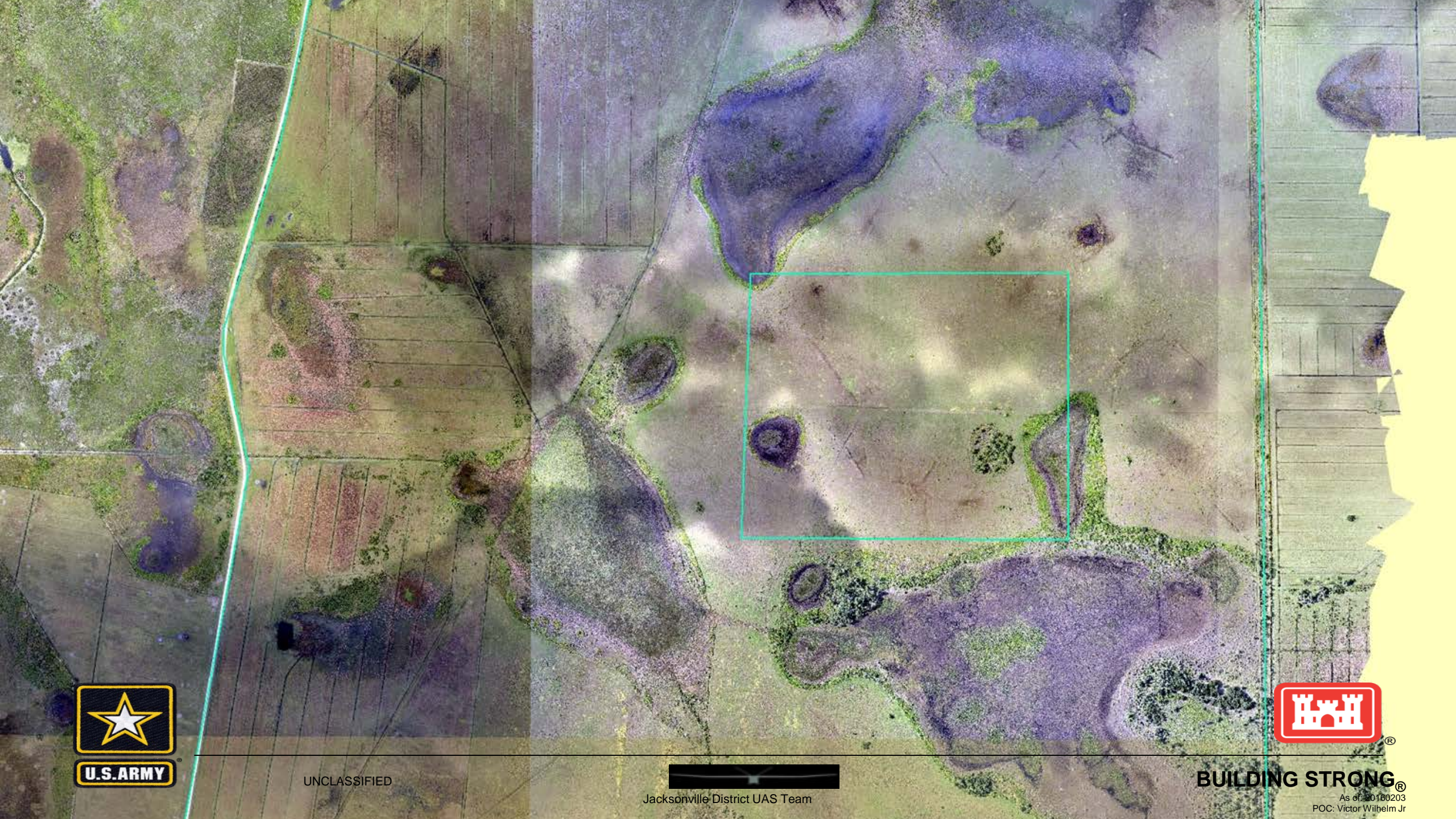


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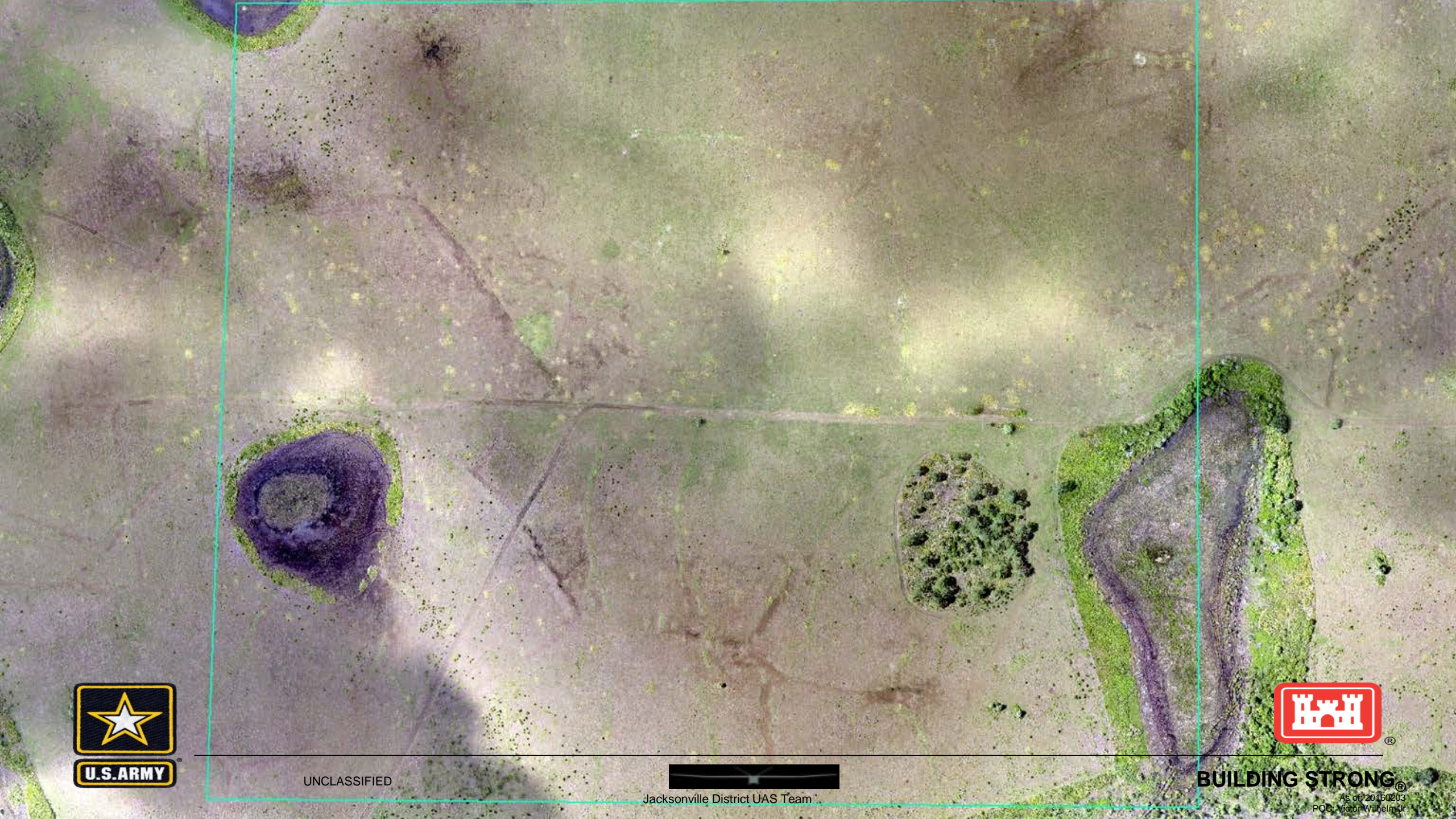
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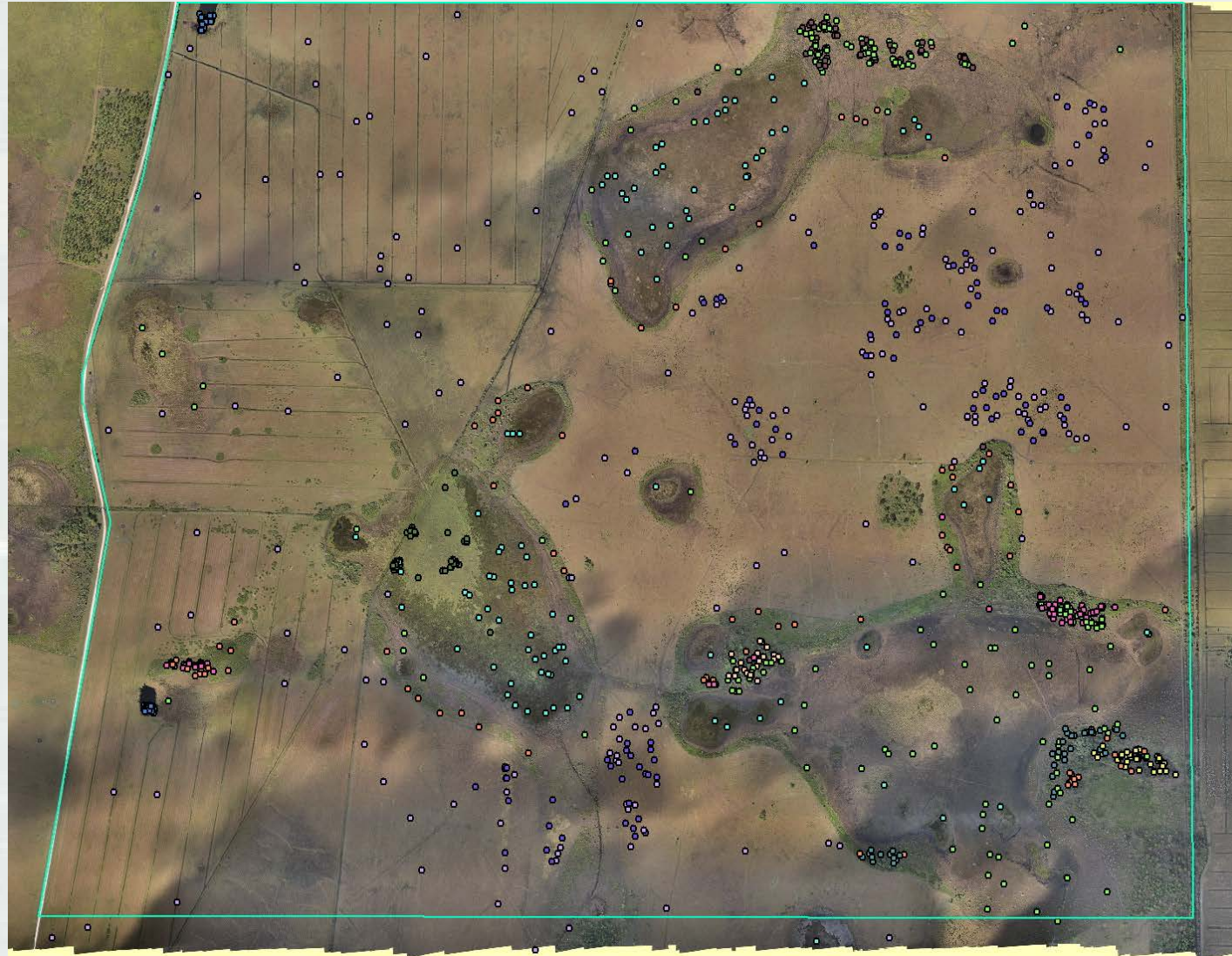
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Classifying Training Data



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Classifying Training Data, cont

| ClassID | Alias | Name | Community |
|---------|-------|--------------------|----------------------------|
| 1 | MFG | Maidencane | Graminoid Freshwater Marsh |
| 2 | SUs | Saw Palmetto | Saw Palmetto Shrubland |
| 3 | WUs | Cabbage Palm | Cabbage Palm Upland |
| 4 | MFB | Hypericum | Broadleaf Freshwater Marsh |
| 5 | SSs | Willow | Willow Shrubland |
| 6 | Ei | Cogongrass | Cogongrass |
| 7 | SSm | Wax Myrtle | Wax Myrtle Shrubland |
| 8 | FHq | Live Oak | Hammock Forest (oak) |
| 9 | HF | Cabbage Palm | Hammock Forest (palm) |
| 10 | WUpF | Slash Pine | Pine Flatwoods |
| 11 | IP | Mixed Pasture Gram | Improved Pasture |
| 12 | CP | Cattle Pond | Surface Water |



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Classifying Training Data, cont

BH_groundtruth_poly, 3/9/2016, Page 1

| FID | Shape * | ID | Class_ID | Name | Level | Community |
|-----|---------|----|----------|------------------------|-------|----------------------------|
| 0 | Polygon | 1 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 1 | Polygon | 2 | MFG | Mixed Graminoid | 3 | Graminoid Freshwater Marsh |
| 2 | Polygon | 3 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 3 | Polygon | 4 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 4 | Polygon | 5 | WUj | Cabbage Palm | 4 | Cabbage Palm Upland |
| 5 | Polygon | 6 | WUj | Cabbage Palm | 4 | Cabbage Palm Upland |
| 6 | Polygon | 7 | SUS | Saw Palmetto | 3 | Saw Palmetto Shrubland |
| 7 | Polygon | 8 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 8 | Polygon | 9 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 9 | Polygon | 10 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 10 | Polygon | 11 | MFG | mixed graminoid | 3 | Graminoid Freshwater Marsh |
| 11 | Polygon | 12 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 12 | Polygon | 13 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 13 | Polygon | 14 | MFGp | Maidencane | 4 | Graminoid Freshwater Marsh |
| 14 | Polygon | 15 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 15 | Polygon | 16 | MFBh | Hypericum | 4 | Broadleaf Freshwater Marsh |
| 16 | Polygon | 17 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 17 | Polygon | 18 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 18 | Polygon | 19 | SSs | Willow | 4 | Willow Shrubland |
| 19 | Polygon | 20 | MFBh | Hypericum | 4 | Broadleaf Freshwater Marsh |
| 20 | Polygon | 21 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 21 | Polygon | 22 | EI | Cogongrass | 4 | Cogongrass |
| 22 | Polygon | 23 | SSM | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 23 | Polygon | 24 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 24 | Polygon | 25 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 25 | Polygon | 26 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 26 | Polygon | 27 | WUj | Cabbage Palm | 4 | Cabbage Palm Upland |
| 27 | Polygon | 28 | SUS | Saw Palmetto | 3 | Saw Palmetto Shrubland |
| 28 | Polygon | 29 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 29 | Polygon | 30 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 30 | Polygon | 31 | MFG | mixed graminoid | 3 | Graminoid Freshwater Marsh |
| 31 | Polygon | 32 | FHq | Live Oak | 4 | Hammock Forest (oak) |
| 32 | Polygon | 33 | FHs | Cabbage Palm | 4 | Hammock Forest (palm) |
| 33 | Polygon | 34 | FHq | Live Oak | 4 | Hammock Forest (oak) |
| 34 | Polygon | 35 | MFGp | Maidencane | 4 | Graminoid Freshwater Marsh |
| 35 | Polygon | 36 | MFGp | Maidencane | 4 | Graminoid Freshwater Marsh |
| 36 | Polygon | 37 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 37 | Polygon | 38 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 38 | Polygon | 39 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 39 | Polygon | 40 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 40 | Polygon | 41 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 41 | Polygon | 42 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 42 | Polygon | 43 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 43 | Polygon | 44 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 44 | Polygon | 45 | EI | Cogongrass | 4 | Cogongrass |
| 45 | Polygon | 46 | EI | Cogongrass | 4 | Cogongrass |
| 46 | Polygon | 47 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 47 | Polygon | 48 | EI | Cogongrass | 4 | Cogongrass |
| 48 | Polygon | 49 | HFj | Cabbage Palm | 4 | Hammock Forest (palm) |
| 49 | Polygon | 50 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 50 | Polygon | 51 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 51 | Polygon | 52 | WUpF | Slash Pine | 4 | Pine Flatwoods |
| 52 | Polygon | 53 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 53 | Polygon | 54 | MFB | Mixed Broadleaf | 4 | Broadleaf Freshwater Marsh |
| 54 | Polygon | 55 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 55 | Polygon | 56 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 56 | Polygon | 57 | WUpF | Slash Pine | 4 | Pine Flatwoods |
| 57 | Polygon | 58 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 58 | Polygon | 59 | MFGp | Maidencane | 4 | Graminoid Freshwater Marsh |
| 59 | Polygon | 60 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 60 | Polygon | 61 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 61 | Polygon | 62 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 62 | Polygon | 63 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 63 | Polygon | 64 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 64 | Polygon | 65 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 65 | Polygon | 66 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 66 | Polygon | 67 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 67 | Polygon | 68 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 68 | Polygon | 69 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 69 | Polygon | 70 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 70 | Polygon | 71 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |

BH_groundtruth_poly, 3/9/2016, Page 2

| FID | Shape * | ID | Class_ID | Name | Level | Community |
|-----|---------|-----|----------|-------------------------|-------|----------------------------|
| 71 | Polygon | 72 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 72 | Polygon | 73 | IP | Mixed Pasture Graminoid | 2 | Improved Pasture |
| 73 | Polygon | 74 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 74 | Polygon | 75 | IP | Mixed Pasture Graminoid | 2 | Improved Pasture |
| 75 | Polygon | 76 | IP | Mixed Pasture Graminoid | 2 | Improved Pasture |
| 76 | Polygon | 77 | IP | Mixed Pasture Graminoid | 2 | Improved Pasture |
| 77 | Polygon | 78 | MFB | Mixed Broadleaf | 3 | Broadleaf Freshwater Marsh |
| 78 | Polygon | 79 | MFGj | Soft Rush | 4 | Graminoid Freshwater Marsh |
| 79 | Polygon | 80 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 80 | Polygon | 81 | SUS | Saw Palmetto | 4 | Saw Palmetto Shrubland |
| 81 | Polygon | 82 | MFBps | Pickelweed-Duck Potato | 4 | Broadleaf Freshwater Marsh |
| 82 | Polygon | 83 | EI | Cogongrass | 4 | Cogongrass |
| 83 | Polygon | 84 | EI | Cogongrass | 4 | Cogongrass |
| 84 | Polygon | 85 | EI | Cogongrass | 4 | Cogongrass |
| 85 | Polygon | 86 | EI | Cogongrass | 4 | Cogongrass |
| 86 | Polygon | 87 | EI | Cogongrass | 4 | Cogongrass |
| 87 | Polygon | 88 | EI | Cogongrass | 4 | Cogongrass |
| 88 | Polygon | 89 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 89 | Polygon | 90 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 90 | Polygon | 91 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 91 | Polygon | 92 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 92 | Polygon | 93 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 93 | Polygon | 94 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 94 | Polygon | 95 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 95 | Polygon | 96 | SSm | Wax Myrtle | 4 | Wax Myrtle Shrubland |
| 96 | Polygon | 97 | SSs | Willow | 4 | Willow Shrubland |
| 97 | Polygon | 98 | SSs | Willow | 4 | Willow Shrubland |
| 98 | Polygon | 99 | SSs | Willow | 4 | Willow Shrubland |
| 99 | Polygon | 100 | SSs | Willow | 4 | Willow Shrubland |
| 100 | Polygon | 101 | CP | Cattle Pond | 1 | Surface Water |
| 101 | Polygon | 102 | CP | Cattle Pond | 1 | Surface Water |

*Vegetation Classification System for
South Florida Natural Areas, 2009*



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