Development of Automated Methods for Using Satellite Imagery to Monitor Changes in Vegetative Communities

Report for Quarter 2/Task 3 in 2021

Submitted to: St. Johns River Water Management District

By

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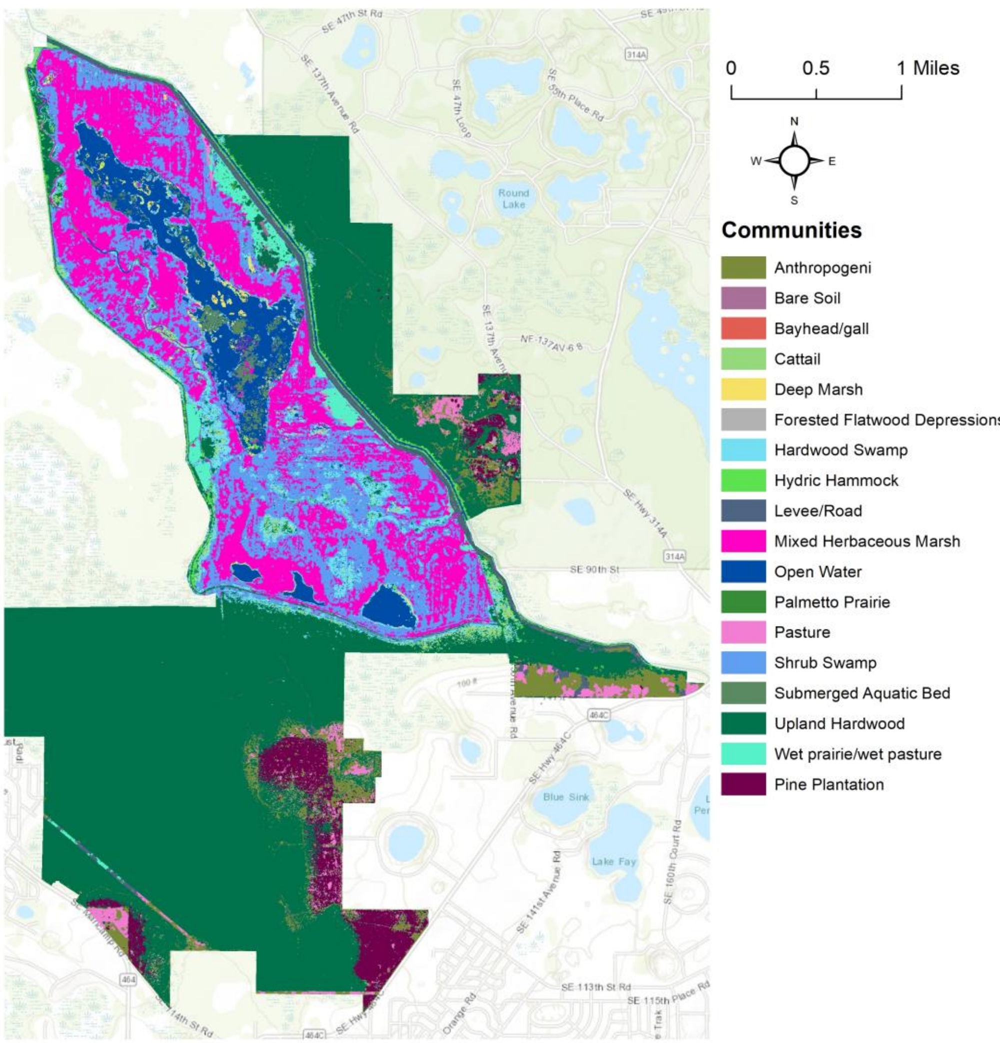

Classified Vegetation Map for Ocklawaha Area from Machine Learning Ensemble Analysis

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In this Quarter, we focused on mapping Ocklawaha Prairie Restoration Area (OPRA) and Lake Apopka North Shore Area (LANS) using 0.3-m, 8-band pansharpened WorldView 2 (WV-2) imagery, and lidar DEM by following the technical procedures reported in Quarter 1. However, for these areas, we applied the segmentation algorithm Large Scale Mean Shift segmentation in OTB/QGIS, an open source GIS package. The tutorial using OTB/QGIS for image segmentation was provided in Quarter 1 report. The results for OPRA and LANS areas are provided in Sections 1-3. We also examined another open source segmentation algorithm Region Growing Baatz in TerraView. We compared 8-band pansharpened imagery with 4-band pansharpened imagery in the classification.

1. Results for Ocklawaha Area

This section provides the results for OPRA using segmentation results from OTB/QGIS.

1.1 Communities to be mapped

For this area, in the original vegetation map data, Building (BD), Parking Lot (PL), and Residential (RE) were revised into Anthropogenic (AN); Levee (LV) and Road (RD) were revised as Levee/Road (LR); Spoil (SP) and Bare Area (BA) were revised as Bare Soil (BS); Floating Marsh (FF) and Water (W) were revised as Water (OW); Aquatic Bed (AB) was changed to Submerged Aquatic Bed (SAB); Water Lilies (DM-N) was changed to Deep Marsh (DM); Transitional Shrub (TS) was revised as Shrub Swamp (SS); Bottomland Hardwoods (BL) was revised into Hardwood Swamp (HS); Bayhead (BH) was revised into Bayhead/gall (BG); Dry Shrub (DS) was revised into Palmetto Prairie (PP); and Shallow Marsh (SM) was revised into Herbaceous Marsh (HM). A large part of this area was mapped as Upland in the original map dataset. We mapped Upland as UH (Upland Hardwood) and PI (Pine Plantation). After the name changes, in total there were 18 communities to be mapped.

1.2 Segmentation

Running segmentation using open source OTB/QGIS was challenging. In total it took five days on a CPU based Dell Workstation to generate some ideal results, leading to 669,720 segments. This was a large number of records and loading this large volume of segments in ArcGIS was difficult, as shown in Figure 1. We thus split the segmentations into three smaller areas/datasets and ran machine learning models one by one, and finally merged three maps into one. This largely increased the work load (Tripled), but was manageable. The split map is shown in Figure 2. Mean and variance of each object were automatically extracted for each object in OTB/QGIS to be used as input features for class prediction.

We also ran the segmentation algorithm Region Growing Baatz in TerraView (a tutorial is provided in Appendix). The results were not acceptable, as shown in Figure 3. Some tiles gave detailed segmentations but some tiles produced big segments which include multiple communities within one segment. **<u>TerraView is not a good choice for segmentation when a large area and large dataset needs to be processed</u>**. We thus used the OTB/QGIS segmentation results in the training and mapping procedure.

1.3 Selected reference samples

Due to the large volume of segments, selecting training samples from the original segments was challenging. We thus used the point based training sample selection approach which was reported in Quarter 1. For this area, we picked a total of 7698 polygons as training samples. More than half of them were Upland Hardwood which is the dominant community in this area. The final selected training polygons are shown in Figure 4.

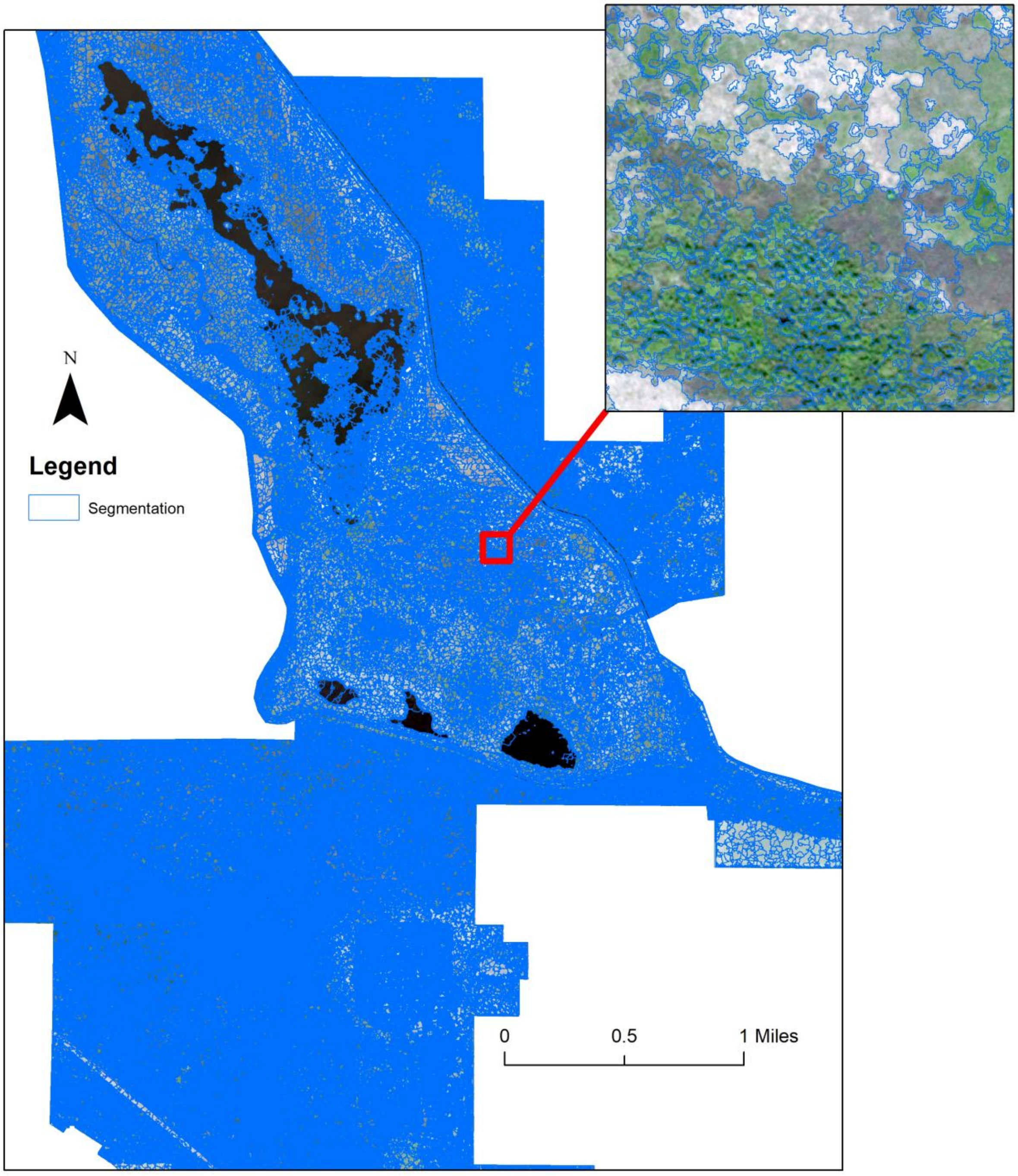


Figure 1. Segmentation from OTB/QGIS with a total of 669,720 segments for Ocklawaha area.

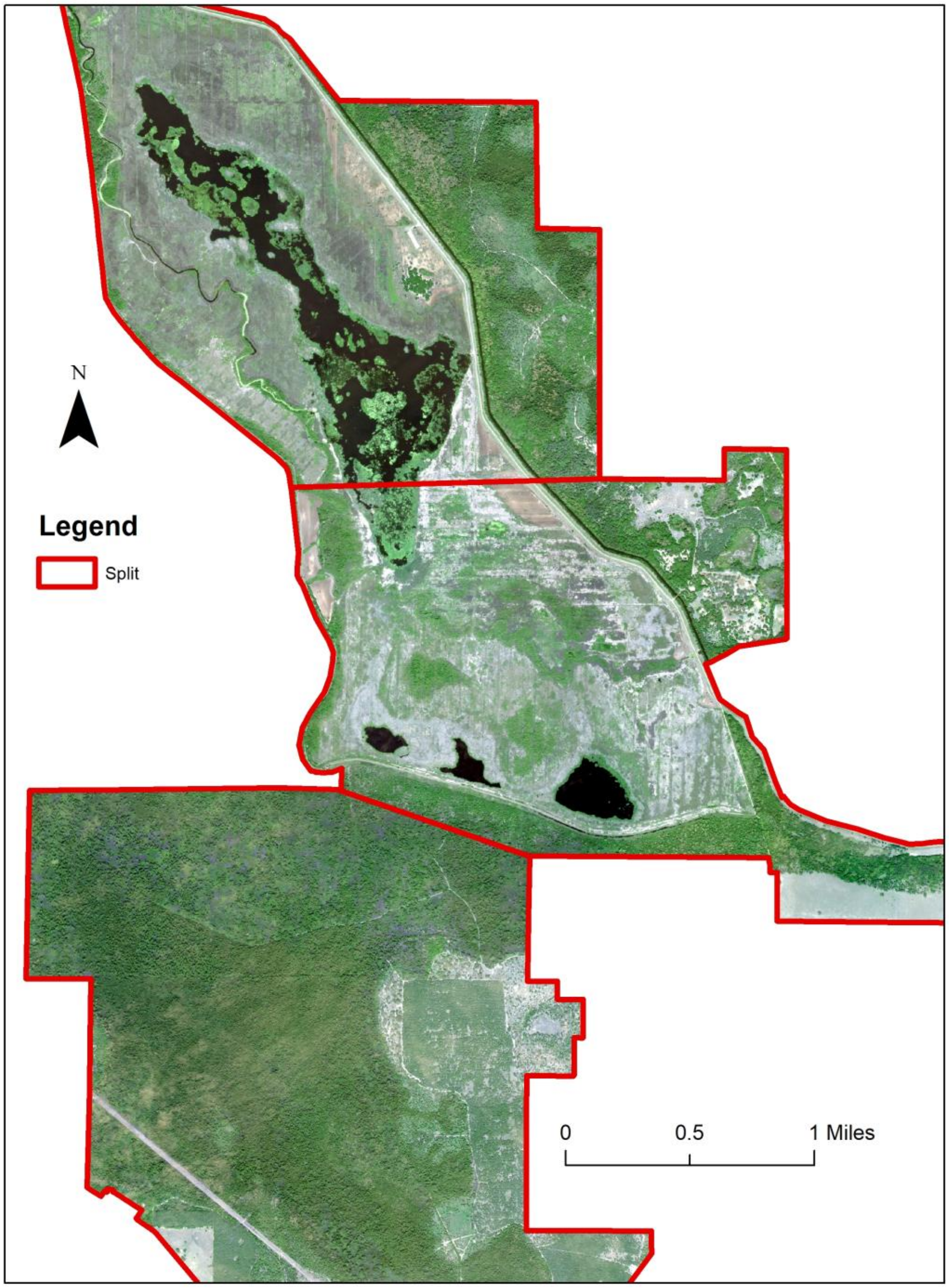


Figure 2. Split of segments into three areas manageable in ArcGIS.

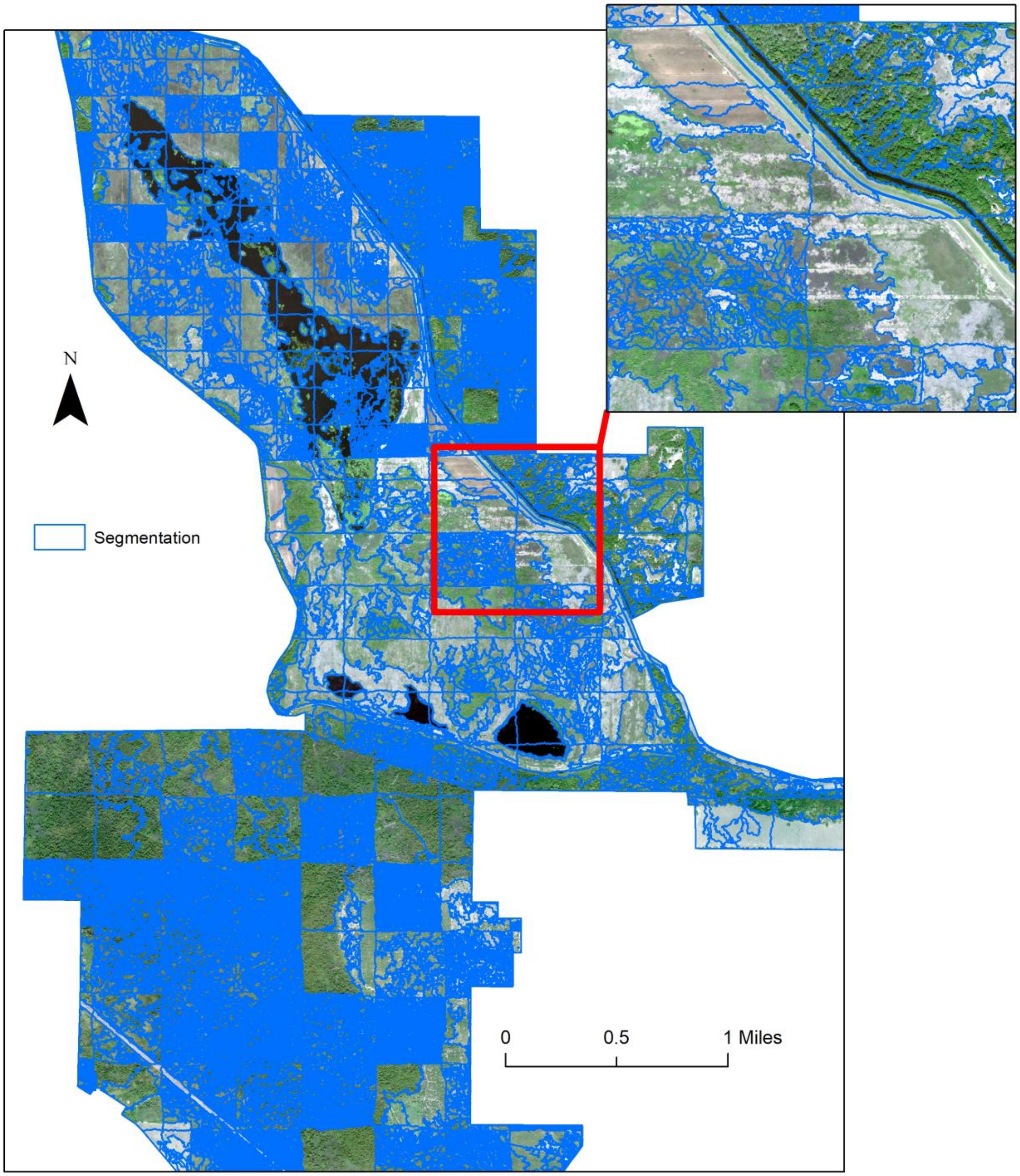


Figure 3. Segmentation results from TerraView. The results are not reasonable for mapping due to the appearance of large segments in which multiple communities appear.

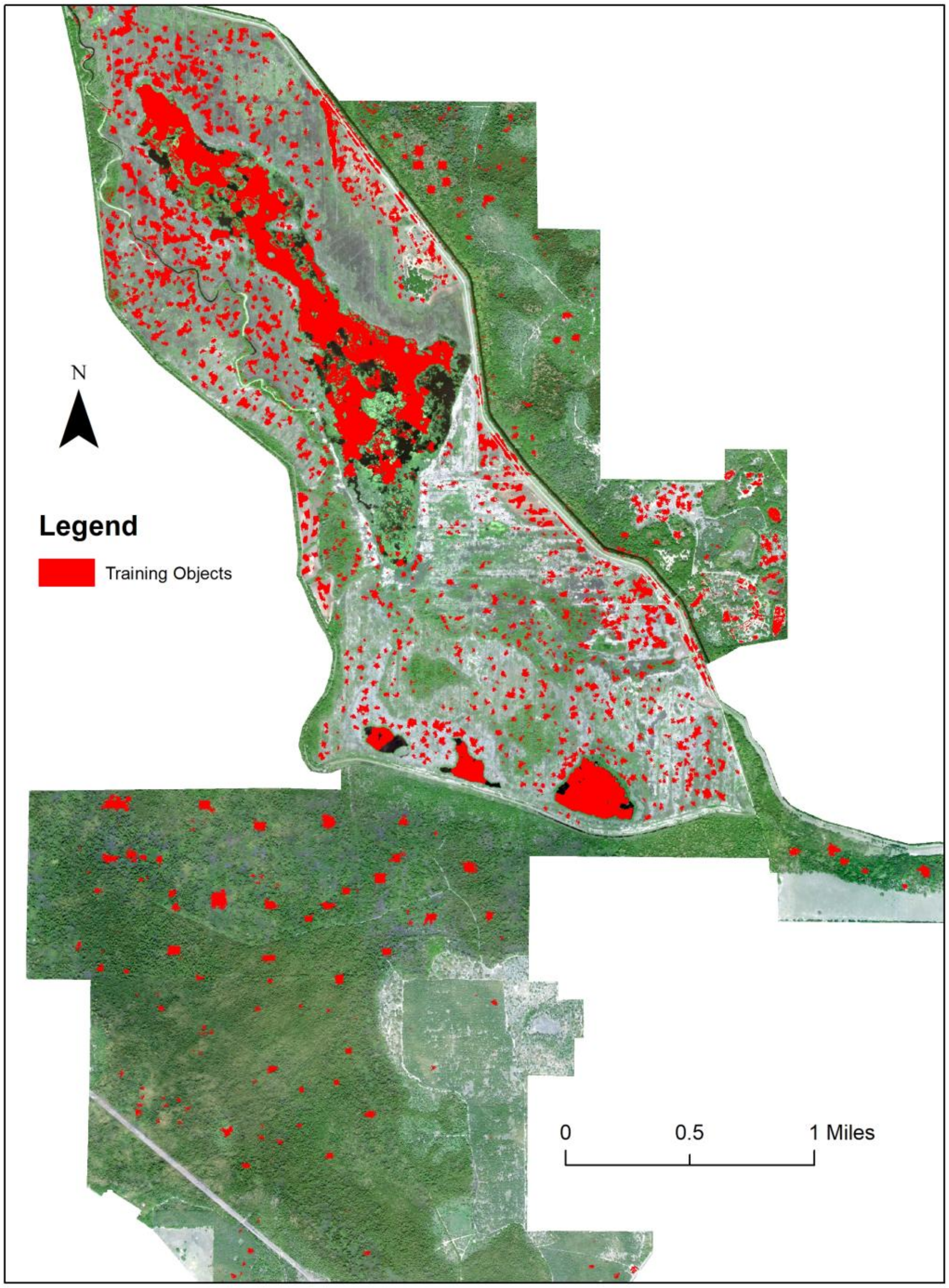


Figure 4. Selected training objects/samples for Ocklawaha area.

1.4 Accuracy assessment

The performance of classifiers ANN, kNN, SVM, RF based on 10-fold cross validation is displayed in Table 1. All achieved an overall accuracy (OA) above 80%. Results from McNemar tests are displayed in Table 2. kNN was dropped due to it having the lowest accuracy. RF and SVM were significantly better than ANN. ANN was significantly better than kNN. There was no significant difference between SVM and RF and both achieved high accuracy. Ensemble analysis of ANN, RF, and SVM achieved an OA of 84.7% with Kappa value of 0.77. Comparison with an inclusion of lidar DEM in the classification is also displayed in Table 1. An addition of lidar DEM increased the OA around 10% and thus is important in the mapping procedure. The error matrix is large due to the classification of 18 communities in this area and has been submitted separately as an Excel file.

Table 1. Performance of each machine learning classifier and ensemble analysis with/without lidar DEM; EA is ensemble analysis of ANN, SVM, and RF.

	ANN	kNN	SVM	RF	EA
Overall Accuracy (%)	83.0/75.3	81.5/72.9	84.6/76.4	84.8/76.5	84.7
Kappa Value	0.74/0.61	0.72/0.60	0.76/0.62	0.77/0.63	0.77

Table 2. McNemar test between different classifiers (* significance with 95% confidence when z-Score is greater than 1.96).

	ANN/kNN	ANN/SVM	ANN/RF	SVM/RF
z-Score	4.0*	6.0*	5.8*	0.7

1.5 Vegetation community mapping

Classification maps from machine learning algorithms, and ensemble analysis are displayed in Figure 5. In general, all classifiers produced a consistent spatial pattern with the existing map, but classification maps provide a more realistic/natural edge of each patch and presence of small patches within large communities. On the northeastern part where hydric hammock presents on the original map (Figure 4b) was misclassified as Upland Hardwood. Hardwood swamp that appeared as small patches in the big patch of Upland was misclassified as Upland Hardwood too. Note that Pine Plantation was mapped while the original map did not map this community. For most regions, three classifiers generated consistent classification, as shown in green in the uncertainty map in Figure 4 (g). Red regions show a “warning sign” where classification from three classifiers are completely inconsistent.

1.6 Analysis

For this area, classification of BG, and PP had a very low accuracy. Class BG is Bayhead/gall and HH is Hydric Hammock, and both were confused with UH (Upland Hardwood). Class PP (Palmetto Prairie) was confused with WP (Wet prairie/wet pasture). In the ANN classification map (Figure 5e), Open Water is misclassified and mapped as PA (Pasture) though the error matrix showed that 13 out of 264 water objects (~5% chance) were classified as PA. Floating marsh was grouped into water in the community name change. This may explain part of the confusion between water and pasture, mainly caused by the confusion of floating marsh and pasture. Thus an ensemble analysis of ANN, RF and SVM was appropriate for this area.

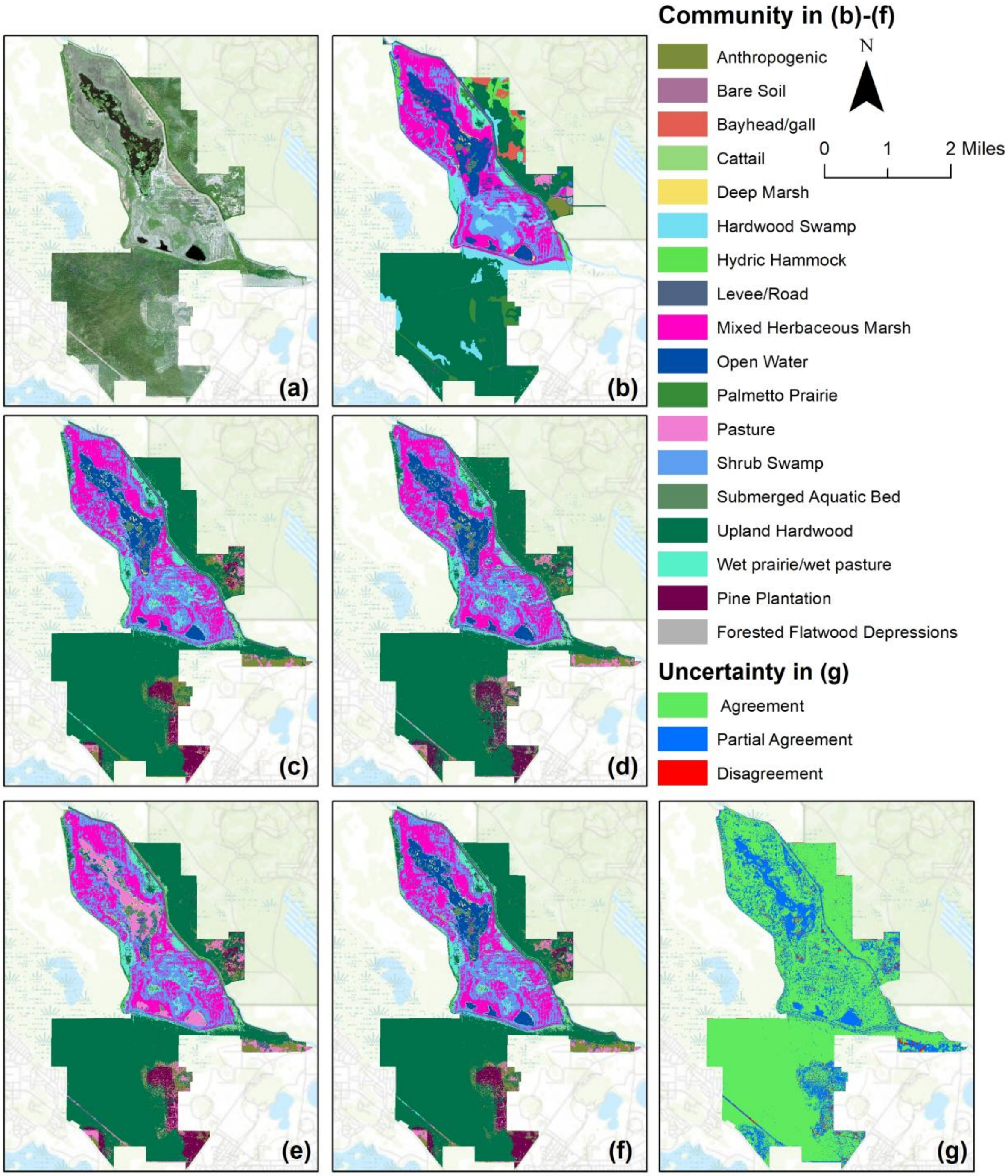


Figure 5. (a) WV-2 pansharpened imagery; (b) reference map from aerial photography; Object-based classifications from (c) SVM, (d) RF, (e) ANN, and (f) Ensemble analysis. (g) Uncertainty from ANN, SVM, and RF.

2. Results for Western LANS

There are two images for LANS with one collected in the west side on Oct. 13, 2019 and the other collected in the east side on April 28, 2017. This section provides the results for the west part by analyzing the 0.3-m and 8-band panchromatic WV-2 imagery collected on Oct. 13, 2019.

2.1 Communities to be mapped

For this area, Building (BD), Farm (FA), Parking Lot (PL) were revised into Anthropogenic (AN); Levee (LV) and Road (RD) were revised as Levee/Road (LR); Spoil (SP) and Barren Areas (BA) were revised as Bare Soil (BS); Floating Marshes (FF) and Water (W) were revised as Water (OW); Lakeshore Emergent (DM-LS) was changed into Deep Marsh (DM); Shallow Marsh (SM) was revised into Mixed Herbaceous Marsh (HM); Transitional Shrub (TS) was revised as Shrub Swamp (SS); and Dry Shrub (DS) was revised into Palmetto Prairie (PP). Upland was further classified into Bare Soil (BS), Crops (AN), Pine Flatwoods (PF), and Upland Hardwood (UH). After name change, in total there were 17 communities to be mapped. Cloud was also observed on this imagery and thus was classified as cloud.

2.2 Segmentation

We generated image objects using the open source OTB/QGIS. Again, it took a few days to get the segmentation results. In total, for this area, there were 141,154 segments (minimum segment size were set to 500 in order to reduce the number of segments). This was a large number of records but was manageable in ArcGIS without splitting into smaller areas. Spectral mean and variance of each object were automatically extracted for each object in OTB/QGIS to be used as input features for class prediction. The map of segmentation results is displayed in Figure 6.

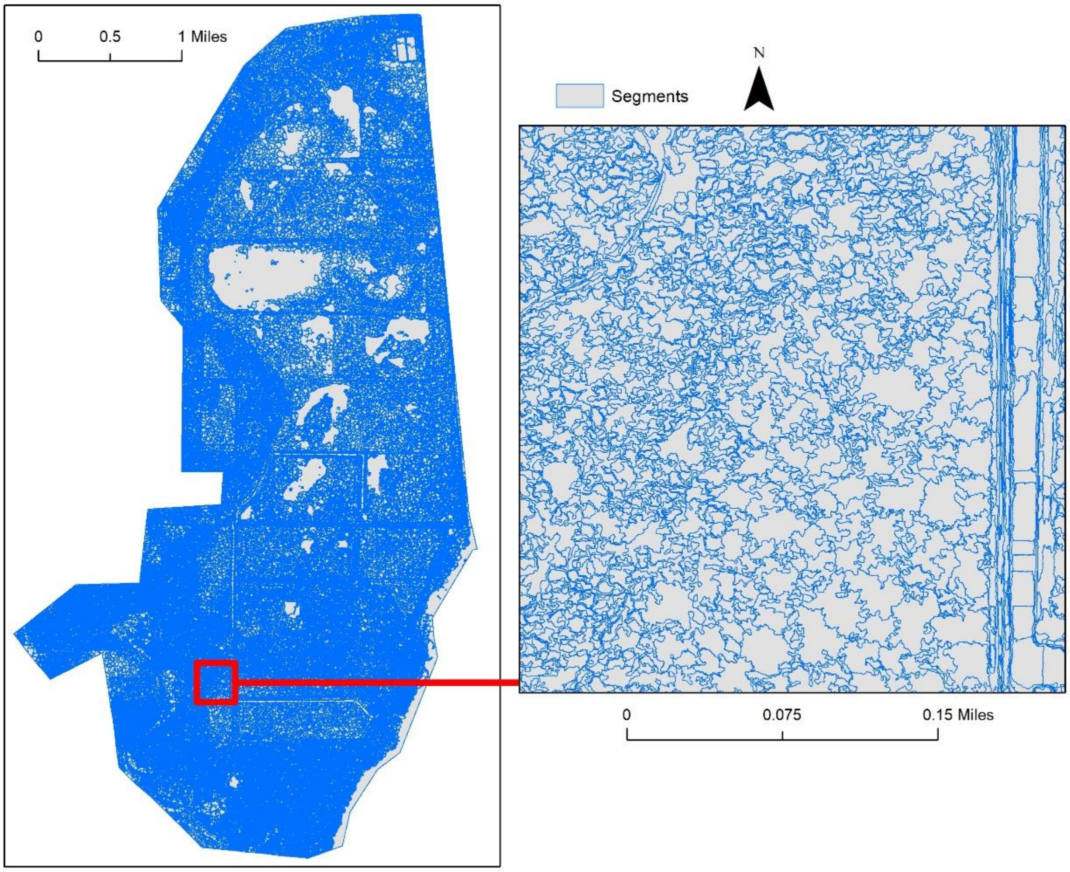


Figure 6. Segmentation from OTB/QGIS with a total of 141,154 segments.

2.3 Selected reference samples

We used the point based training sample selection approach which worked well for handling many segments. For this area, we edited 9910 training points and finally got 7386 training objects after spatially joining the training points with image segments. A map of edited points and selected training objects is displayed in Figure 7. To further detail areas labeled as Upland in the original vegetation dataset, we loaded in a 2014 Land Use Land Cover dataset, and identified Pine Flatwoods (PF), Upland Hardwood (UH), Bare Soil (BS), and crops (AN) within Upland regions. Training samples were selected for these classes within Upland regions.

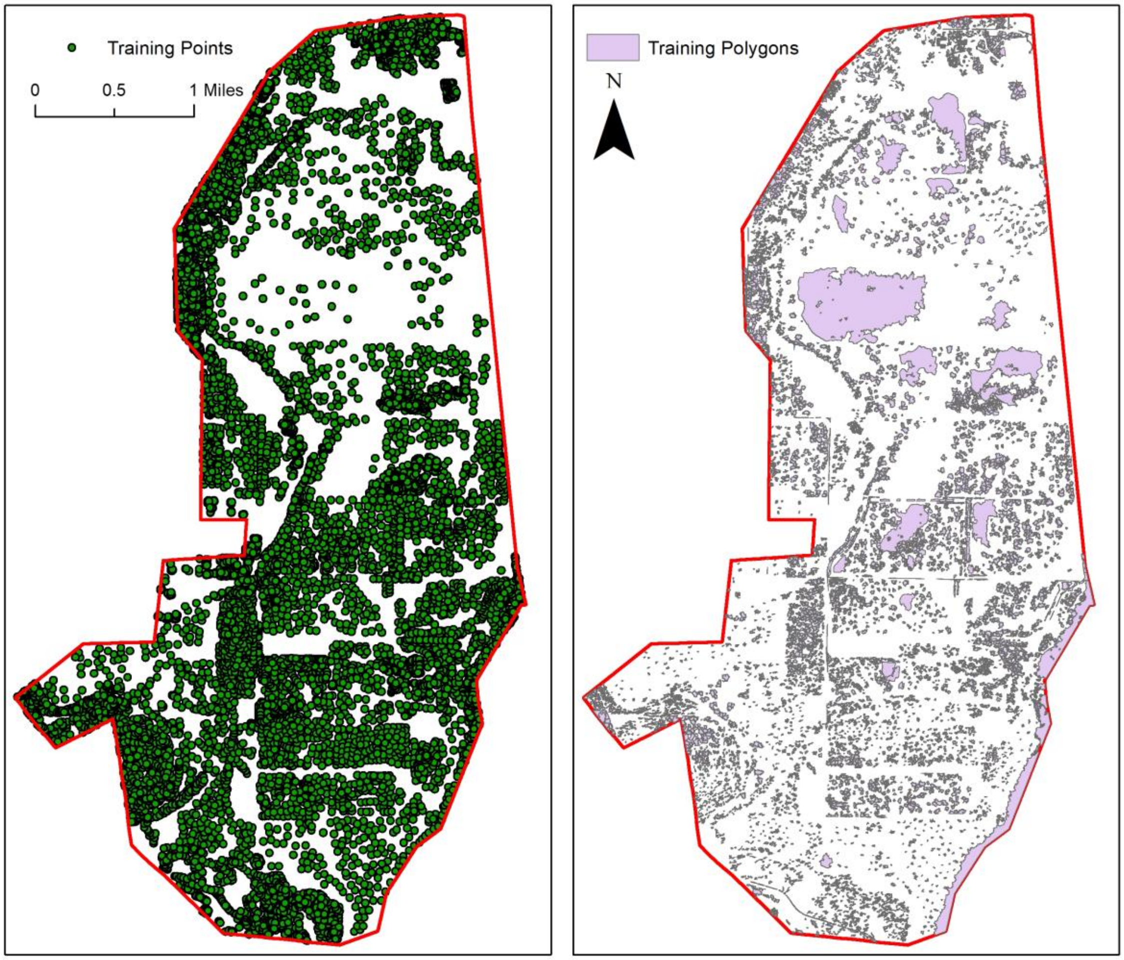


Figure 7. Edited training points and selected training objects for western LANS.

2.4 Accuracy assessment

The performance of classifiers ANN, kNN, SVM, RF based on 10-fold cross validation is displayed in Table 3. All achieved an OA above 65%. RF achieved the best result with an OA of 74.3% and Kappa value of 0.71. Results from McNemar tests are displayed in Table 4. RF was significantly better than ANN, SVM and kNN. Thus for this area, ensemble analysis was not conducted. Comparison with an inclusion of lidar DEM in the classification is also displayed in Table 3. An addition of lidar DEM increased the OA around 10% and thus is important in the mapping procedure. The error matrix is large due to the classification of 16 communities in this area and has been submitted separately as an Excel file.

Table 3. Performance of each machine learning classifier and ensemble analysis with/without lidar DEM.

	ANN	kNN	SVM	RF
Overall Accuracy (%)	65.3/57.6	65.3/54.2	66.4/56.3	74.3/64.8
Kappa Value	0.60/0.51	0.61/0.48	0.61/0.49	0.71/0.60

Table 4. McNemar test between different classifiers (* significance with 95% confidence when z-Score is greater than 1.96).

	ANN/kNN	ANN/SVM	ANN/RF	SVM/RF
z-Score	0.03	2.92*	17.9*	16.1*

2.5 Vegetation community mapping

Classification maps from machine learning algorithms are displayed in Figure 8. In general, all classifiers produced a consistent spatial pattern with the existing map, but classification maps provide a more realistic/natural edge of each patch and presence of small patches within large communities. Regions covered by cloud could not be mapped. Lower left corner in the original vegetation map was Upland which was further detailed into Bare Soil (BS), Crops (AN), Pine Flatwoods (PF), and Upland Hardwood (UH) in the classification map, as shown in Figure 9. For most regions, three classifiers generated consistent classification, as shown in green in the uncertainty map in Figure 8 (f). Red regions show a “warning sign” where classification from three classifiers are completely inconsistent.

2.6 Analysis

For this area, classification of Hydric Hammock (HH) and Palmetto prairie (PP) had a very low accuracy. HH was confused with Shrub Swamp (SS), Hardwood Swamp (HS), and Upland Hardwood (UH). PP was confused with HS, and UH. Both HH (covers about 1%) and PP (covers about 0.27%) are minor communities for this area. Limited training samples are available for minor communities. This will impact the effective identification of these minor communities.

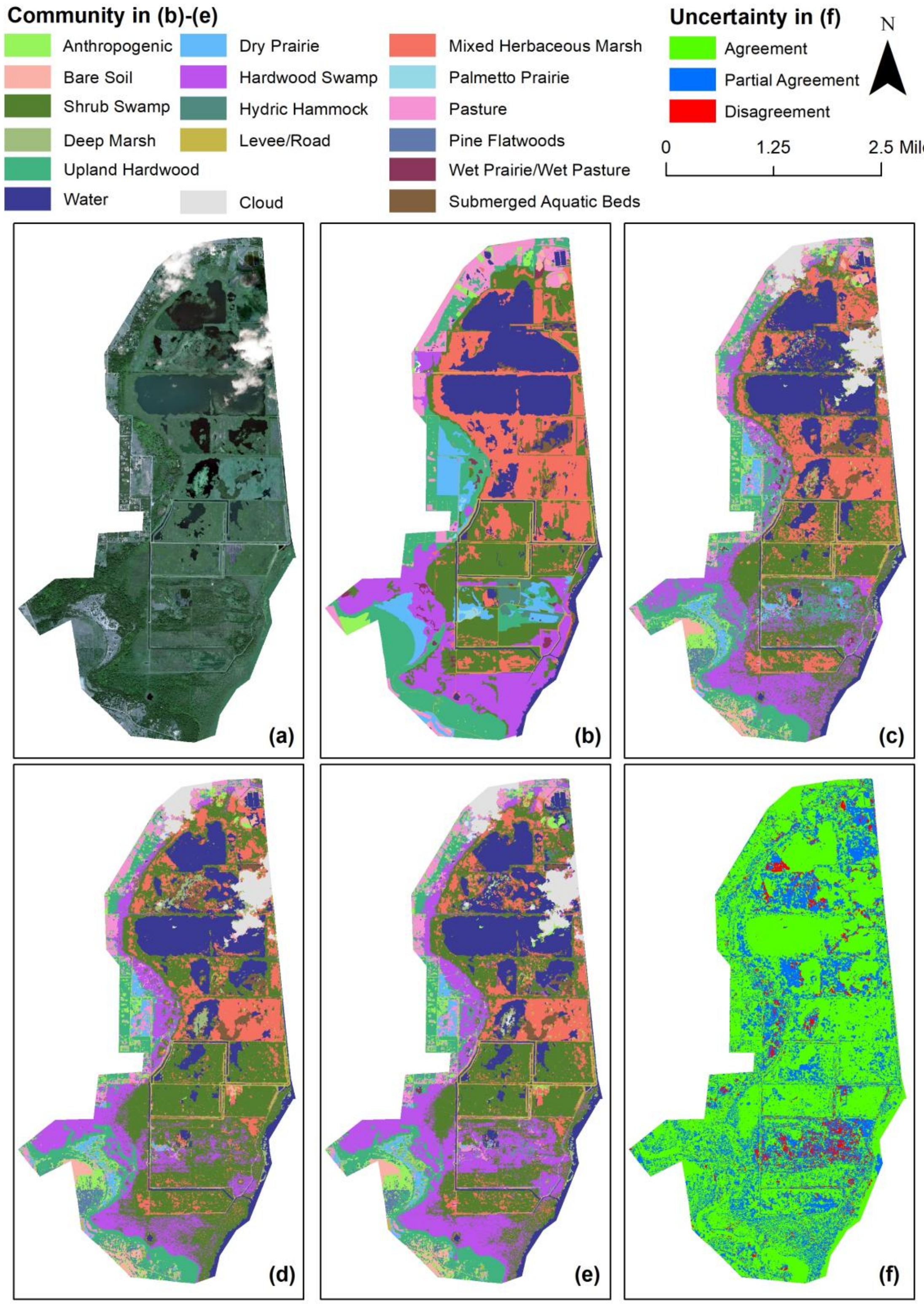


Figure 8. (a) WV-2 pansharpened imagery; (b) reference map from aerial photography; Object-based classifications from (c) RF, (d) SVM, (e) ANN, and (f) Uncertainty from ANN, SVM, and RF.

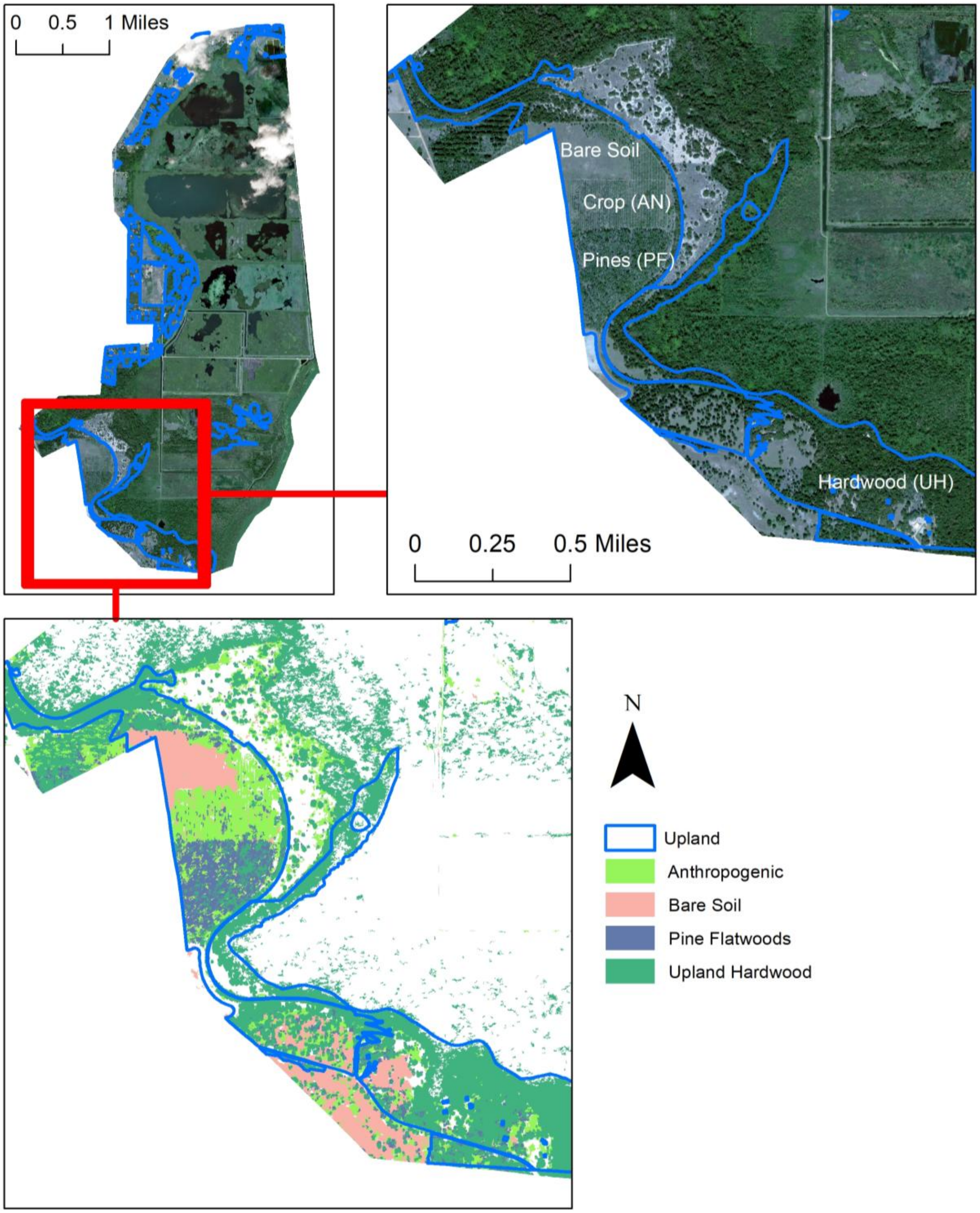


Figure 9. Upland in the original vegetation dataset was further classified as Bare soil (BS), crops (AN), Pine Flatwoods (PF), and Upland Hardwood (UH).

3. Results for Eastern LANS

This section provides the results for eastern LANS by analyzing the 0.3-m and 8-band panchromatic WV-2 imagery collected on April 28, 2017.

3.1 Communities to be mapped

For this area, Building (BD), Farm (FA), Sod Farm (SF), Parking Lot (PL), and Commercial Industrial (CI) were revised into Anthropogenic (AN); Levee (LV) and Road (RD) were revised as Levee/Road (LR); Spoil (SP) and Barren Areas (BA) were revised as Bare Soil (BS); Floating Marshes (FF) and Water (W) were revised as Water (OW); Lakeshore Emergent (DM-LS) was changed into Deep Marsh (DM); Shallow Marsh (SM) was revised into Mixed Herbaceous Marsh (HM); Transitional Shrub (TS) was revised as Shrub Swamp (SS); and Dry Shrub (DS) was revised into Palmetto Prairie (PP). Upland was further classified into Citrus Crops (AN), Pine Flatwoods, and Upland Hardwood (UH). Cypress (CY) and Forested Depressions (FD) are minor communities for this area. Classification of these two communities produced 0% in accuracy due to limited training samples. Thus these two communities were not mapped. After name change, in total there were 16 communities to be mapped. Cloud was also observed on this imagery and thus was classified as cloud.

3.2 Segmentation

We generated image objects using the open source OTB/QGIS. Again, it took more than 10 days to get the segmentation results. In total, for this area, there were 336,234 segments (minimum segment size were set to 500 in order to reduce the number of segments). This was a large number of records but was manageable in ArcGIS without splitting into smaller areas. Spectral mean and variance of each object were automatically extracted for each object in OTB/QGIS to be used as input features for class prediction. The map of segmentation results is displayed in Figure 10.

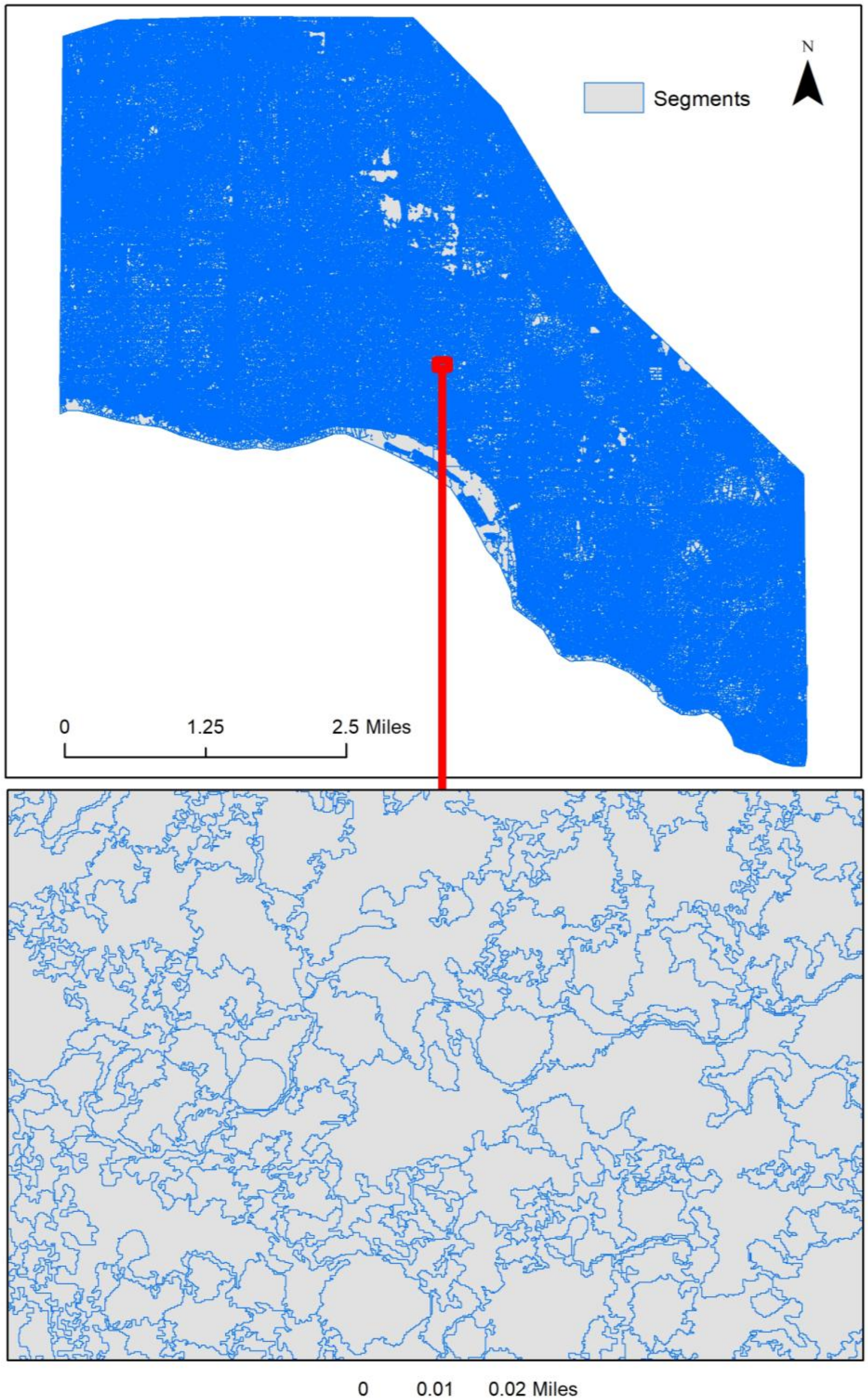


Figure 10. Segmentation from OTB/QGIS with a total of 336,234 segments.

3.3 Selected reference samples

We used the point based training sample selection approach which worked well for handling a large number of segments. For this area, we edited 5609 training points and finally got 5055 training objects after spatially joining the training points with image segments. A map of edited points and selected training objects is displayed in Figure 11. To further detail areas labeled as Upland in the original vegetation dataset, similarly, we loaded in a 2014 Land Use Land Cover dataset, and identified Pine Flatwoods (PF), Upland Hardwood (UH), and citrus groves (AN) within Upland regions. Training samples were selected for these classes within Upland regions.

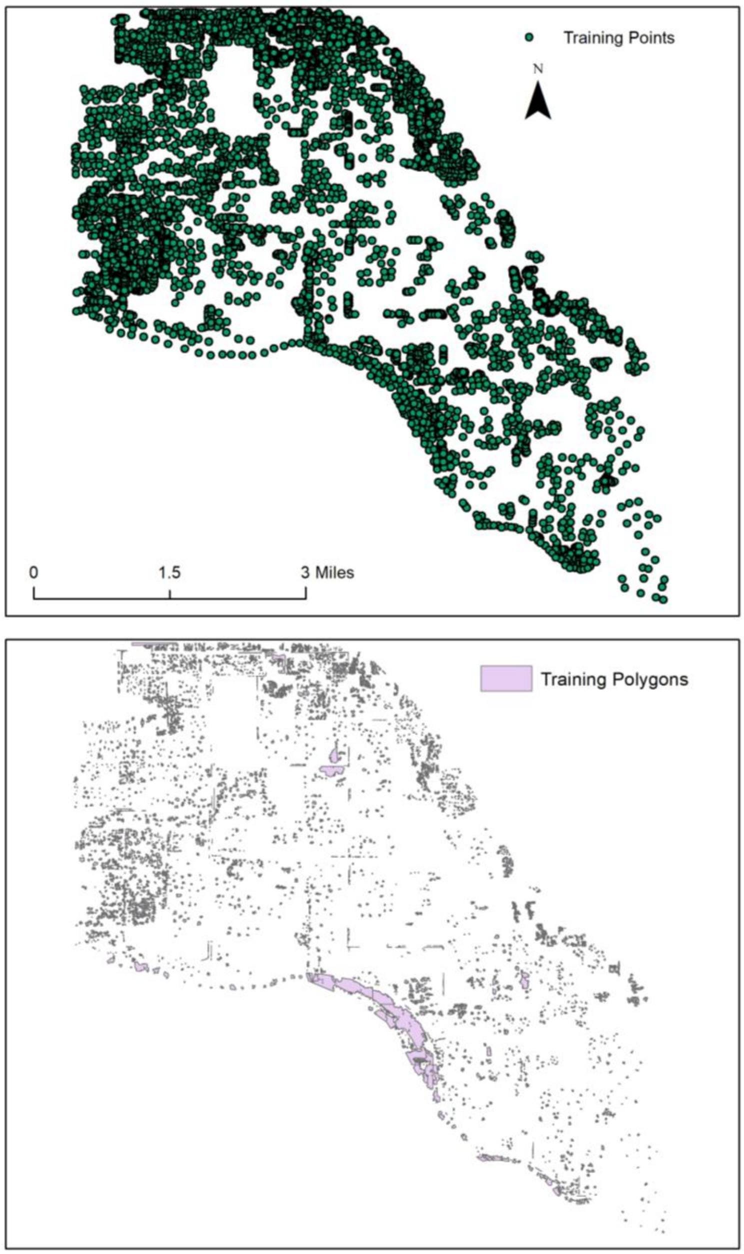


Figure 11. Edited training points and selected training objects for eastern LANS.

3.4 Accuracy assessment

The performance of classifiers ANN, kNN, SVM, RF based on 10-fold cross validation is displayed in Table 5. All achieved an OA above 65%. RF achieved the best result with an OA of 74.3% and Kappa value of 0.71. Results from McNemar tests are displayed in Table 6. RF was significantly better than ANN, SVM and kNN. KNN produced the worst result. Thus for this area, ensemble analysis of mapping result was not conducted. Comparison with an inclusion of lidar DEM in the classification is also displayed in Table 5. The contribution from lidar DEM is small. An addition of lidar DEM even decreased kNN classification accuracy. The error matrix is large due to the classification of 17 communities in this area and has been submitted separately as an Excel file.

Table 5. Performance of each machine learning classifier and ensemble analysis with/without lidar DEM.

	ANN	kNN	SVM	RF
Overall Accuracy (%)	65.3/64.8	52.7/57.8	67.7/61.9	73.1/73.1
Kappa Value	0.60/0.60	0.46/0.52	0.63/0.56	0.69/0.69

Table 6. McNemar test between different classifiers (* significance with 95% confidence when z-Score is greater than 1.96).

	ANN/kNN	ANN/SVM	ANN/RF	SVM/RF
z-Score	17.8*	4.8*	13.0*	9.4*

3.5 Vegetation community mapping

Classification maps from machine learning algorithms are displayed in Figure 12. In general, all classifiers produced a consistent spatial pattern with the existing map, but classification maps provide a more realistic/natural edge of each patch and presence of small patches within large communities. Regions covered by cloud could not be mapped. Uplands were further detailed into citrus groves (AN), Pine Flatwoods (PF), and Upland Hardwood (UH) in the classification map, as shown in Figure 13. For most regions, three classifiers generated consistent classification, as shown in green in the uncertainty map in Figure 12 (f). Red regions show a "warning sign" where classification from three classifiers are completely inconsistent.

3.6 Analysis

For this area, Dry Prairie (DP) was confused with Mixed Herbaceous Marsh (MH), and Submerged Aquatic Beds (SAB, a minor community) was confused with open water which includes water and free-floating plants. Palmetto Prairie (PP, a minor community) was confused with DP, HM, and Shrub Swamp (SS). Hardwood Swamp (HS) was confused with Shrub Swamp (SS) and Upland Hardwood (UH).

Both eastern and western LANS produced a lower accuracy than targeted accuracy of 85%. This can be caused by the complication of communities in this area due to inundation, multiple spectral signatures within a community, training sample selection, and/or segmentation. We will run eCognition multiresolution segmentation for this area to see if there is any improvement and compare the mapping results by data processing.

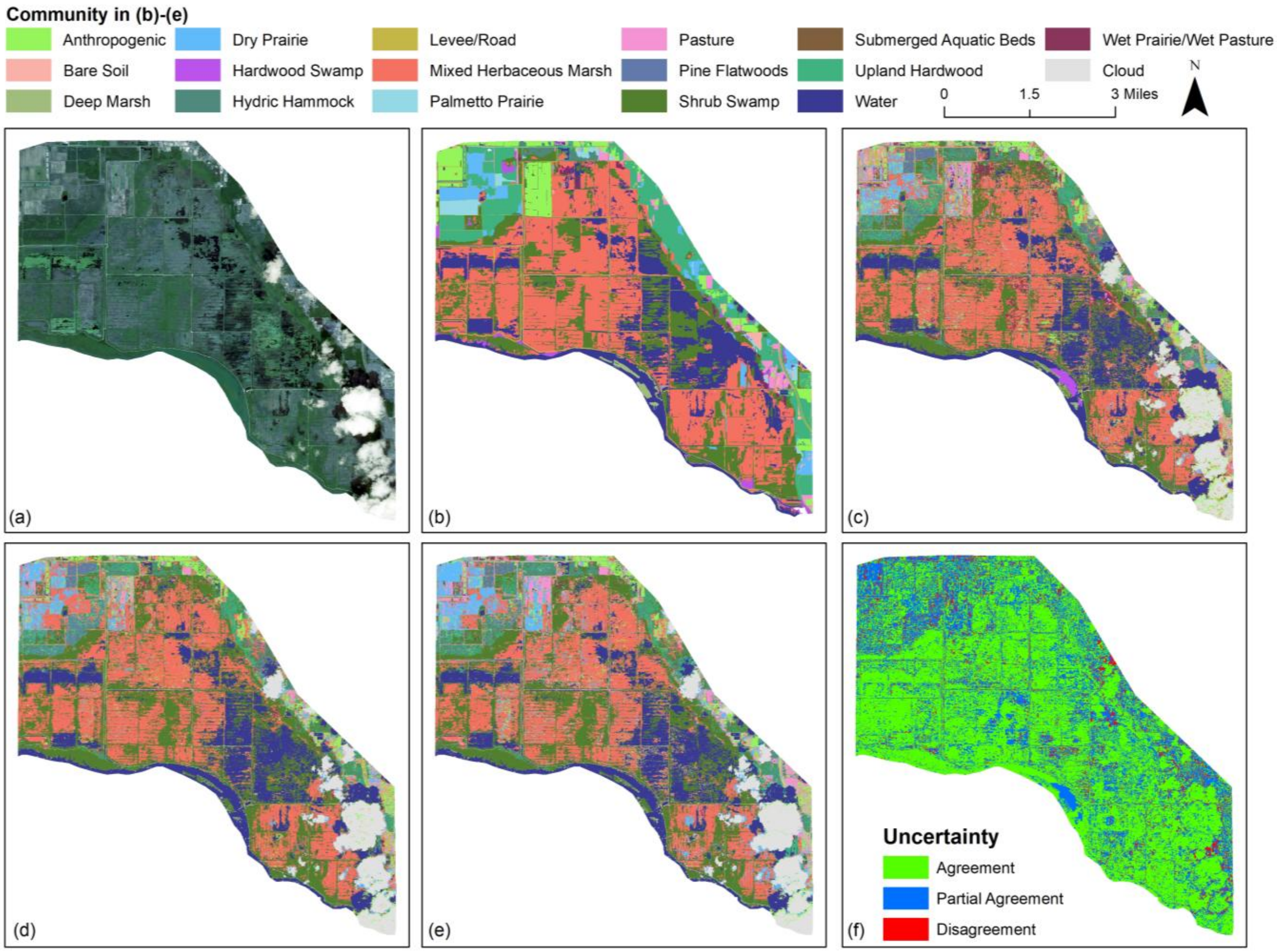


Figure 12. (a) WV-2 pansharpened imagery; (b) reference map from aerial photography; Object-based classifications from (c) RF, (d) SVM, (e) ANN, and (f) Uncertainty from ANN, SVM, and RF.

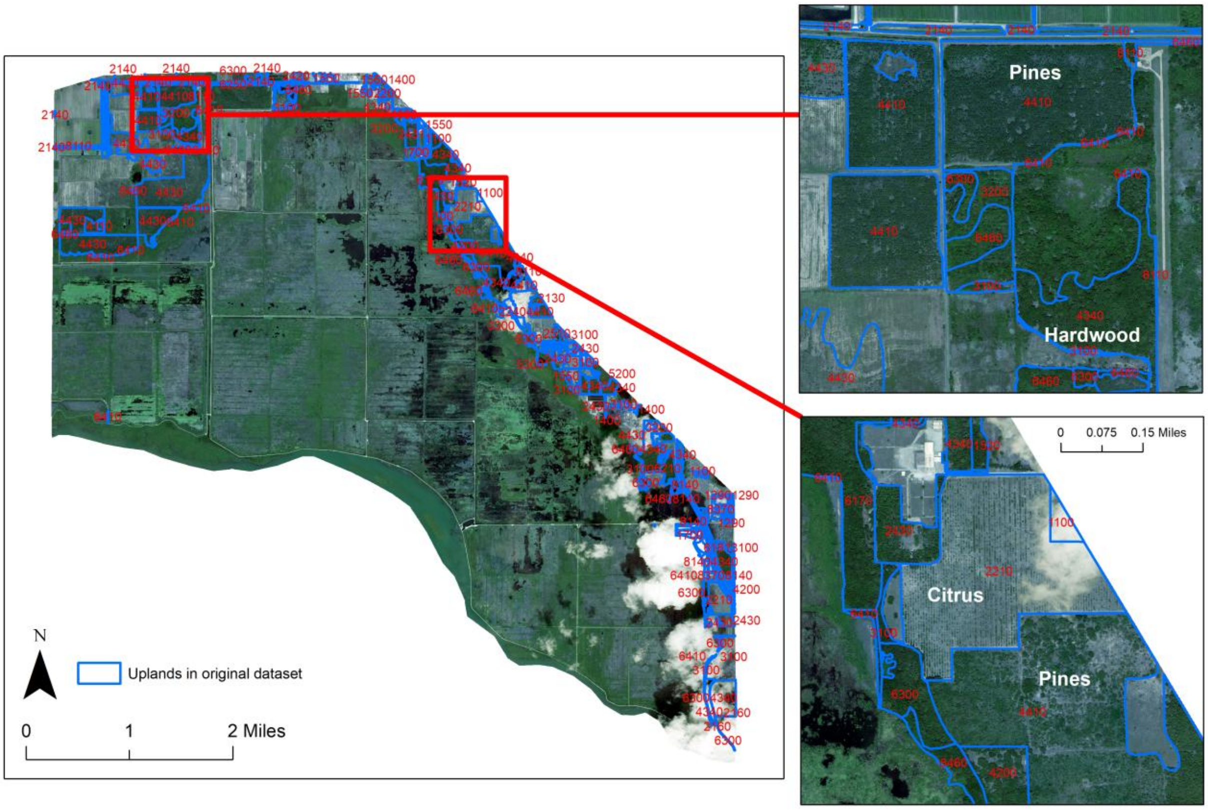


Figure 13. Uplands in the original vegetation dataset was further classified as Pine Flatwoods (PF), Citrus (AN), and Upland Hardwood (UH). 2014 Land Cover Land Use (LCLU) dataset labeled as red text (LCLU code) on the map helped identify pines, citrus, and hardwood to be used for training sample selection for upland areas.

4. Comparison of 8-band vs. 4 band

We compared 8-band panchromatic WV-2 imagery with 4-band panchromatic imagery for vegetation community classification. The OA and Kappa values from ANN, kNN, SVM, and RF classifications for OPRA, western LANS and eastern LANS are listed in Tables 7-9, respectively. The accuracy is slightly decreased using the 4-band panchromatic imagery for mapping OPRA and western LANS. For eastern LANS, application of 8-band imagery was more effective with a higher accuracy (Table 9). An inclusion of 4 extra bands using the 8-band panchromatic imagery in the classification procedure largely increases data volume, and thus application of 8-band panchromatic WV-2 imagery is not necessary. Application of eCognition will largely reduce the number of segments and reduce data volume. We will compare the results from eCognition and examine the necessity of 8-bands in mapping.

Table 7 Classification accuracies using 8-band/4-band 0.3-m panchromatic WV-2 imagery for community mapping in OPRA.

	ANN	kNN	SVM	RF
Overall Accuracy (%)	83.0/81.9	81.5/79.8	84.6/82.9	84.8/84.1
Kappa Value	0.74/0.72	0.72/0.70	0.76/0.74	0.77/0.76

Table 8 Classification accuracies using 8-band/4-band 0.3-m panchromatic WV-2 imagery for community mapping in western LANS.

	ANN	kNN	SVM	RF
Overall Accuracy (%)	65.3/63.6	65.3/63.9	66.4/66.1	74.3/73.4
Kappa Value	0.60/0.58	0.61/0.59	0.61/0.61	0.71/0.70

Table 9 Classification accuracies using 8-band/4-band 0.3-m panchromatic WV-2 imagery for community mapping in eastern LANS.

	ANN	kNN	SVM	RF
Overall Accuracy (%)	65.2/60.5	52.7/48.2	67.7/60.1	73.1/69.6
Kappa Value	0.60/0.54	0.46/0.41	0.63/0.54	0.69/0.65

5. Identified issues

The issue is mainly from the segmentation procedure. So far the Large Scale Mean Shift segmentation in OTB/QGIS is the only applicable algorithm in open source packages. But it took a long time to segment an image with a big size like this project (a few weeks for one imagery). In addition, this segmentation produces many segments which is challenging to handle in ArcGIS. To effectively deal with the large volume of segments from this algorithm, we had to spatially split the segmentation file into small files and run classification one by one. This would largely increase working time. In contrast, the multiresolution segmentation algorithm in eCognition produces reasonable segments and a manageable size of segmentation file for each area. We will run the mapping procedure using eCognition, and compare accuracy, time required in segmentation, segmentation quality, and data volume with OTB/QGIS to evaluate the usefulness of the open-source segmentation in next quarter.

6. Files for Quarter 2, 2021

Products in 2021 quarter 2 are summarized in Table 10, and are distributed to District via the District's ftp site.

Table 10. Products in Quarter 1 provided by FAU.

Areas	Products
Ocklawaha	ArcGIS shape files of ANN, SVM, RF, Ensemble Analysis, Uncertainty; Excel file of error matrix
Eastern Lake Apopka	
Western Lake Apopka	

Appendix 1: Tutorial Using TerraView for Image Segmentation

Background: We need to find a replacement for the multiresolution segmentation algorithm integrated in eCognition. ArcGIS Pro Mean Shift segmentation cannot generate a reasonable segmentation. Open source Large Scale Mean Shift segmentation which can be implemented in Python 3.5 or QGIS (https://www.orfeo-toolbox.org/CookBook/recipes/improc.html#large-scale-mean-shift-lsms-segmentation) can produce a reasonable segmentation but runs very slow. For segmenting imagery for one project area, we tested running the OPRA imagery on a normal high performance CPU Workstation, it took 5 days). The open source GIS software library/package and platform TerraLib/ TerraView has integrated two region-growing based segmentation algorithms. One is called "Region Growing Baatz" which uses the same algorithm as the multiresolution segmentation in eCognition developed originally by Baatz and Schäpe (2000). However, eCognition optimizes the algorithm by integrating a scale parameter to control the segment size and also it can export spectral mean, standard deviation and texture attributes automatically for each segment. Our tests showed that for the project area imagery, this algorithm does not work well. For a small area (<1 km^2) it may produce reasonable segmentation results.

1. Brief introduction of TerraLib and TerraView

TerraLib/TerraView is an open source GIS software library/platform available at wiki:about - TerraLib5 (inpe.br). You can quickly go through the web to know more about this GIS platform.

2. Download TerraView at wiki:downloads - TerraLib5 (inpe.br). The current version is 5.6.1. Download TerraView-5.6.1-win64.exe for Windows 64 bit system.

Download

TerraView Latest Releases

TerraView 5.6.1

Date	Platform	File	Documentation
2020/11/27	Win64	TerraView-5.6.1-win64.exe	Help_TView5.6.1 [1)]
2020/11/27	Mac OS Sierra	TerraView-5.6.1-macosx.dmg	
2020/11/27	Linux Ubuntu 18.04 LTS	TerraView-5.6.1-Ubuntu-18.04.tar.gz [2)]	

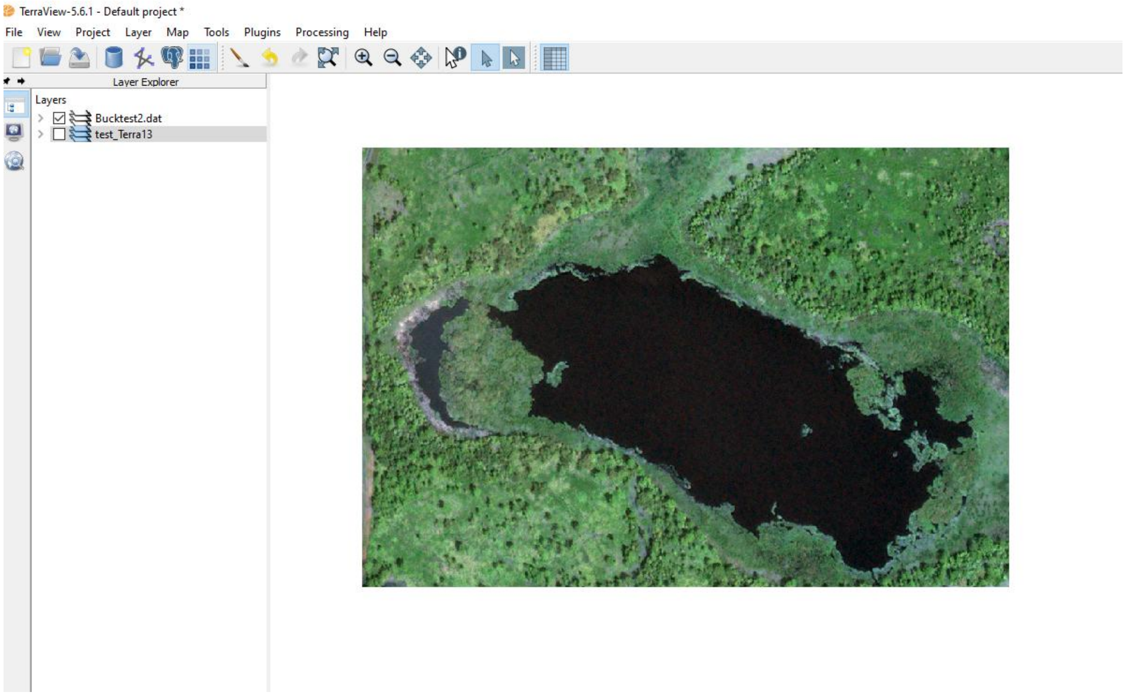
3. Install TerraView and Launch TerraView

4. Load in the raster imagery in TerraView

Go to: Project->Add Layer-> Raster File. Both *.tif, *.dat can be loaded in TerraView.

To show the imagery after load in, click the Zoom Extent Icon ()

A test image for part of Buck Lake area as a raster .dat file is loaded and shown in TerraView as below.

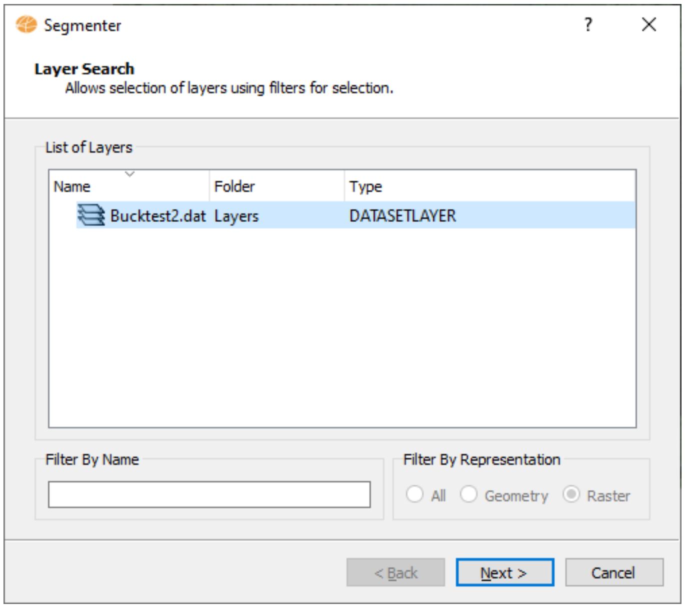


Interface of TerraView after loading in the imagery.

5. Run Region Growing Baatz

Region Growing Baazt is located at: Processing->Raster Processing->Segmenter…
The wizard will go through the segmentation procedure.

- Wizard Page 1: select the raster layer you want to segment, and then click Next



Wizard page 1 interface.

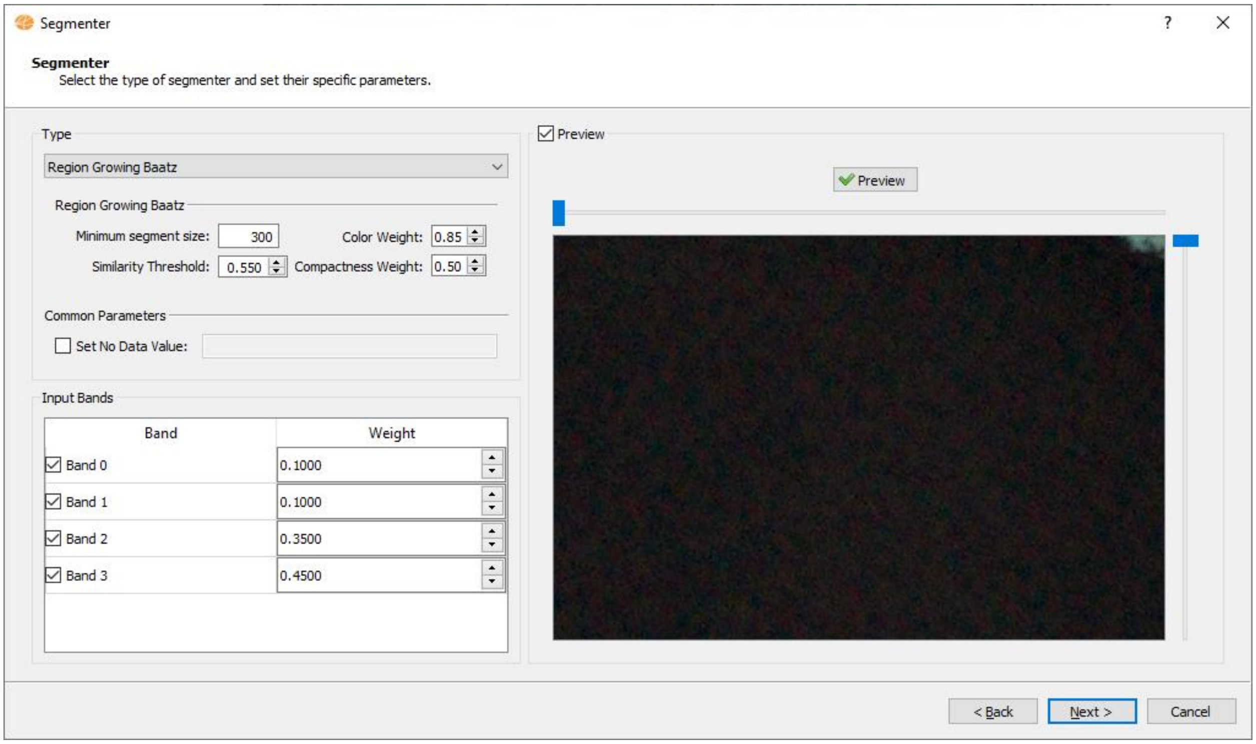
- Wizard Page 2 - Segmentation interface: Set parameters required by Region Growing Baatz.
  Type - Choose the method of segmentation and set the specific parameters required.
  Here we select Region Growing baatz

  Minimum segment size: A positive minimum segment size (pixels number).
  Here we set it to 300
  Similarity Threshold: Use lower values to merge only those segments that are more similar - Higher values will allow more segments to be merged - valid values range: positive values - default: 0.1.
  Here we set it to 0.55
  Color Weight: The weight given to the color component, default: 0.75, valid range: [0,1].
  Here we set it to 0.85
  Compactness Weight: The weight given to the compactness component, default: 0.5, valid range: [0,1].
  We set it to default 0.5

  Common Parameters:

  No Data: If checked, no data value will be used as the no-data value for input rasters.

  Select the *Input Bands* to be segmented by checking its box. For Baatz method, it is also possible to change *Weight* (The weight given to each band (note: the bands weights sum must always be 1) or an empty vector indicating that all bands have the same weight.)
  Preview - optionally click onto check the segmentation of a small box of the image.
  Press **Next** to go to next step, **Back** to check the previous wizard page or **Cancel** to close the dialog.
  Here note that, we set a higher Color weight because spectral value is more important than shape value because our projects areas are natural landscapes. We can also set a higher weight for NIR and Red band because they are more important for vegetation delineation than other bands.
  Screenshot of Wizard page 2 for Buck Lake is displayed below.



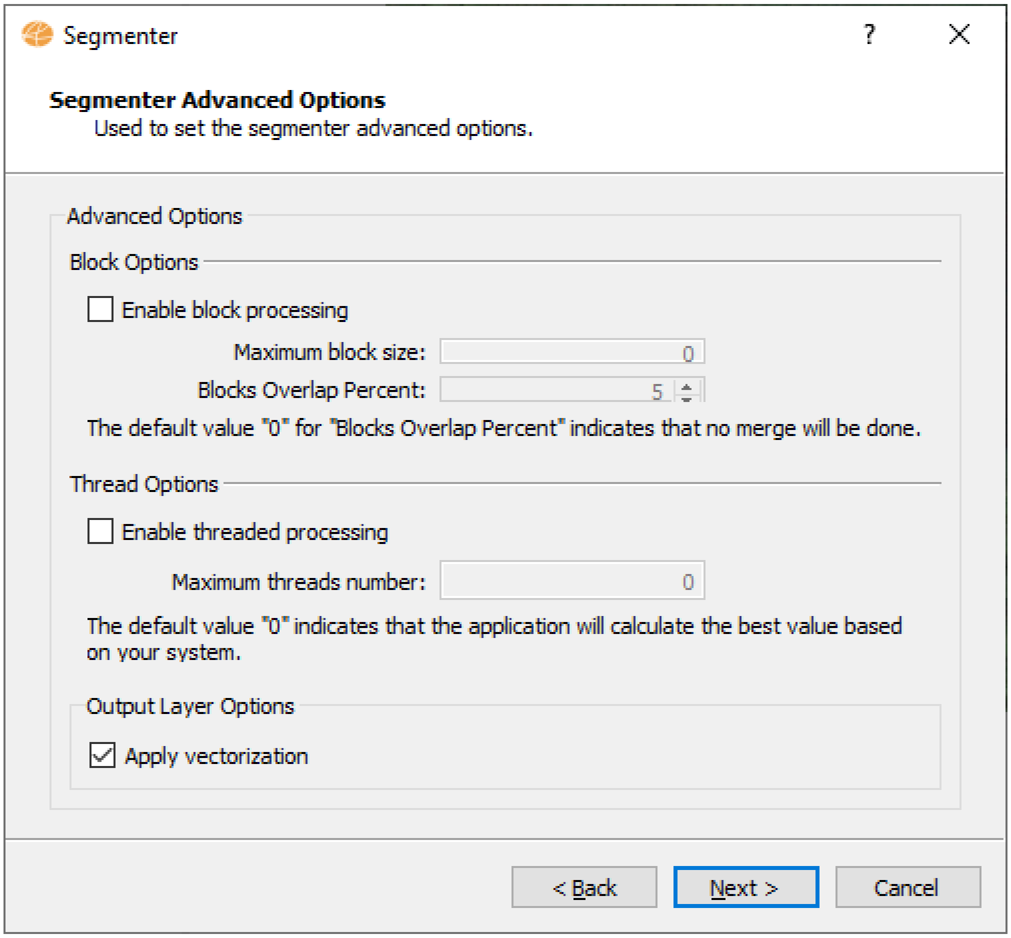
Wizard page 2 interface.

- **Wizard Page 3 - Segmentation Advanced parameters interface.**

Optionally, use this page to change default values of advanced parameters related with performance.

Block options:
Enable block processing: If checked, the original raster will be split into small blocks, each one will be segmented independently and the result will be merged (if possible) at the end.
Enable block merging: If checked, a block merging procedure will be performed
If the imagery is relatively small, just simply uncheck block processing
Thread options:
Maximum block size: The input image will be split into blocks with this width for processing, this parameter tells the maximum block lateral size (width or height). The default behavior, the size will be defined following the current system resources and physical processors number.
Maximum threads number: The maximum number of concurrent threads. The default behavior is: automatically found.

Check Apply vectorization



Wizard Page 3 interface.

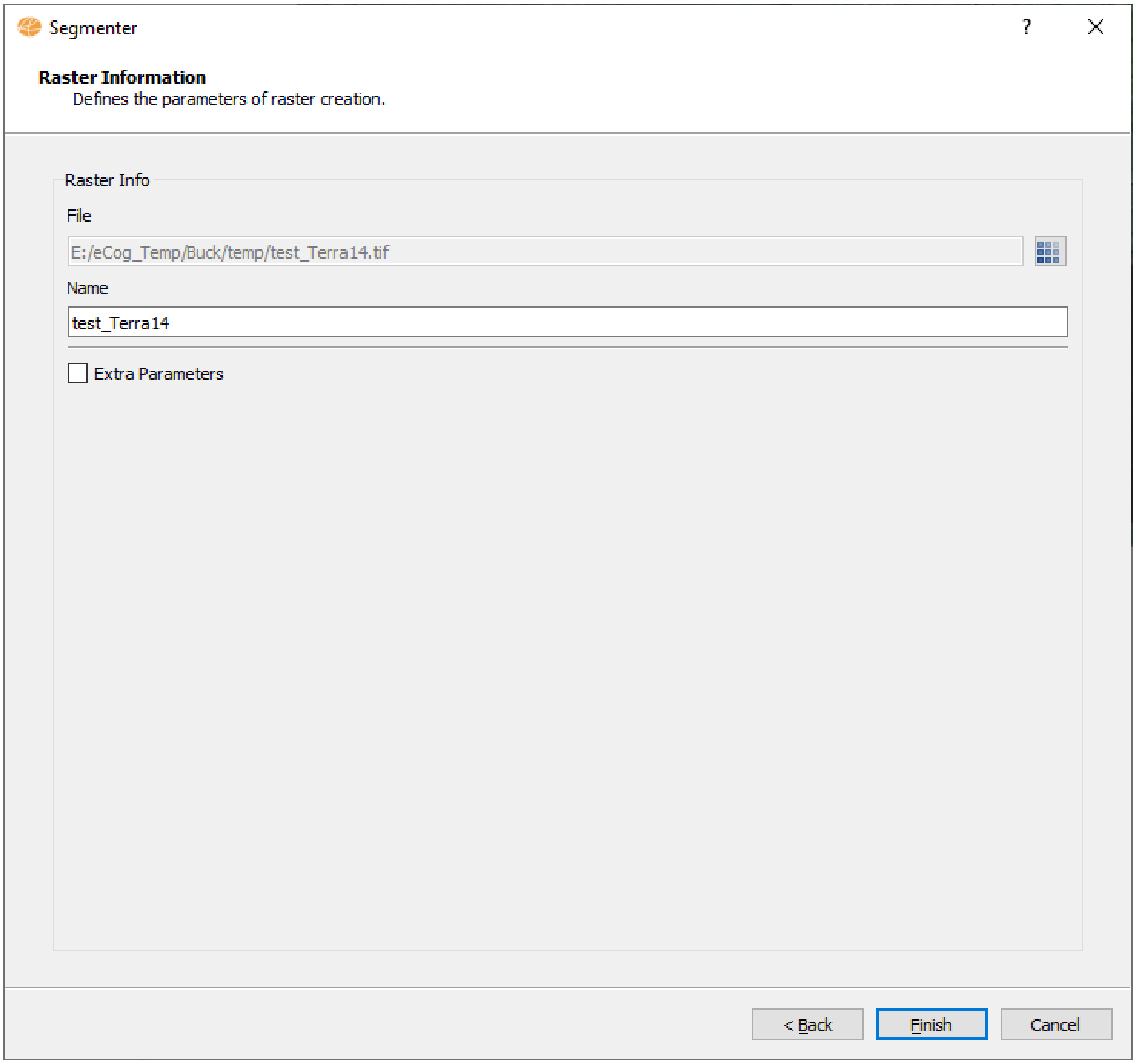
- **Wizard Page 4 - Output Raster information**

Raster Info - First press  and inform the folder where the resulting file will be saved.
Name - inform the raster name.
Extra Parameters - if there are some, see the details on how to inform then here.

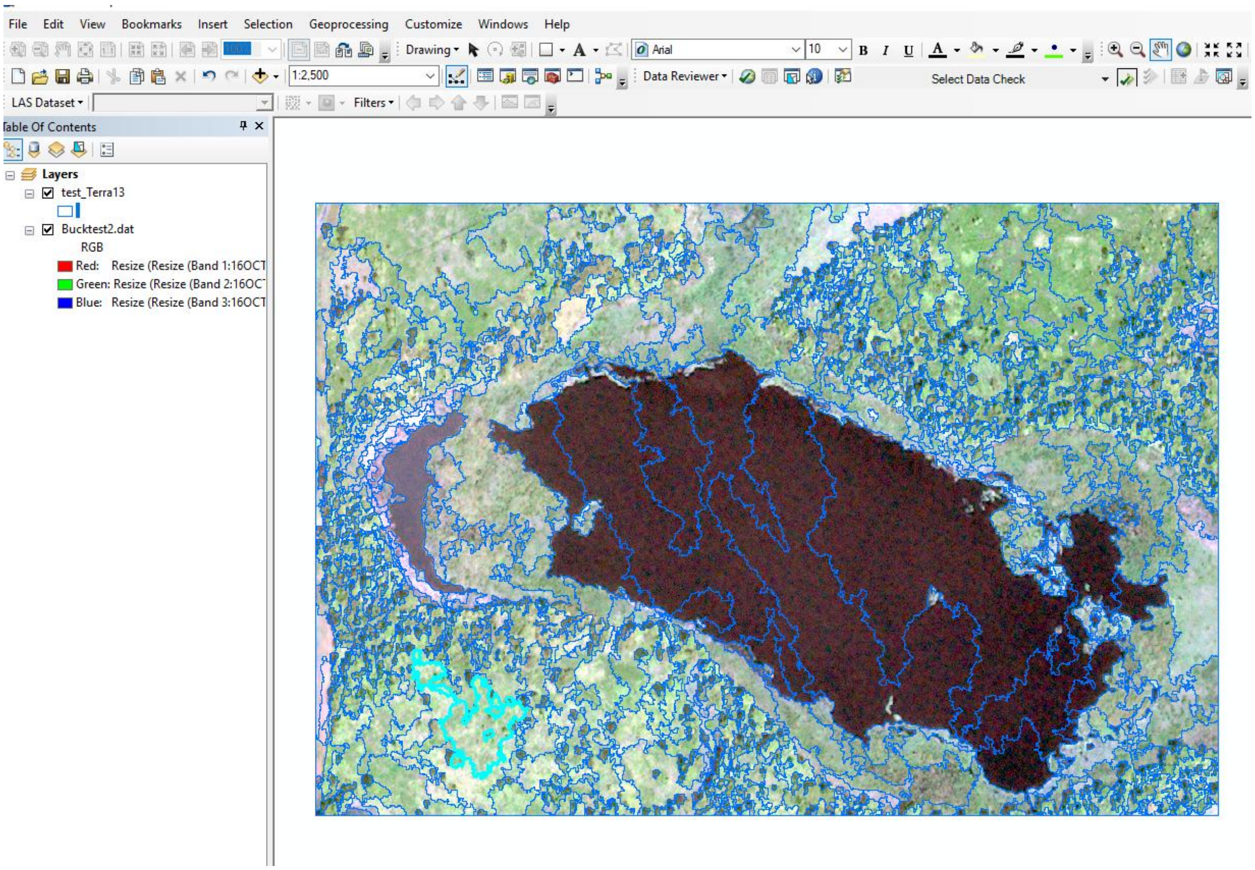
Press **Finish** to save the resulting segmented raster or **Back** to go to the previous wizard page.

An ArcGIS shapefile is also saved with the same name as the raster segmentation tif file in the same folder you selected. This is what we need.

Screenshot of Wizard Page 4 and segmentation result for part of Buck Lake is shown below.



Wizard page 4 interface.



References

Baatz, M. and Schäpe, A. “Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation”. In: XII Angewandte Geographische Informationsverarbeitung, Wichmann-Verlag, Heidelberg, 2000.